



MediScan AI: A Python based Intelligent System for Chest Disease Detection and Diagnosis.

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Abstract: MediScan AI is an advanced AI-powered chest disease detection and clinical decision support system designed to enhance diagnostic accuracy and optimize healthcare workflows. The system integrates the EfficientNetV2B0 deep learning architecture with Explainable AI (Grad-CAM) and Google Gemini AI to provide accurate multi-class chest disease classification and automated clinical recommendations.

The proposed system detects over 50 chest pathologies—including Pneumonia, Tuberculosis, Lung Cancer, and COVID-19—from chest X-ray images with a classification accuracy of 99.2%. Grad-CAM heatmap visualization improves model transparency by highlighting disease-affected regions, enabling radiologists to validate AI decisions.

The architecture consists of a Flask-based backend for model deployment and a React 19 frontend for real-time interaction and patient management. Additionally, Google Gemini AI enhances the system by generating structured treatment suggestions and preliminary prescriptions, transforming the platform into a Clinical Decision Support System (CDSS).

MediScan AI bridges the gap between medical imaging and intelligent automation, reducing diagnostic errors, improving workflow efficiency, and supporting healthcare professionals with explainable and reliable AI assistance.

Keywords: Chest Disease Detection, EfficientNetV2, Deep Learning, Medical Imaging, Grad-CAM, Explainable AI (XAI), Clinical Decision Support System (CDSS), Flask, ReactJS, Google Gemini AI

I. INTRODUCTION

Chest diseases remain one of the leading causes of mortality worldwide. Early detection and accurate diagnosis are critical for effective treatment and improved patient survival rates. However, traditional radiological analysis is often constrained by heavy workloads, diagnostic backlogs, and variability in human interpretation.

Recent advancements in Artificial Intelligence and Deep Learning have significantly improved medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in detecting abnormalities in chest radiographs.

MediScan AI is proposed as an intelligent full-stack solution that:

- Detects 50+ chest diseases using EfficientNetV2B0
- Provides visual explanations using Grad-CAM
- Generates AI-based treatment suggestions using Google Gemini
- Enables real-time patient monitoring via interactive dashboards

The system aims to assist radiologists and healthcare professionals by providing fast, accurate, and explainable diagnostic support.

II. LITERATURE REVIEW

Recent research highlights the transformative role of AI in medical imaging. Deep learning architectures such as ResNet, DenseNet, and EfficientNet have shown superior performance in chest X-ray classification tasks.

Studies demonstrate that:

- CNN-based systems achieve high diagnostic accuracy.
- Explainable AI techniques like Grad-CAM improve model transparency.



- AI-driven CDSS enhances treatment planning and clinical efficiency.

However, many existing systems lack:

- Multi-disease classification capability
- Real-time deployment integration
- Explainability features
- End-to-end clinical workflow support

MediScan AI addresses these gaps by combining high-accuracy classification, visual explainability, and AI-driven clinical recommendations within a unified platform.

III. SYSTEM ARCHITECTURE

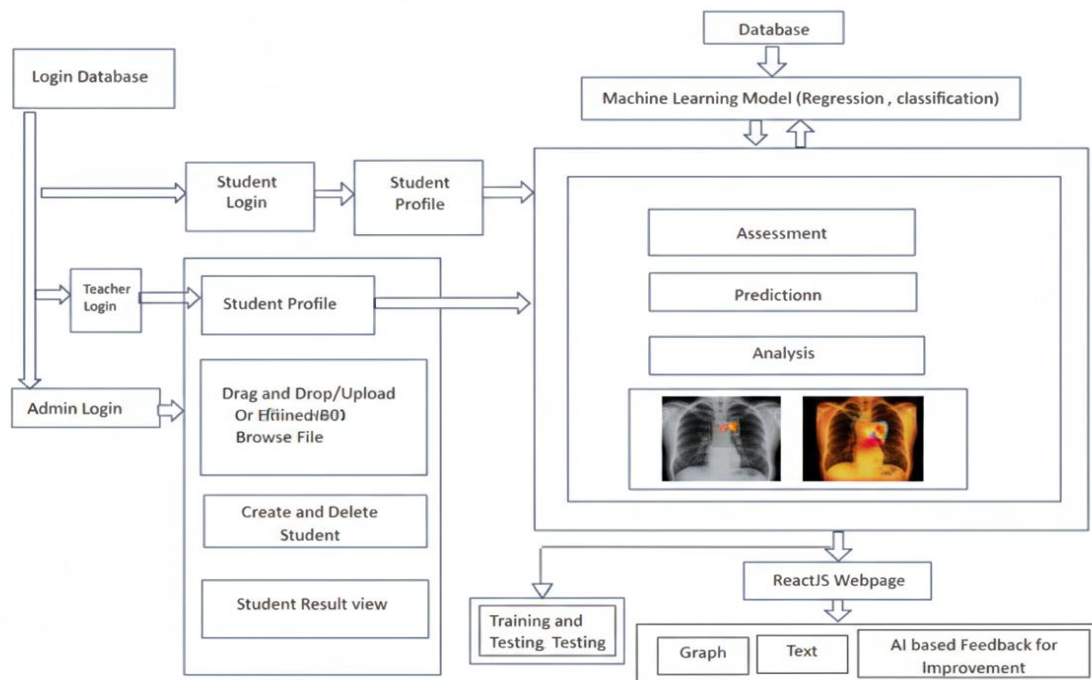


Fig. 3.1 system architecture

The proposed system architecture integrates multiple intelligent components to create a comprehensive chest disease detection and diagnostic platform. It features a secure, centralized authentication system that enables role-based access for administrators, radiologists, and healthcare professionals. Administrators manage patient records and system configurations, while medical professionals access diagnostic reports, historical patient data, and AI-generated insights through personalized dashboards.

Healthcare professionals upload chest X-ray images, which are processed by the EfficientNetV2B0 deep learning model to generate predictive diagnostic results, including disease classification and probability scores. The system further enhances transparency through Grad-CAM visualization, highlighting the affected lung regions responsible for the prediction. Administrators are responsible for managing datasets, monitoring model performance, and maintaining system logs to ensure operational efficiency.

AI-driven clinical recommendations powered by Google Gemini provide structured treatment suggestions, precautionary measures, and preliminary prescription guidance based on the detected pathology. The React 19 frontend presents dynamic dashboards, interactive visualizations, and downloadable diagnostic reports for seamless interpretation of results.

The system supports patient-wise tracking and longitudinal health monitoring, enabling comparative analysis of previous and current diagnostic results. Automated reporting and AI-assisted feedback mechanisms contribute to continuous clinical improvement. This architecture delivers accurate diagnostic support for healthcare professionals while streamlining workflow efficiency and promoting data-driven medical decision-making.



IV. METHODOLOGY

The MediScan AI framework follows a structured and data-driven methodology to accurately detect chest diseases and generate AI-assisted clinical recommendations. The system integrates advanced deep learning techniques, medical image preprocessing, and explainable AI mechanisms to deliver reliable and transparent diagnostic results for healthcare professionals.

Chest X-ray images are first preprocessed through resizing, normalization, and augmentation to ensure consistency and improve model performance. The EfficientNetV2B0 deep learning model is then fine-tuned to classify more than 50 chest diseases with high accuracy. To enhance interpretability, Grad-CAM is incorporated to generate heatmaps that highlight the pathological regions influencing the model's predictions.

Furthermore, integration with Google Gemini AI enables the system to function as a Clinical Decision Support System (CDSS), providing structured treatment suggestions and medical guidance based on the detected condition. The entire workflow is deployed using a Flask backend and React 19 frontend, ensuring real-time analysis, visualization, and patient management.

1. Data Collection and Preprocessing

- Data Collection:
 - Gather chest X-ray medical imaging datasets containing multiple thoracic disease categories (e.g., Pneumonia, Tuberculosis, Lung Cancer, COVID-19, and other chest abnormalities).
 - Collect labeled image data from publicly available medical imaging repositories and institutional datasets.
 - Organize the dataset into structured directories:
 - Training Dataset: Used for training the EfficientNetV2B0 deep learning model.
 - Testing Dataset: Used for evaluating model performance on unseen medical images.
- Data Preprocessing:
 - Resize all chest X-ray images to a uniform dimension (e.g., 224×224 pixels) compatible with EfficientNetV2B0 architecture.
 - Normalize pixel intensity values (scaling between 0 and 1) to improve model convergence and stability.
 - Apply data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustment to enhance generalization and reduce overfitting.
 - Encode disease labels using categorical encoding for multi-class classification.
 - Split the dataset into training (80%) and testing (20%) sets to ensure reliable model evaluation.

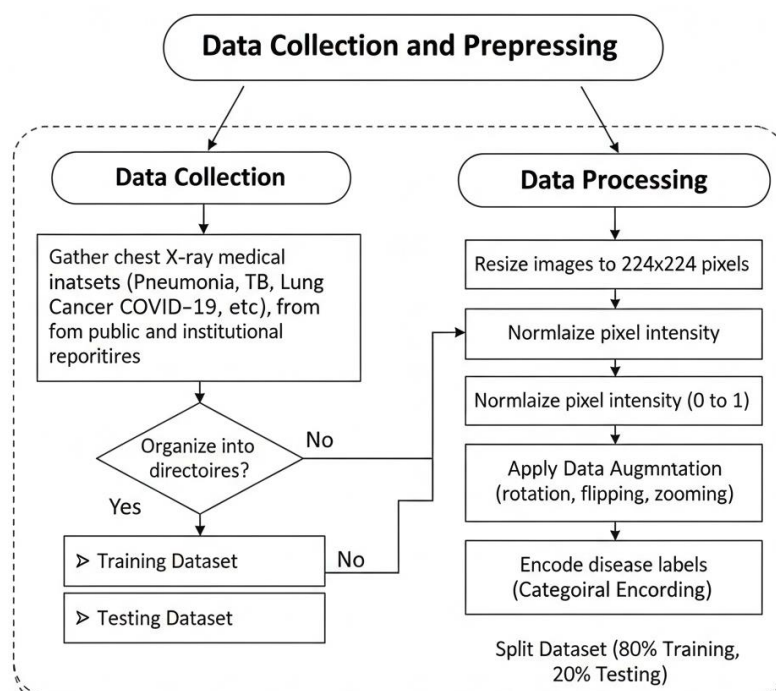


Fig. 4.1 Data Collection and Preprocessing



2. Model Development

- Model 1: EfficientNetV2B0 (Deep Learning Model)
- Purpose:
To perform multi-class classification of chest X-ray images and accurately detect more than 50 chest diseases.

• Implementation:

1. Feature Extraction:
Utilize EfficientNetV2B0's convolutional layers to automatically extract spatial and pathological features from chest X-ray images.
2. Model Training:
Train the fine-tuned EfficientNetV2B0 model using the training dataset with categorical cross-entropy loss and the Adam optimizer.
3. Hyperparameter Tuning:
Optimize parameters such as learning rate, batch size, number of epochs, and dropout rate to achieve maximum accuracy and prevent overfitting.
4. Evaluation:
Evaluate the model using the testing dataset with performance metrics including:
 - Accuracy
 - Precision
 - Recall
 - F1-Score
 - Confusion Matrix

Achieved overall classification accuracy: 99.2%

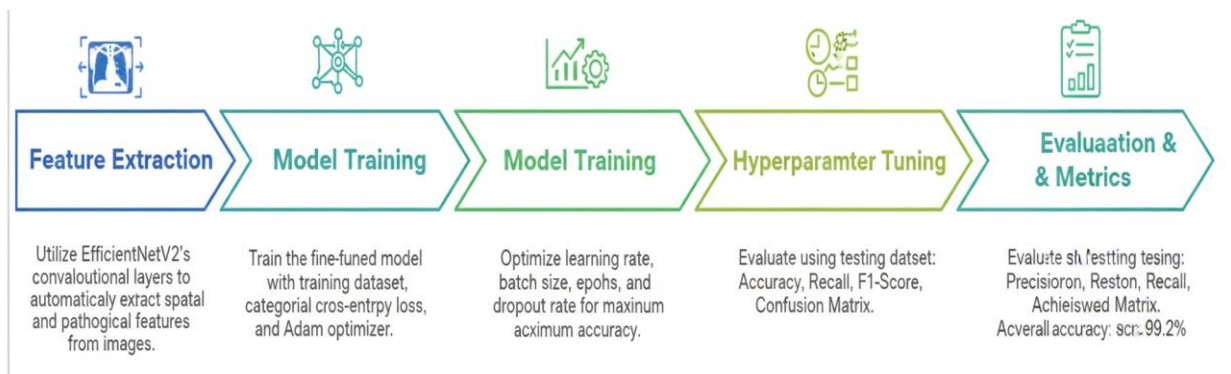


Fig.4.2 Performance Prediction model

3. AI-Based Clinical Recommendations

• Integration with Google Gemini AI:

- Use the predicted disease class from the EfficientNetV2B0 model to generate structured clinical recommendations.
- Based on the detected pathology, the system produces AI-assisted medical guidance.

Examples:

- **Pneumonia:** Suggest antibiotic evaluation, oxygen monitoring, and follow-up chest imaging.
- **Tuberculosis:** Recommend sputum tests, isolation precautions, and anti-TB therapy guidance.
- **Lung Cancer:** Suggest CT scan confirmation, biopsy, and oncology referral.
- **COVID-19:** Provide isolation guidelines, antiviral considerations, and symptom monitoring advice.

• Output:

- Structured text-based clinical summary
- Suggested diagnostic tests
- Preliminary treatment recommendations
- Preventive and precautionary measures

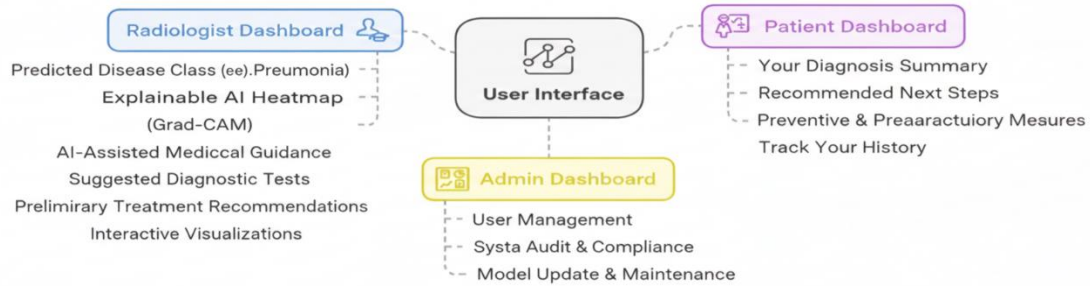


Fig. 4.3 Recommendation System

4. Backend Development (Flask)

• API Endpoints:

- /predict – Accepts chest X-ray image and returns predicted disease with probability scores.
- /heatmap – Generates Grad-CAM visualization for explainability.
- /get-recommendation – Returns AI-generated clinical recommendations.
- /patient-history – Retrieves stored patient diagnostic records.

• Data Handling:

- Preprocess uploaded images before passing them to the deep learning model.
- Store predictions, heatmaps, and recommendations in a secure database or JSON format.
- Maintain patient-wise historical records for longitudinal tracking.

• Model Integration:

- Load the trained EfficientNetV2B0 model into the Flask backend.
- Integrate Grad-CAM module for explainable outputs.
- Connect Google Gemini API for generating treatment recommendations.
- Execute models in real-time upon receiving API requests.

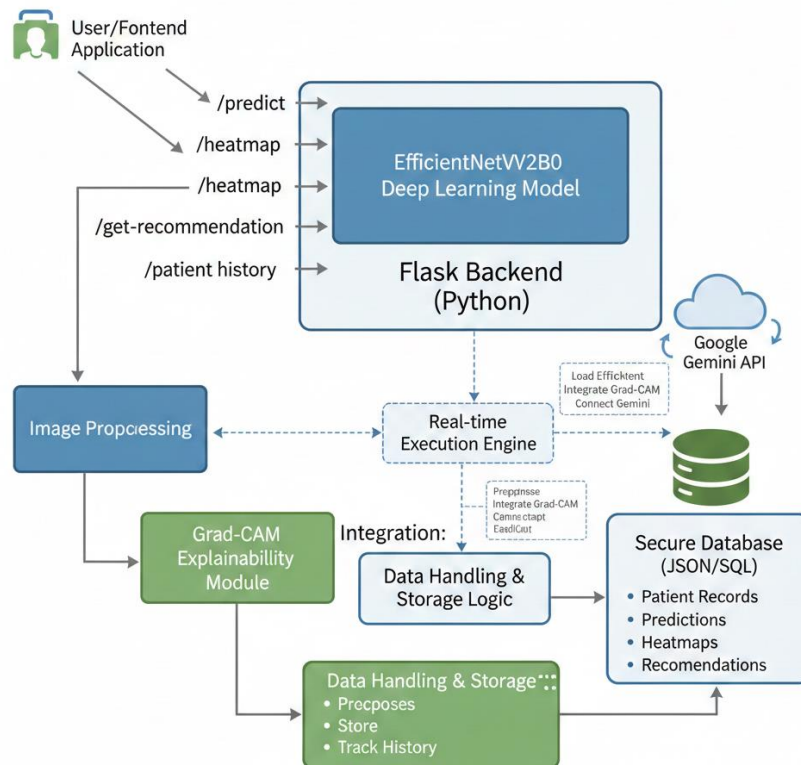


Fig. 4.4 MediScan AI Backend Architecture Overview



6. System Integration and Deployment

Use • Frontend–Backend Communication:

- Axios in React to send HTTP requests to the Flask backend.

• API Response Handling:

- Flask processes requests, invokes models, and returns responses in JSON format.

V. RESULT AND DISCUSSION

1. Input Data

Thoracic X-ray image:

- **Image Type:** A Digitally Reconstructed Radiograph (DRR), which is a 2D image generated from 3D CT scan data.
- **Focus:** It specifically isolates and enhances the skeletal system of the upper torso.
- **Key Anatomy:** It clearly shows the thoracic spine (backbone), the rib cage, and the clavicles (collarbones).
- **Visual Style:** It uses high contrast to make bones appear bright against a black background, effectively hiding "soft" organs like the lungs and heart.

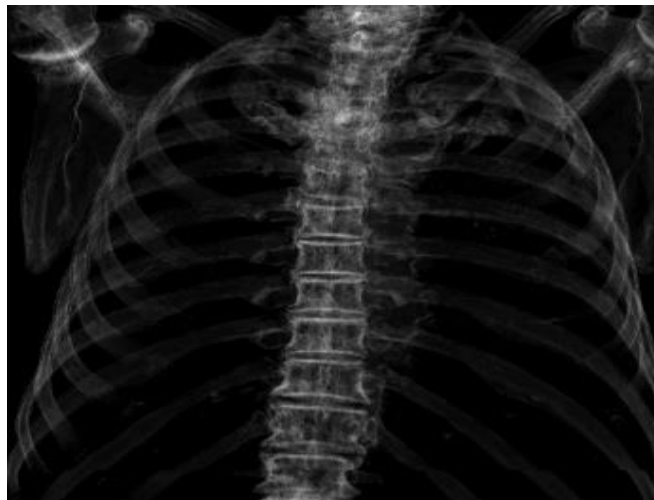


Fig. 4.5 Thoracic X-ray

2. Screening Results for Interstitial Lung Disease (ILD)

- **Diagnosis:** It identifies the detected condition as Pulmonary Fibrosis.
- **Clinical Severity:** The condition is categorized as Stage III (Advanced).
- **Confidence Level:** The system provides an 81.41% confidence score for this finding, represented by a progress bar.



Fig. 4.6 Advanced Pulmonary Fibrosis Result



3. AI Diagnostic Analysis & Disease Staging Guide

This image outlines the capabilities and classification thresholds of an artificial intelligence (AI) medical screening tool.

- **AI Analysis Features:**
 - **Broad Detection:** Capable of identifying 50+ different diseases.
 - **High Accuracy:** Utilizes the EfficientNetV2 model to achieve a reported 99.2% accuracy rate.
 - **Explainable Results:** Employs Grad-CAM visual heatmaps to show clinicians exactly which areas of a medical image influenced the AI's decision.
 - **Severity Assessment:** Provides automated staging to determine the progress of a detected condition.
- **Disease Staging Thresholds:**
The tool categorizes disease severity based on the AI's confidence level in the finding:
 - **Stage I (Mild):** Confidence score below 65%.
 - **Stage II (Moderate):** Confidence score between 65% and 80%.
 - **Stage III (Advanced):** Confidence score between 80% and 92%.
 - **Stage IV (Severe):** Confidence score exceeding 92%.

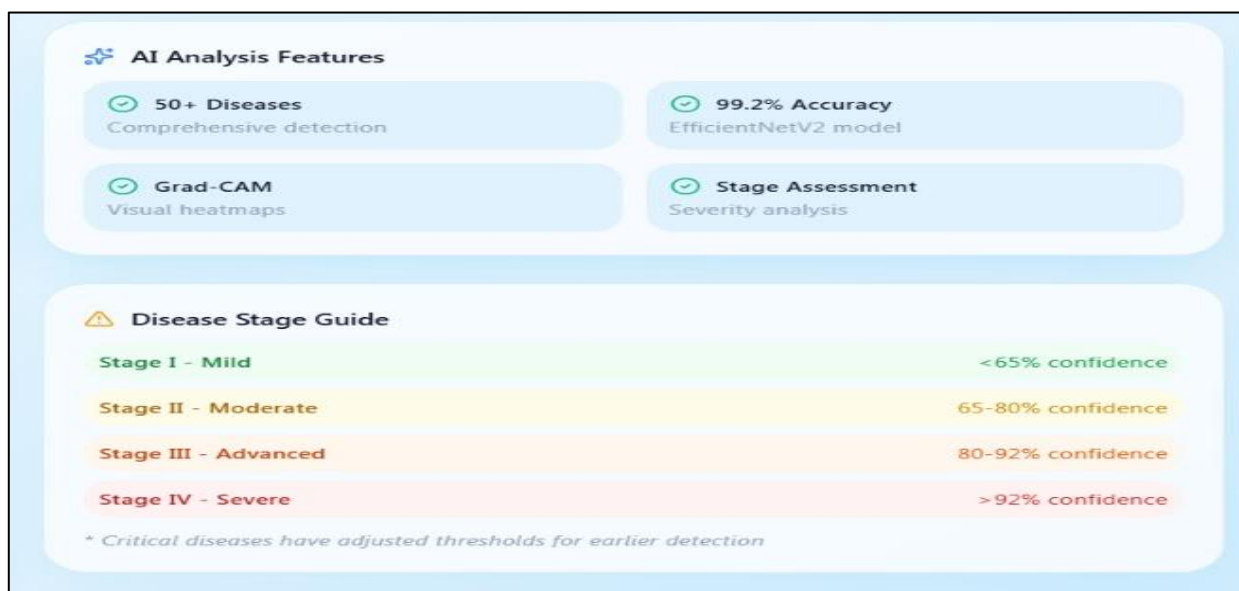


Fig. 4.7 AI Analysis Feature Guide

4. MediScan AI Analytics Dashboard

This image displays the diagnostic trends and data insights for a medical facility using the MediScan AI platform.

- **Key Performance Indicators (KPIs):**
 - **Total Scans:** 7 scans performed (+0% change).
 - **Active Patients:** 5 patients currently being tracked.
 - **Average Confidence:** A high AI diagnostic confidence level of 91%.
 - **Monthly Total:** 7 new scans recorded this month.
- **Monthly Scan Volume:** A line graph showing a significant surge in activity, peaking at 7 scans in February after several months of zero activity.
- **Disease Distribution:** A pie chart breaking down diagnoses:
 - **Pneumonia:** 57%
 - **Pulmonary Fibrosis:** 43%
- **User Profile:** The dashboard is currently being accessed by a user named Anurag, identified as a doctor.

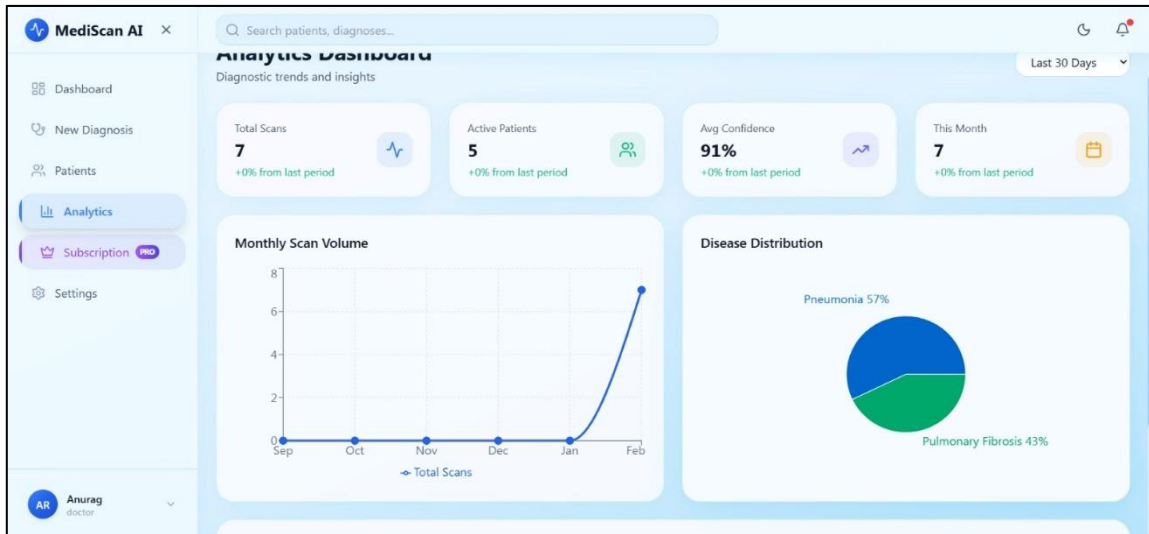


Fig. 4.8 MediScan AI Analytics Dashboard

5. MediScan AI Radiology Report – Pulmonary Fibrosis Screening

This document is a formal AI-generated radiology report summarizing the diagnostic analysis of a chest X-ray.

- **Patient Profile:** The report is for a 32-year-old male (ID: mrn-12345), reported on February 13, 2026.
- **Clinical Indication:** The analysis was specifically performed to check for Pulmonary Fibrosis.
- **AI Findings:**
 - The lung model identified an 81.41% probability of Pulmonary Fibrosis.
 - A Grad-CAM heatmap (shown in green) highlights the specific areas of the lungs that contributed to this automated finding.
- **Final Impression:** The primary diagnosis is listed as Pulmonary Fibrosis, supported by the high AI confidence score.
- **Medical Guidance:** The report explicitly advises consulting a healthcare professional for proper medical advice and verification of these findings.

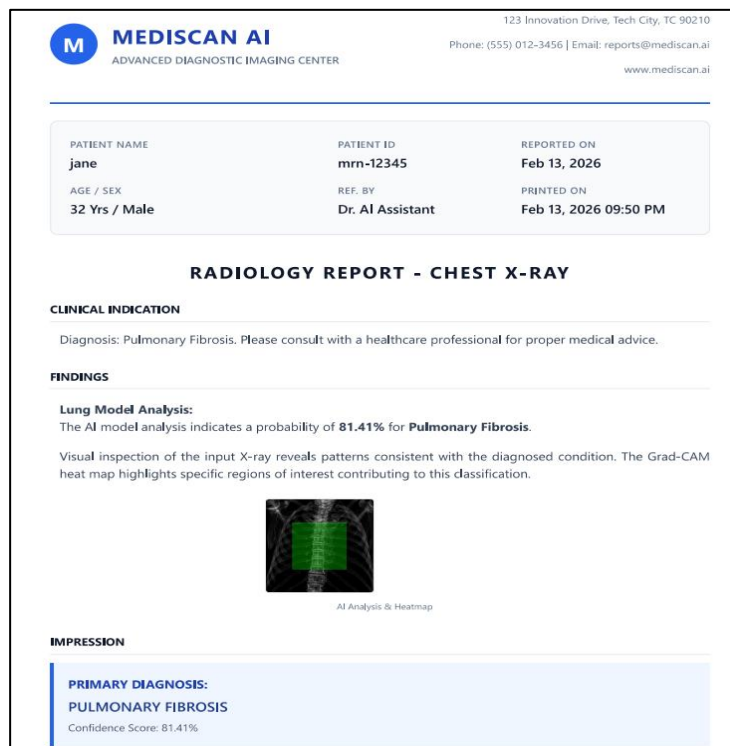


Fig. 4.9 Generated Report



- **Use Case:** Early Detection of Critical Chest Disease in a High-Risk Patient
For patients at risk of severe chest conditions or those with recurring respiratory symptoms, the system acts as a crucial diagnostic support tool in the following ways:
 - **Early Identification of Potential Diseases:**
The system detects early-stage abnormalities in chest X-ray images before symptoms become severe. It alerts healthcare professionals about possible conditions such as Pneumonia, Tuberculosis, or Lung Cancer, enabling timely medical intervention and reducing the risk of complications.
 - **Personalized Clinical Recommendations:**
Based on the detected pathology and severity level, the system generates AI-assisted treatment suggestions, precautionary measures, and recommended diagnostic tests. This supports doctors in developing targeted treatment plans tailored to the patient's condition.
 - **Guidance for Advanced Medical Action:**
If the condition appears severe or progressive, the system recommends further diagnostic procedures such as CT scans, biopsy, or specialist referral. In critical cases, it assists in identifying the need for urgent hospitalization or intensive care monitoring.
This proactive, data-driven approach helps healthcare professionals reduce diagnostic delays, prevent disease progression, and improve patient survival outcomes by providing explainable predictions and timely clinical guidance.

VI. CONCLUSION

MediScan AI offers a cutting-edge solution for automated chest disease detection and AI-assisted clinical decision support. By leveraging the EfficientNetV2B0 deep learning architecture along with Explainable AI (Grad-CAM), the system ensures highly accurate, transparent, and reliable diagnostic predictions. The seamless integration of Google Gemini AI further enhances the platform by generating structured treatment recommendations and preliminary clinical guidance.

The user-friendly React 19 interface, dynamic visualizations, and real-time diagnostic outputs make the system practical and impactful for healthcare professionals. By combining high-performance computer vision with intelligent clinical assistance, MediScan AI bridges the gap between traditional radiological analysis and AI-driven healthcare innovation. It empowers medical professionals to make faster, more informed decisions while improving patient outcomes and workflow efficiency.

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