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Smart Lung Health Monitoring and Doctor–Patient Assistance System

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ABSTRACT

Lung diseases are among the major health concerns worldwide, requiring early detection and continuous monitoring. This paper presents an intelligent, web-based prediction system that utilizes patient vital parameters such as heart rate, temperature, oxygen level, and other health indicators to predict the likelihood of lung disease risk. The system provides two main user roles—Doctor and Patient. Patients can log in, input their vital signs, and receive real-time predictions categorized as “Normal” or “At Risk,” along with a personalized plan including medicine, food, and lifestyle recommendations. Doctors can log in to a secure dashboard to view pie chart visualizations, access patient records, and provide consultation or operation advice. The system is implemented using Flask and Python integrated with a trained deep learning model. The proposed framework enables efficient, accessible, and AI-assisted early diagnosis support for both patients and healthcare practitioners.

Keywords: Lung disease, Deep learning, Flask, Patient vitals, Health monitoring, Web application.

INTRODUCTION

Lung-related issues are life-threatening conditions that require accurate and timely detection. Early prediction using non-invasive vital parameters can effectively assist healthcare professionals and minimize diagnostic delays. Traditional prediction systems rely on manual analysis and laboratory reports, causing delays and inaccuracies. The proposed system aims to develop a web-based platform that predicts lung disease risk using only patient vitals, thus simplifying health assessment and remote monitoring. The solution enables data-driven decisions and promotes digital healthcare accessibility.

RELATED WORK

Several research studies have proposed machine learning and deep learning-based medical prediction systems. Existing works primarily focus on image-based diagnosis or symptom-based classification. However, most systems lack real-time, dual-role (Doctor/Patient) interfaces and integrated advisory features. Studies using decision trees, logistic regression, and CNNs have shown satisfactory performance but often require complex data and computing resources. Our framework distinguishes itself by emphasizing vital-based risk prediction, lightweight architecture, and clinician-friendly dashboards.

PROPOSED SYSTEM

The proposed system consists of a Flask-based web platform that processes patient vitals to predict potential lung disease risks. It features two major roles: Doctor and Patient. The application flow is structured as follows:

- Welcome Page – Select Role (Doctor / Patient)
- Patient Role – Login → Enter Vitals → Predict → Result (Normal / Risk) → View Personalized Plan (Medicine + Food + Lifestyle + Advice) → Thank You Page
- Doctor Role – Login → Dashboard (Pie Chart Visualization) → Select Category (Risk / Normal) → View Patient List → Open Recommendation → Consult / Operation Advice → Thank You Page

The architecture integrates a backend Flask server, a deep learning model for classification, and a lightweight visualization module for real-time feedback. The modular design ensures scalability and supports addition of further datasets such as X-rays in future versions.

MODULES DESCRIPTION

- Login Module – Provides authentication for both roles using username and password.
- Vital Entry Module – Patients input parameters like SpO₂, temperature, and heart rate.
- Prediction Module – Utilizes pre-trained model to classify patient state as “Normal” or “At Risk.”
- Dashboard Module – Displays a pie chart of patient distribution and allows doctors to view records.
- Recommendation Module – Generates medicine, diet, and lifestyle advice automatically.

Each module communicates through Flask routes, ensuring efficient front-end and back-end connectivity.

DATASET USED

The system is trained using anonymized datasets obtained from Kaggle containing patient vital sign records, including oxygen saturation, temperature, and pulse rate. Data preprocessing involved removing missing or inconsistent entries, normalizing values, and splitting data into 80% training and 20% testing sets. Pandas and NumPy libraries were used for data handling, and TensorFlow/Keras were used for model training.

SYSTEM ARCHITECTURE

The Lung Disease Risk Prediction System follows a client-server model. The front end is built using HTML, CSS, and JavaScript for user interactivity. The backend Flask framework handles prediction requests, loads the trained model (.h5 format), and sends predicted outcomes to the user interface. The workflow:

Input Vitals → Flask Model Route → Prediction → Result & Recommendations → Dashboard Visualization

A schematic figure can be added here showing data flow between model, Flask API, and UI.

IMPLEMENTATION & RESULTS

The model achieved strong accuracy during testing, with effective classification between “Normal” and “At Risk” patients based on vital input. Flask routes were built for login authentication, prediction calls, and chart visualization using Matplotlib. The output is displayed in tabular and graphical formats for doctors, while patients receive text-based outcomes with personalized health plans.

Screenshots:

Fig. 1 – Welcome Page

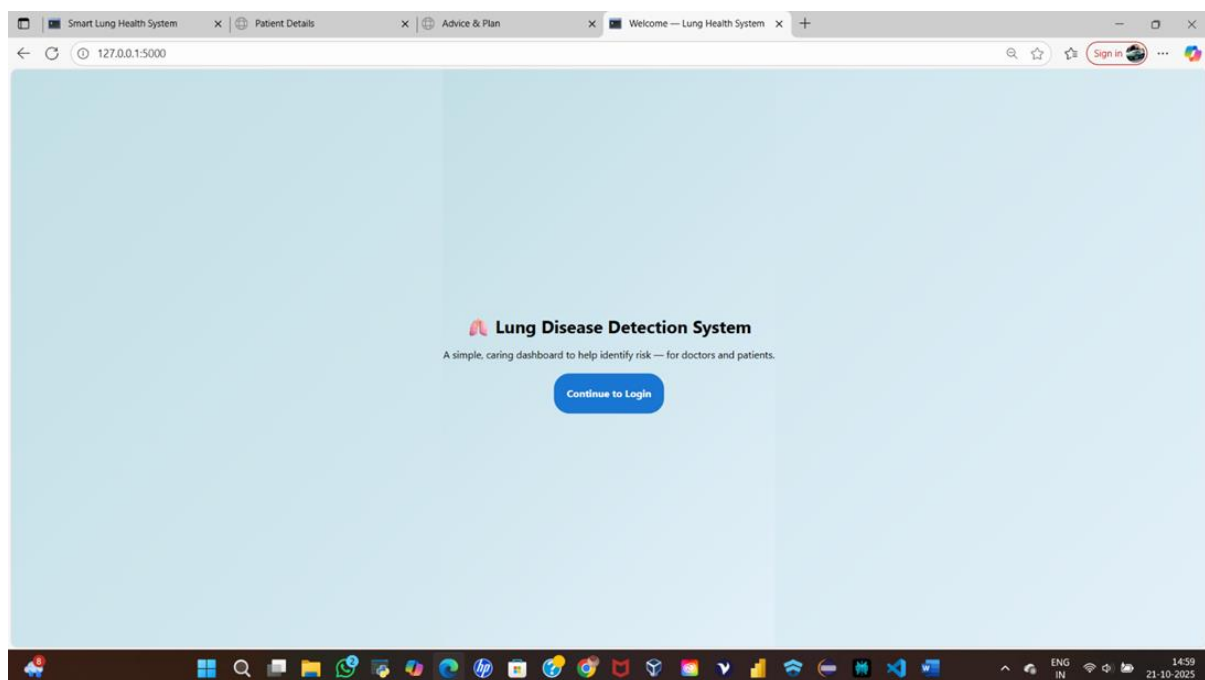


Fig. 2 – Patient Input Form

The screenshot displays a web application titled "Patients - Normal" in the browser tab. The address bar shows the URL "127.0.0.1:5000/patients/Normal". The main content area is a list of patient records, each consisting of an ID, a status, and an "Open" button. The records are as follows:

ID	Status	Action
5362	Status: Normal	Open
5363	Status: Normal	Open
5370	Status: Normal	Open
5371	Status: Normal	Open
5373	Status: Normal	Open
5375	Status: Normal	Open
5378	Status: Normal	Open
5380	Status: Normal	Open
5381	Status: Normal	Open
5383	Status: Normal	Open
5384	Status: Normal	Open
5385	Status: Normal	Open

The bottom of the screen shows a Windows taskbar with various application icons and a system clock indicating 15:08 on 21-10-2025.

Fig. 3 – Prediction Result Page

The screenshot displays a web application titled "Patient Details" in the browser tab. The address bar shows the URL "127.0.0.1:5000/patient_details/2493". The main content area is a "Patient Details" form with the following sections:

Patient Info

```
{ 'id': '2493', 'oxygen': 89.0, 'pulseRate': 111.0, 'temperature': 100.0, 'status': 'Positive', '__status_norm': 'At Risk' }
```

Auto-prediction: At Risk

Medicines (with dosage)

- Morning:** Paracetamol 500mg
- Afternoon:** Vitamin C 1000mg
- Night:** Cough Syrup 5ml

Food Recommendations

- Morning:** Fruits & oats
- Afternoon:** Rice, dal & vegetables
- Night:** Soup or light meal

Lifecycle Guidance

Walk 20 mins daily, maintain hydration, sleep 7-8 hours.

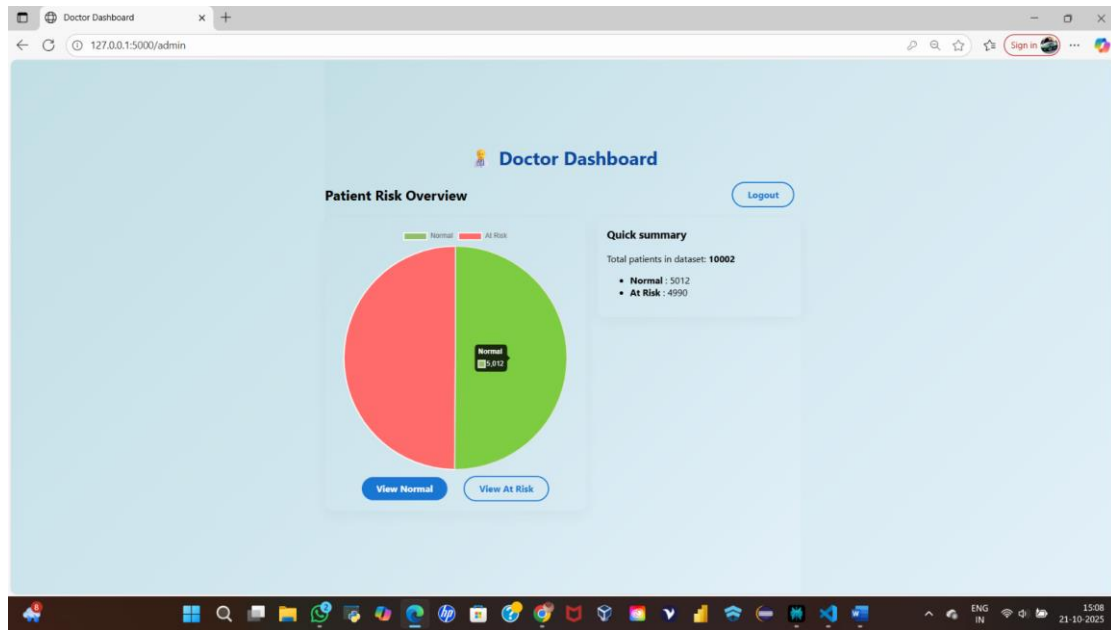
Doctor Follow-up

- Consult senior?** Yes
- Operation needed?** No

A "Back" button is located at the bottom of the form.

The bottom of the screen shows a Windows taskbar with various application icons and a system clock indicating 15:09 on 21-10-2025.

Fig. 4 – Doctor Dashboard (Pie Chart Visualization)



DISCUSSION

The preliminary results demonstrate the efficiency of vital-based risk prediction even without medical imaging. Flask's modular design ensures smooth integration of model inference and user management. The proposed architecture can serve as a foundation for larger AI-based healthcare management systems. Clinical validation and expanded dataset integration are the next logical steps.

CONCLUSION AND FUTURE WORK

This study presents a robust, Flask-based prediction and advisory system that leverages patient vitals for early lung disease risk prediction. It simplifies interactions for patients and doctors while offering data-driven recommendations. Future developments will focus on real-time IoT integration for automatic vital data collection, inclusion of additional biomarkers, and optional X-ray datasets for hybrid diagnostic accuracy. The system's scalable design ensures adaptability to future healthcare research.

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