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RespiraSense

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Final Year Project

March 19, 2025

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Abstract

Lung Disease is one of the most commonly occurring health conditions that is significantly impacting lives of individuals and worsening their quality of life. This has prompted the need for more efficient, timely, and accessible diagnostic solutions. Concurrently, Artificial intelligence is the answer towards making advanced healthcare more accessible to a broader population. In this project, we propose a web application catering to doctors and patients. Doctors will be able to use the model to identify respiratory conditions including tuberculosis, COVID-19, and pneumonia, while the patients will be able to make use of a doctor recommendation system and a chatbot to check their symptoms. Additionally, RespiraSense will also provide a platform to store medical information such as reports and test results securely. The model will be developed using deep and machine learning algorithms and utilizing advanced image processing techniques on medical imaging data, specifically chest X-rays. Overall, this user-friendly and accessible design aims to improve patient care by enabling timely treatment and easy integration into the healthcare system.

Executive Summary

Advancements in technology have enabled the development of advanced AI algorithms that are capable of accurately assessing health conditions. By analyzing physiological data, such as chest x-rays, these AI systems can extract critical information that aids in diagnosing respiratory diseases. It is inevitable that machine and deep learning approaches will be integrated given the growing need for rapid and affordable diagnostic tools. This is especially favorable in environments where there is a constraint on relevant resources. Ultimately, this would help identify conditions such as Tuberculosis, Pneumonia and Covid-19 among others improving the quality of service in healthcare.

In order to create our own model for the identification of respiratory disorders from chest x-rays, this paper aims to evaluate several machine learning and deep learning models for the categorization of medical pictures and feature extraction. Researchers investigating AI models for the identification of respiratory diseases, including pneumonia, COVID-19, and tuberculosis, are the target audience for this publication.

This document also elaborates the project vision we have for our project, “RespiraSense”. Our project aligns with the sustainable development goal of good health and well-being. Developing an efficient diagnostic system for Respiratory Diseases is another critical factor in improving the outcome in healthcare. Factors such as timely detection and accurate analysis are crucial for achieving effective diagnosis of conditions like Pneumonia, COVID-19, and Tuberculosis. Therefore, our goal is to put in place a system that analyzes chest x-rays using sophisticated AI algorithms in order to improve the accuracy and speed of diagnostic procedures. In the end, this will help healthcare professionals make prompt, well informed decisions that will enhance patient care.

Our project’s objectives include classifying respiratory diseases (Pneumonia, COVID-19, and Tuberculosis) with the use of chest X-ray images, enabling real-time analysis of lung conditions, developing a web application for user friendly interaction with the diagnostic model, integrating a chatbot to assist users in assessing their symptoms, implementing a recommendation system for patient care, and allowing patients to securely store their medical information and diagnostic history.

The document then goes on to place emphasis on the detailed literature review of existing papers done in accordance with our topic and gives insights of each method. Since our topic focuses on respiratory disease detection thus, we have done vast research in this area. In addition to that, we have also done research on other modules of our project including the chatbot system and the hospital or doctor recommendation system. The research work has provided us insights such as, utilizing pre trained models achieves optimal accuracy levels, which is critical in medical applications.

RespiraSense has three major modules. Under the section of proposed methodology and approach, in-depth description of the modules has been given. The implementation of disease detection using a pre-trained DenseNet201 model for classifying chest X-rays, a machine learning based doctor / hospital recommendation system tailored to patient needs and location, and a symptom-checking chatbot that utilizes the OpenAI API for contextual interactions and enhanced diagnostic accuracy. In addition to that, details of the dataset and the preprocessing steps is given. The dataset, which was obtained from Kaggle, consists of publicly accessible sets of training, testing, and validation chest X-ray pictures for the following conditions: bacterial pneumonia, viral pneumonia, tuberculosis, COVID-19, and normal lungs. The preprocessing stages consist of categorizing the pictures, scaling them for the DenseNet201 model, performing augmentation techniques including width and height shifts, and normalizing pixel values.

To conclude, the project's objectives, scope, and alignment with sustainable development goal help identify its potential to bring positive change to the healthcare sector.

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Chapter 1 Introduction

According to the World Health Organization; among the top 10 worldwide causes of mortality in recent years, respiratory illnesses have contributed the most. [1]. Lungs are responsible for the crucial task of supplying oxygen to every cell of the human body. Therefore, any compromise to this role can lead to anything from mild respiratory discomfort to severe respiratory issues, causing life threatening complications. Additionally, identifying the symptoms of respiratory conditions can be challenging in some cases. However, with advancements in technology, Artificial Intelligence models have emerged that can accurately detect lung diseases.

The state of technology now allows for the precise evaluation of an individual's health with the use of potent artificial intelligence algorithms. These types of applications are in high demand, as they can help detect lung diseases early on and provide valuable insights into a person's respiratory condition. Since Pneumonia, Covid-19 and Tuberculosis remain to be leading causes of severe respiratory illness, constructing a web application for this is a noteworthy idea to improve the health sector.

RespiraSense aims to develop a system that can extract critical information from chest x-rays. Since respiratory diseases cause a notable change in the lung structure, we can detect them using machine learning. The model will be able to analyze chest x-rays in real time, allowing it to classify the condition of the lungs and identify any signs of disease. In addition to this, users will also be able to store their medical information, and patients will be suggested to the nearest available doctors based on their diagnosed condition.

1.1 Purpose of this Document

This document serves as a summary of how our Final Year Project (FYP) will be planned, carried out, and evaluated. It seeks to create a web-based tool that will help the medical field identify lung conditions and improve patient treatment. The project will also prioritize delivering a smooth user experience and designing an interface that is easy to use. The main purpose of our study is to examine several deep learning and machine learning models for the extraction of features from and categorization of chest X-rays in order to create a model for the detection of lung illnesses, namely tuberculosis, COVID-19, and pneumonia. The research question we aim to answer is: Can we develop a web based application that can improve diagnosis of respiratory diseases and contribute towards making health care more accessible? The project's approach, design, execution, testing, and assessment will all be included in this report, along with its limits and future work.

1.2 Intended Audience

The intended audience for this document are the researchers that are exploring AI models for the detection and classification of respiratory diseases; particularly Pneumonia, Covid-19 and Tuberculosis. Moreover, the panel of professors who will be evaluating the project are also part of the intended audience.

1.3 Definitions, Acronyms, and Abbreviations

The following are the definitions, abbreviations, and acronyms used in this document:

UI: User Interface

Agile: Agile Development

SCRUM: Scrum Development

SDG: Sustainable Development Goal

FYP: Final Year Project

ML: Machine Learning

DL: Deep Learning

AI: Artificial Intelligence

CNN: Convolution Neural Networks

GPU: Graphics Processing Unit

RAM: Random Access Memory

VRAM: Video Random Access Memory

CPU: Central Processing Unit

OS: Operating System

GB: Gigabyte

GUI: Graphical User Interface

API: Application Programming Interface

JS: JavaScript

MERN: MongoDB, Express.js, React.js, and Node.js

IDE: Integrated Development Environment

USMLE: United States Medical Licensing Examination

TP: True Positives

TN: True Negatives

FP: False Positives

FN: False Negatives

1.4 Conclusion

In conclusion, RespiraSense is developed to revolutionize the healthcare industry by providing an AI-powered diagnostic tool that seamlessly integrates with a user-friendly platform. By combining advanced machine learning techniques with intuitive features like real-time scan analysis, and a personalized patient dashboard, the system ensures that both patients and healthcare providers can easily manage and track respiratory health. The platform is built with a strong focus on accuracy, scalability, and ease of use. The team is committed to provide a solution to make healthcare more accessible and efficient.

Chapter 2 Project Vision

This chapter will give you a detailed overview about the problem statement, goals and objectives, and scope.

2.1 Problem Domain Overview

The system will enhance the diagnostic process of detecting Pneumonia, Covid-19 and Tuberculosis by making use of AI/ML models to analyze chest X-rays and accurately detect these diseases at an early stage. The system is going to be designed with both patients and doctors in mind, offering a user-friendly platform. Patients will be able to upload their medical images and receive diagnostic insights, while storing their medical records securely. Users will be able to view and access nearby doctor recommendations and their information based on their condition. Further, A chatbot feature will be implemented to assist users in tracking symptoms and gaining any possible knowledge about their health conditions.

2.2 Problem Statement

Particularly in developing nations, respiratory illnesses continue to be a major worldwide health concern, contributing to high death rates and overburdened healthcare systems. Early detection is critical for effective treatment, but traditional diagnostic methods relying on manual chest X-ray interpretation are often slow, prone to error, and inaccessible to many due to the limited availability of skilled radiologists. The need for an efficient, accurate, and accessible diagnostic tool is evident. RespiraSense addresses this gap by automating the analysis of chest X-rays, providing a reliable, real-time diagnostic solution.

2.3 Problem Elaboration

Accurate detection of lung diseases is crucial, but traditional diagnostic methods are often slow and reliant on the expertise of radiologists, who may not be always available. This leads to delays in diagnosis and treatment, resulting in worsened patient outcomes. Furthermore, manual interpretation of chest X-rays is prone to human error, which can lead to misdiagnosis. Another challenge is the lack of accessible, secure platforms for patients to store and manage their medical data, which complicates continuity of care. There is a gap between the detection of diseases and finding appropriate medical help, with patients often struggling to locate nearby healthcare providers at the time of need.

The problem can be divided into two sub-problems. First, the need for an accurate and automated system to analyze chest X-ray images and detect respiratory diseases. This will be tackled by training deep learning models, to recognize patterns in X-rays associated with different lung conditions. Secondly, creating a user-friendly web interface that allows both doctors and patients to interact with the diagnostic tool efficiently.

2.4 Goals and Objectives

The primary goal of RespiraSense is to provide a centralized platform for users to be able to identify potential risks and dangers to their lungs, to accurately detect and classify lung diseases, focusing on conditions identified through chest X-ray images. Our main objectives are:

- Combining different datasets containing chest x-ray images
- Training a model to correctly detect Pneumonia, Covid-19 and Tuberculosis
- Allowing doctors access to the diagnostic model
- Developing a web application for ease in use of the model
- Integrate a chat bot to assist users in assessing their symptoms

2.5 Project Scope

RespiraSense will consist of a web application designed while keeping both doctors and patients in mind. The application will include a recommendation system to suggest the nearest doctors, a secure platform for storing medical reports and test results, and a chatbot to assist users with symptom checking. Furthermore, the core diagnostic model will primarily use Artificial Intelligence to detect lung diseases and be built using Keras with TensorFlow as the backend. To train the model we will be using a dataset of chest x-rays from Kaggle, then pre processing the images in it for the machine learning model.

The frontend will be built using the React.js library for a dynamic and responsive user interface. Flask will be used for the integration of the frontend with the backend, serving the AI model as an API. The MERN stack will be utilized to manage the full-stack development, providing a robust structure for data handling, user management, and interaction.

Finally, testing will be conducted iteratively, focusing on the accuracy of the AI model. The responsiveness of the user interface and the overall functionality of the system will also be tested to ensure a user-friendly application and reliable final product. The project will be developed using SCRUM project management and agile development principles.

The project deliverables will consist of:

- An efficient web-based app for disease diagnosis and improved patient care
- Complete documentation of the design, implementation, and testing process
- A fully detailed user manual for the application

The project scope does not include the following:

- Providing hosting or server infrastructure for the application
- Developing mobile applications (iOS or Android)

This project scope will be used as a guide throughout the development

2.6 Sustainable Development Goal (SDG)

The SDG our project is going to target is good health and well-being as it will innovate the process of detecting lung diseases before it is too late. It will help save many lives and enhance public health.

Figure 2.1: Good Health and Well-Being

2.7 Constraints

Following are some constraints related to the project:

Time: The project must be completed within a one-year timeframe, requiring that each module and task be completed within its designated schedule.

Work Resources: Three members will work on this project in order to complete it.

Scope: The scope of the project should be achievable within a one year time period. This means focusing on core functionalities, such as the AI-based diagnostic system, chatbot, and doctor recommendation feature, without adding additional features that may compromise the project's timely completion.

Quality: The system should be reliable, user-friendly, and robust in its performance, ensuring accuracy in diagnosis and security in handling patient data.

2.8 Business Opportunity

The healthcare industry is the main target of this project as it addresses a critical gap in the healthcare industry due to the timely and accurate detection of respiratory diseases using AI. RespiraSense presents itself as a cost-effective, scalable solution for both healthcare providers and patients. The integration of features such as symptom checking, and doctor recommendations makes the system highly attractive for hospitals, clinics, and other health facilities. The project can capitalize on partnerships with healthcare institutions, insurance companies, and government health programs.

2.9 Stakeholders Description/ User Characteristics

The users of this system will be doctors or healthcare providers, patients, and ourselves the developers.

2.9.1 Stakeholders Summary

The doctors would rely on the system's AI-based diagnostic tools to assist in identifying respiratory diseases, reviewing patient medical data, and making informed clinical decisions.

Patients benefit directly from the system by receiving timely diagnostic insights, storing their medical records securely, and accessing personalized recommendations for healthcare providers.

As developers, we are responsible for building and maintaining the RespiraSense system, ensuring it meets both functional and performance expectations. We ensure the implementation of AI algorithms and the integration of features.

2.9.2 Key High-Level Goals and Problems of Stakeholders

Time Saving: The time required for diagnosing respiratory diseases would be drastically reduced. Traditionally, diagnosis can take hours or days as doctors manually review chest X-rays. With RespiraSense's AI-driven diagnostic system, the analysis of X-rays and the identification of diseases can be done within minutes, speeding up the treatment process and allowing healthcare providers to handle a larger number of patients.

Automatic Operation: Doctors will only need to upload X-rays for analysis, and the system will automatically diagnose and suggest potential conditions.

Unbiased and Consistent Results: The AI model will follow predefined criteria for diagnosing diseases, ensuring that every patient receives an unbiased and consistent diagnosis.

Chapter 3 Literature Review / Related Work

This section provides an elaborate and detailed literature review of existing research done in relation with the chosen topic and gives us comprehensive insights and detailed knowledge of each technique and various algorithm.

3.1 Definitions, Acronyms, and Abbreviations

ML: Machine Learning

DL: Deep Learning

AI: Artificial Intelligence

CNN: Convolution Neural Networks

CapsNet: Capsule Neural Network

GAN: Generative Adversarial Networks

VGG: Visual Geometry Group

STN: Spatial Transformer Network

DNN: Deep Neural Network

ACM: Association for Computing Machinery

CAD: Computer Aided Detections

RF: Random Forest

3.2 Detailed Literature Review

This section covers notable literature published in the domain of AI driven healthcare applications focusing upon respiratory disease detection and personalized patient care such as medical chatbots and recommendation systems.

3.2.1 Chatbots and Their Applications in Medical Fields

This research paper mainly focuses on using AI and its applications in medical fields and their possible impacts. The authors discussed the extensive use of chatbots in heath sector highlighting their possible outcomes. The research made in this article is valuable for our project as chatbot is an essential feature which we plan to add in our system.

3.2.1.1 Summary of the research item

Viswanath et al. discuss the application of Chatbots in the medical sector; reviewing both their current status and their future prospects. They analyzed their findings after conducting a thorough literature review that spanned across five different databases. This analysis showed that with the development of AI such as ChatGPT, there has been an increase in the usage of Chatbots in the health sector. Lastly, they concluded that although AI powered Chatbots hold promise they can not yet replace medical professionals and that data privacy concerns remain to be addressed in a satisfactory manner.

3.2.1.2 Critical analysis of the research item

The analysis of the article reveals both strengths and weaknesses. Firstly, the article conducted the literature review with articles from 5 unique and credible databases however the reliability of the studies it reviewed was not discussed.

Secondly, the article is spread over a wide scope as it covers the applications of chatbots in various medical fields including infectious diseases. It also discussed clinical as well as non clinical settings. However, there is a definitive lack of quantitative data and instead the writing is majorly narrative. Additionally, cost effectiveness is not discussed either which is one of the aims behind our own project.

3.2.1.3 Relationship to the proposed research work

This paper relates to our Chatbot module, as the aim of the paper is to analyze the future and the current trends of automated Chatbots in the health sector. Moreover, it supports our aim to integrate a chatbot in RespiraSense as it concludes that AI powered Chatbots are "highly effective".

3.2.2 Machine learning-assisted prediction of pneumonia based on non-invasive measures

The paper explores machine learning models to predict pneumonia using non invasive diagnostics. It proposes using Random Forest and XGBoost to enhance diagnostic accuracy.

3.2.2.1 Summary of the research item

Effah et al. in their study published in the National Library of Medicine discuss the use of ML models in the prediction of Pneumonia while focusing upon the non invasive diagnostic approaches. They do this using both physical and laboratory parameters. Pneumonia is a global health issue, responsible for high mortality rates; this has led to an increased demand in faster and more rapid diagnostic tools in place of conventional methods. The authors argue that in the case of respiratory diseases such as Pneumonia, diagnostic uncertainties can be significantly reduced by implementing ML models that use clinical data.

The researchers considered a sample size of 535 patients and 45 various parameters ranging from socioeconomic to hematological. Additionally, in order to fairly evaluate the predictive ability of the ML models, feature extraction, Imbalanced Dataset Analysis and SMOTE Analysis were used.

From their study, they found that RF and XGBoost were the most reliable. They concluded that integrating ML models greatly improves the accuracy of the predictions and that they offer a way forward in diagnostics despite privacy concerns regarding AI.

3.2.2.2 Critical analysis of the research item

The detailed investigation of this article presented both strengths and weaknesses as presented below:

Strengths:

- There was a wide range of ML applications that were used in this research. Among the eight models analyzed, RF and XGBoost were also used that are especially known to deal with complex data.
- The models were also tested under different conditions so their execution could be fairly tested. For instance, multiple feature selection techniques were used along with the usage of an imbalanced dataset and SMOTE adjusted data.
- The measurement approach taken by the authors to check the models' effectiveness also included various performance parameters and evaluation metrics. These included accuracy, precision, recall, and f1 score.

Weaknesses:

- The sample size for the dataset was fairly limited as the entire study was based upon a 535-patient dataset. This could make the results less reliable.
- Additionally, the dataset used also has concerns about the generalization as the study is based singularly upon patients in China instead of a wider region.
- The study has not provided justification for all the models that it used. It focused upon RF and XGBoost while the rest of the ML models, such as decision trees, were given less importance.

3.2.2.3 Relationship to the proposed research work

This paper relates to multiple modules of our project. First and foremost, in both the study and RespiraSense, accurate pneumonia diagnosis is a priority. Secondly, the evaluation metrics used can be used as inspiration when setting benchmarks to evaluate the performance of our own ML model. Moreover, the study also provides basis for our project by stressing on the fact that it is impossible to rely only clinical symptoms to provide an accurate diagnosis. A non invasive approach is supported.

3.2.3 An Improved Densenet Deep Neural Network Model for Tuberculosis Detection Using Chest X-Ray Images

The paper introduces CBAMWDnet which is an advanced deep learning model for tuberculosis detection from chest X rays. It improves diagnostic performance by utilizing DenseNet201.

3.2.3.1 Summary of the research item

Huy and Lin [3] talk about an enhanced DL Model, CBAMWDnet for Detection of Tuberculosis from Chest X-Ray (CXR) Images. This model integrates the Convolutional Block Attention Module (CBAM) and the Wide Dense Net Architecture of Densenet201. It further improves its ability to obtain context based information from the images. The authors further stress that the only effective approach towards the treatment of Tuberculosis is early diagnosis. In regard to that, deep learning techniques are promising tools when concerned with medical images.

During evaluation, the CBAMWDnet acquired the best result among existing models with the accuracy of 98.80% on the total dataset. The study analyzes different models such as InceptionV3, AlexNet, and ResNet50. Following that, the results indicate that the quality and quantity of data significantly influence the model's performance.

The authors conclude that, although advanced algorithms such as CBAMWDnet can significantly enhance diagnostic capabilities, the actual issue stays in data quality. They claim that deeper research into deep learning models for medical applications is needed. Overall, this work contributes towards Tuberculosis detection and establishes a precedent for future studies in the same area.

3.2.3.2 Critical analysis of the research item

Strengths:

- The accuracy of the CBAMWDnet model is 98.80%, which indicates a capacity to accurately identify tuberculosis in chest x-ray images. This demonstrates high performance.

- The article also compares the models with other architectures. It shows that the proposed model performed superior to the rest. This highlights the importance and advantages of CBAMWDnet as the optimal solution.

Weaknesses:

- The dependency on data quality continues to be a weakness. The model is greatly dependent on the quality and variety of the training data. This makes its generalization capability poor in practicality as the data may not always represent the situation accurately.
- The computational complexity of the proposed model is high. Therefore, it has multiple parameters and needs more resources. This can make it less accessible and unscalable.

3.2.3.3 Relationship to the proposed research work

The relation of this paper is to our disease detection module. This is because according to the article the authors aim to detect Tuberculosis, which falls under the scope of our disease detection module. Moreover, the relevance is greatly increased as both the proposed model in this article and the proposed model of RespiraSense use DenseNet201.

3.2.4 A deep learning approach for classification of COVID and pneumonia using DenseNet-201

The paper highlights DenseNet201 for classifying COVID 19 and pneumonia from chest X rays. It proposes the use of transfer learning on high quality datasets to assist medical professionals in diagnosis.

3.2.4.1 Summary of the research item

Sanghvi et al. take an alternative to the traditional diagnostic approaches and use DenseNet201 to identify Covid-19 and Pneumonia from chest x ray images. This is done with the aim of helping medical professionals with the usage of transfer learning while complying with HIPAA standards.

Their model is trained on a Kaggle dataset and uses transfer learning to achieve the best results. Their work process started with acquiring Chest x rays from a radiology department which was then followed by technicians posting the images for assessment. After verification, these images are then sent to the AI model that categorizes them as either Normal, Pneumonia or Covid 19 images.

The paper further discusses the potential of x-rays

3.2.4.2 Critical analysis of the research item

The detailed investigation of this article presented both strengths and weaknesses as presented below:

Strengths:

- The methodology section of the research is thorough as it incorporates the complete data preprocessing steps alongside all the details about the model architecture and training process. Relevant diagrams and flowcharts are also included for clarification wherever needed.
- The dataset used contains 15,153 images which enhances the validity of the results produced by the ML model.
- Ethical concerns are also addressed as HIPAA standards are discussed and their compliance explained.
- The authors have also compared and contrasted their results with DenseNet201 and other similar methods to improve the reliability.

Weaknesses:

- Although the dataset size is sufficiently large, the study does not mention the geographical range and whether the chest x-rays were taken from a singular region or from over a larger region.
- The paper briefly suggests more design of medical image analysis applications in the future, however it does not offer any exploration into future work. There are no suggestions as to how the current model may be expanded for different diseases.
- The paper fails to account for the negative consequences of over dependence on pre-trained models.

3.2.4.3 Relationship to the proposed research work

Both RespiraSense and this research are focused upon detecting Covid 19 and Pneumonia from images of chest x rays using DenseNet201 as the DL model. In addition to that, the proposed model supports our aim of providing a user interface where the medical professional uploads the images which the model then classifies.

3.2.5 A systematic review of healthcare recommender systems

This paper provides a brief yet valuable review of heath care recommendation systems by thorough examination of multiple articles, highlighting possible challenges faced by HRSs and provide guidelines for future endeavors.

3.2.5.1 Summary of the research item

Etemadi et al. [5] have discussed the open issues, techniques and challenges of healthcare recommendation systems in their review published in ScienceDirect. The review dived deep into a collection of 41 articles that were published after 2010 and before 2022. These articles cover multiple categories including content based, collaboration based, knowledge based, context based and hybrid systems. Some of the challenges considered are cold start problem, unstandardized medical regulations and the issue of scalability. The paper further goes into details regarding HRS categorization and emphasizes how these systems cam contribute towards disease prevention, cost reduction and the overall improvement of healthcare services.

On the other hand, the authors mention that the HRSs are still in the early stages with several challenges facing them. These challenges include data privacy concerns and the non standardization in the evaluation metrics.

The review provides a roadmap to researchers and medical professionals which outlines directions for the future. The authors conclude that scalable solutions that promote accuracy, trust and usability are needed.

3.2.5.2 Critical analysis of the research item

The detailed investigation of this article presented both strengths and weaknesses as presented below:

Strengths:

- The authors provide a wide and comprehensive coverage of 41 studies on the topic of HRSs. Due to this, several categories as mentioned above are covered, and multiple tools in assessing these studies are used.
- The review also presents a scientific structure or taxonomy for classifying HRSs. These would make the work of researchers and medical practitioners more systematic.
- Real-life challenges with healthcare providers are also addressed. By addressing these issues, the paper provides insights that can be implemented to enhance the functionality and trust in HRSs.

Weaknesses:

- The review relies on international journals and conferences; however, it does not consider national or non-English publications. This could lead to publication bias and also limits diversity.
- The review does not have a standardized framework in place for the evaluation of the articles. Therefore, it is unable to provide a clear solution or fixed benchmarks for the assessment of HRSs

in the future.

- There is repetition in the review that HRSs are at early stages of development. This gives the readers the impression that the insights are more theoretical rather than practical.

3.2.5.3 Relationship to the proposed research work

The relation of this review is to the hospital or doctor recommendation system module of our project. By drawing from the review, our recommendation system can use collaborative or content based approach to recommend hospitals according to past data. Moreover, the review places great importance on reliable systems that keep data confidential. This is also one of the aims of RespiraSense to implement data privacy and protection through access control.

3.2.6 Detection of COVID-19, pneumonia, and tuberculosis from radiographs using AI-driven knowledge distillation

The paper discusses a knowledge distillation framework for detecting COVID 19, pneumonia, and tuberculosis using simpler AI models. The proposed solution through knowledge distillation, focuses upon high accuracy and efficiency in resource limited settings.

3.2.6.1 Summary of the research item

Kabir et al. propose a knowledge distillation framework that can be used to identify Covid 19, Pneumonia and Tuberculosis from chest x-rays using simple AI models. The proposed framework trains a less complex student network to obtain a very high degree of accuracy through the use of a larger, more complex teacher network. The simpler network mimics the complex one which allows it to implemented in or deployed in environments where there is a constraint on resources.

Chest x rays were taken from patients diagnosed with the above mentioned respiratory conditions and others with healthy lungs. The datasets were then divided into different sets to test the model's effectiveness on them. According to the results that were obtained; this knowledge distillation method improved efficiency, obtained high accuracy and precision while also decreasing the computation time due to the reduced complexity of the student network.

The authors concluded that this technique can be extended in the future to include other types of medical imaging such as CT scans. They also believe that more knowledge distillation techniques with a greater patient demographic can be used to improve the performance. Moreover, the proposed framework was concluded to have huge potential in real life medical environments as a powerful diagnostic tool.

3.2.6.2 Critical analysis of the research item

The detailed investigation of this research work is presented below:

Strengths:

- The article explains the knowledge distillation framework in great detail. This is done by applying it to the detection of respiratory diseases.
- The paper goes into great depth when discussing the data collection and preprocessing steps. Emphasis is placed upon quantitative data which is important in a paper focused upon the results of AI techniques.
- Clear-cut evaluation metrics are used. The use of the right metrics such as precision, recall, and accuracy helps in the uncomplicated assessment of the model's performance.

Weaknesses:

- The focus of the article may be considered narrow. This is because it is broadly focused on an individual problem, that is chest x-rays. This will limit the appeal to what could be a wider audience.
- There is negligible discussion on how the proposed model compares to the other existing diagnostic techniques. Lack of comparison on this topic prevents the highlighting of benefits over other diagnostic tools.

3.2.6.3 Relationship to the proposed research work

It closely aligns with the objectives of our project as both are focused upon using AI techniques including but not limited to knowledge distillation, for the detection of respiratory diseases. The article also focuses upon the same 3 diseases as RespiraSense, namely Covid 19, Pneumonia and Tuberculosis. Moreover, the need for real time applications that can be implemented in medical or clinical settings is also emphasized upon. This supports the development of our project. Lastly, we can also draw from the data preprocessing steps as we will be performing them on chext x rays too.

3.2.7 Intelligent Pneumonia Identification from Chest X-Rays: A Systematic Literature Review

This research is another significant yet detailed review of detecting pulmonary diseases especially pneumonia from chest x-rays. Multiple research papers are reviewed in this paper, some challenges are identified and their solutions are proposed too.

3.2.7.1 Summary of the research item

The research provided a comprehensive literature review for pneumonia automatic detection using chest radiography. Four reliable and highly cited data sources (IEEE Explore, Science Direct, ACM, Springer Link) are used for the research purposes. Eight large publicly available datasets are considered for this review. This research provided an overview of the in-use medical practices and highlighted the importance of pneumonia detection in medical field. It summarized the major role of machine learning and deep learning for the interesting diagnostic of lung disease. This study has identified data pre-processing steps for re-sizing chest radiographs and noise cancellation. After identifying several critical challenges, this paper provided brief solutions in overcoming those challenges. Limitations of this review were also discussed providing a future direction for an improved literature review.

3.2.7.2 Critical analysis of the research item

The detailed investigation of this research work is presented below:

Strengths

- This research provided a great initiative in understanding the quality of majorly available public datasets by providing a detailed comparison.
- The authors have identified that handling and analysis of class imbalances is a critical challenge in pneumonia detection techniques..
- It provides a detailed comparison on automatic detection for the medical practitioners. This will help them to choose the best methodology for real-time detections.

Weaknesses

- This paper provides a great analysis on existing studies and algorithms; however, it lacks the investigation of real-world limitations.
- This review has highlighted GAN as an effective tool for dataset imbalance issues, whereas the limitations of GAN have not been considered.
- This research laid more focus on deep learning methods, without fully analyzing machine learning algorithms.
- Although the highly imbalanced dataset problem has been discussed, there is limited discussion over the deployment of these models in real-world scenarios.
- It lacks the discussion around new advancements in this medical field.

3.2.7.3 Relationship to the proposed research work

The above review paper provides a strong foundation for our proposed research work on lung disease detection using machine learning. It provided a detailed analysis over the datasets, data sources, currently available methodologies and existing challenges. The discussion on datasets will help us to choose the one with less issues such as class imbalances. It provided us with a direction for implementing data augmentation techniques to balance datasets. The challenges mentioned in the conclusion section will help us to work on those shortcomings efficiently. We can focus more on the improvement of our proposed model to work best in real-time scenarios. In conclusion, this review has provided us with a systematic literature review for understanding the existing research in a better way.

3.2.8 Joint Diagnosis of Pneumonia, COVID-19, and Tuberculosis from Chest X-ray Images: A Deep Learning Approach

This article focuses on the development of a deep learning model to diagnose pneumonia, COVID 19, and tuberculosis from chest X rays. It employs a CNN to achieve high accuracy while simultaneously addressing dataset imbalance issues through various steps [8].

3.2.8.1 Summary of the research item

The research developed a deep learning model for the diagnosis and detection of three different lung diseases using chest X-rays, mainly COVID-19, Tuberculosis TB and pneumonia. The abstract claimed that a patient has a higher chance of more than one disease present in them. This paper has also provided a brief analysis of existing joint research work. Three different Kaggle datasets were used for this analysis. The research involved pre-processing of medical images, which involved re-sizing them to 300 x 300 dimensions. For multi-classification of chest radiographs, a CNN model was deployed. This model achieved an accuracy of 99.66percent, 98.10percent and 96.27percent for Pneumonia, TB and Covid-19 respectively. Afterwards, the performance of the designed model was evaluated on multiple metrics against each of the three lung highly contagious diseases.

3.2.8.2 Critical analysis of the research item

Strengths

- An interestingly high accuracy has been achieved with the above research model, in contrast to similar studies in the same field.
- The research has also highlighted the advantages and limitations of the existing joint research work.

- The authors have consolidated working over three fatal and critical lung diseases, whereas most of the existing research only focuses on one disease at a time.

Weaknesses

- For COVID-19, the analysis was carried out on an imbalanced dataset, which resulted in lower accuracy and is a major limitation of this study, given that it is the major cause of fatality recently.
- Independent datasets were not used for validating and testing the training model, which can be a critical limitation for deployment in clinical environments.
- In the conclusion, the authors mentioned using pre-trained models and transfer learning; this approach could have been incorporated into the research work for enhanced results.

3.2.8.3 Relationship to the proposed research work

The above research work laid a strong foundation for our proposed research project in terms of highlighting the critical challenges and limitations. The CNN model and architecture used in this research can be our starting point. We can work on improving the imbalances of the datasets before training our model on them. A strong framework for multi class detection provided in this research can help us with major considerations for our research work. We can use more diverse datasets with less issues for training and evaluation of our proposed model. The state of the art comparison provided at the end of the research paper can be our guiding torch for measuring and enhancing the performance metrics of our proposed model.

3.2.9 Reliable Tuberculosis Detection Using Chest X-Ray with Deep Learning, Segmentation and Visualization

This study highlights tuberculosis detection using nine CNNs and chest X-ray images, focusing on segmentation techniques for improved performance. It integrates visualization methods to increase reliability in TB diagnosis [9].

3.2.9.1 Summary of the research item

This study aimed to utilize nine convolutional neural networks (CNNs) and chest radiographs for the precise detection of tuberculosis (TB). Out of those nine, ChexNet was classified as the top performing model. Segmentation techniques have also been used to help in classification performance. A comprehensive list of public datasets is employed for creating two different databases of 3500 images each of normal and infected lungs. One of them was for TB classification and the other one was lung segmentation. These datasets were pre-processed due to different size of input images in order to resize images of X-ray. Experimental results identified DenseNet201 has achieved the highest accuracy, sensitivity and precision. Visualization techniques have been utilized for an enhance visual representation of CNNs. This research work concluded that lung segmentation is critical for computer aided diagnostics. It claimed that by using this fast approach, many lives can be saved from wrong diagnosis.

3.2.9.2 Critical analysis of the research item

The detailed investigation of this research work is presented below:

Strengths:

- The study explored tuberculosis disease detection by wide-ranging use of nine different CNNs. This approach provides a valuable comparison between different model performances.
- Segmentation techniques have been utilized with a major focus on model performance and efficiency.
- Visualization was used for making the model more reliable by providing better visuals.
- The performance of this research work was also compared with the recent published research in a similar domain.

Weaknesses:

- The study focused on utilizing public datasets, which may lack diversity in terms of gender, age, and other population-related metrics.
- No discussion around AI ethics in the paper is a significant concern, given the risks of data privacy leakage and other critical health decisions.
- The comparison of this study with recent similar research work showed that the accuracy of their model is 98.6%, whereas the other achieved a slightly higher accuracy of 99.8%, although there was a mismatch between the sizes of datasets being used.
- While the DenseNet201 model provides accuracy and precision, it is slow and expensive in terms of computation. This can be troublesome if used for real-time detections.

3.2.9.3 Relationship to the proposed research work

Our project work and this research article are highly relevant as we both are working towards the lung diseases prediction by utilizing different datasets. Machine learning techniques are employed in both research work, for reliable detection of diseases by using X-ray images. In order to enhance the precision of our machine learning models, we are planning to understand their mentioned approach. This will help us for the creation of an efficient and precise machine learning model for lung disease detection. They have used visualization for enhancing their model so that professionals can trust those AI decisions. This will be valuable in our project work for developing a tool for doctors and clinicians. The major focus of both research and development works is to provide a useful prediction tool for saving patients lives, as lung diseases are leading death contributors in the world.

3.2.10 Lung Disease Detection Using Deep Learning

This research paper classifies multiple lung diseases using deep learning techniques on chest radiographs from the Chest x ray14 dataset. The proposed model combines a CNN and a pre trained VGG16 model to automate disease detection. Moreover, it also highlights the need for accuracy improvements [10].

3.2.10.1 Summary of the research item

In the research titled ”Lung Disease Detection Using Deep Learning”, the authors aimed for multiple lung disease classification and detection using chest radiographs via deep learning techniques. A large publicly available dataset, “Chest X-ray14” was utilized with the intention of automating disease detection. This huge dataset contained 1024 x 1024 sized 112,120 medical images. A CNN was proposed along with a pre-trained VGG16 model for better image classification. Their proposed best model CNN +VGG + data + STN achieved a 69.3percent accuracy. However, it requires more time and power for algorithm improvements. To conclude, the results achieved from this work are less remarkable and highlighted major improvements. Still this serves as strong foundation in this emerging research field.

3.2.10.2 Critical analysis of the research item

The detailed investigation of this research work is presented below:

Strengths:

- The detection research work was focused on a comprehensive list of 14 different lung diseases, mainly pneumonia, edema, fibrosis, and others.
- This is one of the first research studies that applied CapsNet for the detection of lung diseases.
- The decision of using a pre-trained VGG16 model is a great initiative, as it is broadly used for enhanced and better-quality medical image extraction.

Weaknesses:

- The accuracy of the proposed model was only 69.3%, which does not meet the requirements for clinical trials in hospitals.

- The utilized dataset includes a list of common and rare lung diseases; however, the paper failed to provide detailed solutions for each of them, especially the rare diseases.
- Although this research group was one of the first to utilize CapsNet, it involved high costs of computations and takes much time for convergence.

3.2.10.3 Relationship to the proposed research work

"RespiraSense" aligns with the above research work by leveraging machine learning algorithms and publicly available datasets for detection of lung disease. The huge dataset can be valuable for us in training our model efficiently. The usage of pre-trained VGG16 model provides us with an opportunity to save resources and time while achieving accuracy. In order to achieve novelty in our work, we can avoid using CapsNet which didn't perform well in the above research work. Handling of class imbalances was not the major focus of above research work. However, we can incorporate it in our work for accurate and enhanced prediction model. In other words, we can optimize all this for our detection of lung disease problem.

3.2.11 Computer-assisted detection of infectious lung diseases: A review

This paper highlights the use of CAD for infectious lungs diseases by highlighting its benefits, methods, classifiers and evaluation criteria.

3.2.11.1 Summary of the research item

The research titled "Computer-assisted detection of infectious lung diseases: A review" reviewed multiple and diverse features of chest radiography and computed tomography (CT). Despite their popularity as a widely used tools for pulmonary infections detections, it has several limitations. The research work puts an emphasis on leveraging computer-aided detections (CAD) for more efficient and reliable diagnostics. The research starts with highlighting major lung diseases and their relevant medical imaging. It then lists CAD benefits and features that can be utilized for detection of pulmonary diseases. Methods for data extraction for medical images and their corresponding classification is also mentioned. The criteria for evaluation and performance of this proposed CAD usage are also identified. The result concluded with the verdict that although CAD can be a valuable diagnostic tool for lung infection detection, it still has some limitations.

3.2.11.2 Critical analysis of the research item

The detailed investigation of this research work is presented below:

Strengths:

- The research offers a comprehensive insight into a diverse range of pulmonary diseases and their current practices for detection.
- The authors highlighted the current limitations of existing tools and identified innovative methods for enhancing accuracy of detection.
- A list of commonly used classifiers has been mentioned for the proposed CAD algorithm.
- For detection, major focus was laid on the shape patterns and textures commonly observed in lung diseases.

Weaknesses:

- The authors presented a theoretical framework without experimenting with a real dataset.
- Limited discussion around the disease's diversity detection was mentioned, which creates a loophole.
- Although the usage of CAD has been recommended by the authors, the research concluded that limitations exist.
- No doubt, CAD algorithms can offer efficiency and reliability, but they are highly dependent on high image quality, which may not be feasible most of the time.

3.2.11.3 Relationship to the proposed research work

This research aligns very well with our proposed work on lung disease detection in several ways. We can motivate our research work over the limitations mentioned in this research. The concept of pattern recognition in terms of shape and texture is common in both the above and our proposed research work. We can also make use of the multiple classification techniques mentioned in above research. The performance metrics mentioned in this research work are also highly relevant for our understanding. We can provide recommendations in our research work over the current limitations mentioned. There is also an interesting mention of automating the detection process, which we can work around to build our framework on that.

3.2.12 Deep features to detect pulmonary abnormalities in chest X-rays due to infectious disease X: Covid-19, pneumonia, and tuberculosis

This research aligns directly with our project highlighting the same three diseases and detection of these from chest x-rays. Multiple data sets were taken into account to for this research and model is proposed for detection too that showed remarkable accuracy rates.

3.2.12.1 Summary of the research item

The research introduces a custom deep neural network model for detection of multiple lung diseases. Cross validation has been conducted by the authors for analysis and evaluation of model performance. Three major lung infections were selected for this study namely COVID-19, tuberculosis and pneumonia. After the experiment, results were compared against similar research work in this field. This comparison concluded that the proposed custom DNN model has achieved greater accuracy for both infectious and healthy chest radiography. A combination of 06 diverse datasets have been selected for this research work.

3.2.12.2 Critical analysis of the research item

Strengths: The detailed investigation of this research work is presented below:

- This research has achieved the highest accuracy for pulmonary disease detection in comparison to similar studies.
- Instead of just focusing on one disease at a time, a set of three lung diseases with a high fatality rate has been considered.
- Six diverse datasets were selected for this experiment, resulting in more reliable and trustworthy results.

Weaknesses:

- Although diverse datasets have been selected for this experiment, the size of the COVID-19 dataset is comparatively small.
- Despite top-notch accuracy results, the discussion of limitations around the DNN model was included in the research.
- Although the results are interesting on publicly available datasets, real tests will depend on checking and evaluating this model with external datasets.

3.2.12.3 Relationship to the proposed research work

This research work has opened several major aspects for our proposed project. It utilized a custom DNN model which is a rare, selected model in the pulmonary disease detection field. Understanding their experimental setup and approach, we can build upon these datasets and performance metrics. The small size of datasets mentioned above can help us to identify and evaluate our testing results on bigger datasets. This will improve efficiency and reliability of our proposed research work. The cross validation is a bit novel, we plan on learning and understanding about it. After that, we will decide we can include it in our project work or not.

3.2.13 Explainable Deep Learning for Pulmonary Disease and Coronavirus COVID-19 Detection from X-rays

This research is helpful for our project as it proposes multi-step respiratory disease detection from chest x-rays identifying pneumonia in scans first and then further differentiating between pneumonia and covid-19.

3.2.13.1 Summary of the research item

The article titled "Explainable Deep Learning for Pulmonary Disease and Coronavirus COVID-19 Detection from X-rays" proposed a 3 step approach for pulmonary disease detection from X-rays. These three steps include Detection of pneumonia in chest x-rays, , Differentiating between pneumonia and covid-19, Detect the presence of COVID-19 in the chest x-rays by localization of infected areas in x-rays symptomatic.

Exploratory examination was taken into account for affirmation of proposed approach that showed the detection of COVID-19 within approximately 2.5 secs with success rate of 0.97 average accuracy.

3.2.13.2 Critical analysis of the research item

The detailed investigation of this research work is presented below:

Strengths

- The study analyzes more than 6500 chest x-rays for this experimental analysis and showed remarkable results too.
- This study uses the VGG-16 model for detection by utilizing transfer learning.
- Multiple layers were included in the VGG-16 architecture, which mainly includes averagepooling2D, flatten, dense, dropout, and another dense layer for reducing vector size.

Weaknesses

- The risk of false negatives and false positives is a great challenge.

3.2.13.3 Relationship to the proposed research work

This study has a close relationship with our research and project. There exploratory work has paved the way for several major aspects for our proposed project. It uses VGG-16, which is a 16 layered CNN which we will be incorporating in RespiraSense. This research focuses on 2 models, first based on differentiating healthy and un-healthy x-ray scans and second one based on differentiating a COVID-19 and any other lung abnormalities. They have also used four performance evaluation metrics of the classifier that includes accuracy, sensitivity, f-measure and specificity which is essential to measure the achievement of the proposed model.

3.2.14 Multiple Lung Diseases Classification from Chest X-Ray Images using Deep Learning Approach

This focuses on lung disease classification using deep learning models such as Xception - based on depth wise separable convolutions.

3.2.14.1 Summary of the research item

The research article titled "**Multiple Lung Diseases Classification from Chest X-Ray Images using Deep Learning Approach"** is aimed to propose a new approach for automatic pulmonary disease detection and classify them using Xception deep learning technique from chest X-rays. Xception is a deep CNN architecture. For this research, the authors took datasets from NIH and Jimma University Medical Center Radiology Department and were pre-processed before training. With a striking accuracy of 97.3%, this paper serves a good point for decision making process for physicians and for multi-class classification of the X-rays into multiple pulmonary diseases.

3.2.14.2 Critical analysis of the research item

A detailed critical analysis of the research article is provided below:

Strengths

- The researchers used a multi-step approach (pre-processing, data preparation, and classification), which further includes a breakdown of steps for lung disease classification using Xception, an excellent approach as it utilizes depth-wise separable and distinct convolutions.
- Fine-tuning of the pre-trained model is done for multi-class classifications, mainly TB, Pneumonia, COPD, Pneumothorax, Lung cancer, and Normal.

Weaknesses

- The size of the datasets was fairly limited, which affects the accuracy of the proposed solution.
- The researchers mainly focus on the pre-processing step, where the image quality and all the disruptions were cleared before actual processing, which is time-consuming and may not always produce expected outcomes.

3.2.14.3 Relationship to the proposed research work

The research based article significantly fosters our proposed project goals. Addressing diagnostic challenges, use of advanced image processing techniques and data preparation and training is exactly what we were looking for our project. The goals of this research paper and our project strongly aligns as it compares the multiple image processing techniques and ways to help support physicians to correctly diagnose lung disease eventually reducing their burden and minimize possible chances of errors.

3.2.15 Chest Diseases Prediction from X-ray Images using CNN Models: A Study

This research paper corresponds to our proposed project as it uses CNN models for chest disease detections mainly pneumonia, TB and covid-19. This paper focuses on evaluation of the CNN models first, comparing their performances and proposing best model for detection. A detailed summary is as follows:

3.2.15.1 Summary of the research item

The research paper titled “Chest Diseases Prediction from X-ray Images using CNN Models: A Study” is another endeavor to automatically predict chest diseases from chest X-rays such as pneumonia, TB and covid-19. This study supports prediction of these diseases using CNN models such as VGG-16, Densenet201 and Resnet50V2, and analyzes their outcomes with regard to accuracy and loss. This study also evaluates these three models, compares them and gives conclusion of Resnet50V2 best model for all these three diseases only and analyses accuracies for each of these three diseases too. This study also follows the similar approach as that of other researchers in which using CNN models distinct and profound characteristics from X-rays have been extracted and their execution is mainly performed in 3 steps: 1. Model Training using CNN models. 2. Comparing the pre-trained models for better accuracy. 3. Selection based on top notch and fine tuned model based on accuracy and loss.

3.2.15.2 Critical analysis of the research item

Strengths

- This study is based on analyzing different datasets for different diseases, pre-processing those

CXRs, and then classifying them into healthy and unhealthy scans. The three CNN models were compared, and their performances were analyzed for the three diseases at hand.

- A strong and detailed explanation of each of these CNN models is provided, and they are compared in detail to offer an in-depth analysis of these models. This also highlights that all three models are highly accurate, but ResNet50V2 is better when other factors, such as speed of training and size, are taken into account.

Weakness

- Fails to predict early-stage diseases.
- Different datasets were used for different diseases.

3.2.15.3 Relationship to the proposed research work

This research paper closely corresponds to our project. This research is focused on same three diseases - pneumonia, TB and covid-19. This research also uses CNN models for disease prediction and detection. This research can further play a pivotal role in development of our project. We will surely take their findings into consideration and work on it for better lung disease detection system.

3.2.16 Automated multi-class classification of lung diseases from CXR-images using pre-trained convolutional neural networks

3.2.16.1 Summary of the research item

The research study named “Automated multi-class classification of lung diseases from CXR-images using pre-trained convolutional neural networks” is another efficient yet remarkable piece of work that highlights the importance of pulmonary diseases these days. This paper contributes by classifying CXRs to different classes such as pneumonia, pneumothorax, TB or normal, provide network for classification and provide detailed analysis of incorrect categorization of the dataset too.

3.2.16.2 Critical analysis of the research item

Strengths

- Improved and practical classification of chest X-rays into five different classes.
- For exploratory analysis, eight pre-trained CNNs were utilized, including AlexNet, Darknet-19, Darknet-53, DenseNet-201, GoogLeNet, InceptionResNetV2, MobileNetV2, and ResNet-18.
- Achieved 97.2% accuracy in predicting the correct pulmonary disease.

- Also highlighted the areas that help in making the respective decisions.

Weakness

- A comparatively large dataset was used (3500 CXRs), but it was smaller in comparison to other studies.

3.2.16.3 Relationship to the proposed research work

This research paper and our goal for this project is same in a sense that we want to contribute to the prediction and detection of pulmonary diseases. This paper also focuses on CNN models which we are planning to use in production of our system too. By fully understanding their experimental implications and analysis, we can make accurate assumptions for our project. This will improve efficiency and reliability of our proposed research work. The cross validation is a bit novel, we plan on learning and understanding about it. After that, we will decide we can include it in our project work or not.

3.2.17 Medical Report Generation and Chatbot for COVID-19 Diagnosis Using Open-AI

The paper outlines the development of an autonomous system that will produce reports for medical experts according to the CT scans of the patients with the COVID-19 virus. The implementation of an AI based diagnostic with a chatbot for patient queries is suggested.

3.2.17.1 Summary of the research item

Mehboob et al [17] in this study aim at developing an automated classification system for Covid 19 that produces medical reports from CT scan images. Focusing upon popular language models such as GPT-3, this research involves creating the most accurate textual reports which are developed from analyzing CT scans. It further proposes a chatbot designed to respond to questions regarding Covid 19.

The research has a multi dimensional methodology. It starts with image segmentation using VGG16 model which classifies patients as Covid 19, normal or other. For the dataset, 2900 Covid CT scan images are used. After preprocessing steps, medical reports are generated.

The proposed system concludes with the successful automation of evaluating and generating reports. Moreover, it is suggested that using language models may be a way forward towards acquiring accurate medical reports in the medical sector to assist professionals. The paper further details the future ways in which the system may be improved, for instance through broadening the range of image types and other diseases.

3.2.17.2 Critical analysis of the research item

A detailed analysis of the research article is provided below:

Strengths:

- The study takes a modern approach to the problems encountered during COVID-19 diagnostics. It clearly explains the AI and DL algorithms that may be employed.
- The methodology tackles the problems of scalability as it can work on a large number of patients. In addition, the proposed model can be effectively implemented in resource-constrained settings, such as hospitals facing staff shortages.
- A clear workflow is provided along with quantitative and qualitative data analysis regarding the proposed diagnostic model and chatbot.

Weaknesses:

- There is limited variability in the dataset, as the study depends on 2900 COVID-19 CT scan images, which cannot cater to large populations or diverse geographical areas. This can also reduce the reliability of the results produced.
- The performance of the model is greatly dependent on the image quality of the scans. Variations can downgrade accuracy, and low-quality images may not respond well to the preprocessing steps provided.
- No attention is paid to ethical concerns regarding data privacy or HIPAA standards.

3.2.17.3 Relationship to the proposed research work

The project is quite relevant to our work firstly, because of the study of AI driven solutions in the diagnosis of respiratory diseases. Both projects aim to enhance the accuracy and efficiency in disease identification. Secondly, it also relates to our chatbot module as RespiraSense would use the OpenAI API which is discussed in terms of GPT-3 in the research work. Lastly, the data preprocessing steps are also relevant in our methodology as we can draw inspiration from them.

3.2.18 Disparities in medical recommendations from AI-based chatbots across different countries/regions

This paper focuses on regional differences in medical advices between AI chatbots. It proposes standardization to ensure accurate healthcare recommendations.

3.2.18.1 Summary of the research item

The study published in the national library of medicine investigates geographical variations in medical advice provided by AI-powered chatbots worldwide. It especially focuses upon adjuvant therapy for endometrial cancer. The researchers made a comparison between the answers of well-known chatbots, including Bard, Bing, and ChatGPT-3.5 originating from four different regions. These were; Indonesia, Nigeria, Taiwan, and the USA. The intent was to evaluate the reliability and quality of information being provided by these AI driven systems. This was to be done by pointing out areas of variation that could negatively impact patient care.

The findings revealed significant differences in the quality of medical recommendations among the chatbots, differing according to regional and local contexts. These variations raised doubts over the dependability of these AI chatbots as sources of medical advice, as varying or limited access may exist across regions to healthcare professionals.

Gumilar et al. [18] conclude that careful evaluation and standardization are to be made in AI-generates medical information for ensuring correct and contextually relevant guidance to the patients. They end by calling for further research to be carried out to enhance AI chatbot performance regarding healthcare recommendations.

3.2.18.2 Critical analysis of the research item

A detailed analysis of the research article is provided below:

Strengths:

- The study examines chatbot replies from four different regions spread over a large demographic to provide a well-rounded view of how they operate differently in various geographic settings.
- The authors sufficiently identify the severe differences that exist in the quality of AI-powered medical recommendations. This is critical for understanding the effects it may have on health and the reliability of health-related information.
- The need for the standardization and regulation of AI health technologies is emphasized. This is important so that policymakers and stakeholders are informed about the need for accurate healthcare information.

Weaknesses:

- The present study's focus on endometrial cancer does not necessarily provide a general understanding of other medical conditions or treatments.

- There is a chance for bias in expert evaluation, as reliance on expert opinions can be subjective and influence how the chatbot's performance is assessed.
- The authors discuss the fact that the output of AI chatbots may be inaccurate; however, they do not go into detail about the technological limitations that could be causing this inaccuracy.

3.2.18.3 Relationship to the proposed research work

The paper has a similar scope to the chatbot module of our project. The study attempts to assess the performance of an AI chatbot in delivering medical recommendations to patients. The chatbot module of our project aims to do the same. Additionally, the study also discusses ChatGPT responses and we aim to use the technology behind it (OpenAI). Moreover, both RespiraSense and the paper focus upon the use of AI to enhance the healthcare delivery system. Therefore, we can take into account the challenges addressed in this study to improve our own project.

3.2.19 Hospital Recommendation System using Machine Learning

The paper highlights a disease prediction system based on symptoms reported by users. It proposes a machine learning solution to enhance timely diagnosis and hospital recommendations.

3.2.19.1 Summary of the research item

Mani et al. [19] deal with an early disease prediction system based on user reported symptoms using the power of machine learning techniques, specifically the Random Forest algorithm. The authors state that people save on so many consequences if diagnosed on time and that most individuals lose track of their health for ignorance until it's very severe. The proposed system aims at relieving the patient and the doctor from the long time and effort spent on prediction. Moreover, The system added features a list of nearby hospitals according to location and ratings in recommending healthcare centers.

The methodology focuses on training a Random Forest classifier based on datasets that combine symptom-disease information to ensure accurate disease prediction. The paper compared a variety of ML approaches including supervised learning. It compares the effectiveness of Random Forest to other ML techniques like Support Vector Machines and Decision Trees. In addition to that, the authors also highlighted the robustness and accuracy with which Random Forest algorithm deals with data, particularly in handling missing data.

The system is concluded to not replace the professional medical assessment but rather be the first step toward better, accessible, and efficient delivery of health care. It can involve further work such as the addition of patient medical history along with other relevant data. In short, the system represents the possibility of ML in changing the medical sector and improving patient care.

3.2.19.2 Critical analysis of the research item

Strengths:

- The study is relevant to modern times as it addresses a current healthcare issue through the use of machine learning.
- The proposed system effectively integrates disease prediction along with hospital recommendations, providing a solution to improve patient access to care.
- The usage of the Random Forest algorithm is a good choice, as it is known for its accuracy and robustness, which enhances the reliability of results.
- The inclusion of user ratings and geographical location for hospital recommendations shows a user-centric approach.

Weaknesses:

- In regards to symptom coverage, the system might not be as precise as expected and may provide incorrect predictions if the dataset used does not cover a large spectrum of symptoms and diseases.
- The Random Forest classifier is highly dependent on the quality of the training data; as a result, poor quality can significantly affect the accuracy of predictions.
- The study does not elaborate much on quantifiable results or make comparisons with other algorithms. This could have further highlighted the advantages of their approach as possibly being the best suited for the task at hand.

3.2.19.3 Relationship to the proposed research work

The paper is closely related to our RespiraSense project as both seek to improve healthcare related decision making through AI. Most importantly, its hospital recommendation system is similar to our recommendation module that we are using to help the patients to identify doctors at the nearest and most appropriate hospitals considering their symptoms and diagnosis.

3.2.20 Energy-efficient model "DenseNet201 based on deep convolutional neural network" using cloud platform for detection of COVID-19 infected patients

The paper focuses on the DenseNet201 model for diagnosing chest diseases specifically COVID-19. It proposes a cloud based solution to enhance detection speed and accuracy in medical imaging.

3.2.20.1 Summary of the research item

Kumar et al.[20] discusses the architecture of DenseNet201 as being in line for a mode of diagnosing chest diseases, including tuberculosis and COVID-19. The DenseNet201 is a CNN with 201 layers that was trained for ImageNet classification and achieved impressive results in classifying chest X rays. This includes the processing of more than 6,000 chest x ray images and achieving an accuracy of 99.24% in 7.47 minutes by using a cloud platform.

According to the study, not only does this model improve detection of COVID 19 but it also has fast classification. This is particularly helpful for professionals to quickly diagnose and treat cases in time. The research primarily shows the use of Grad-CAM for visualizing the infected regions on X-rays. In addition, this research also emphasizes upon the benefits of the possible use of DenseNet201 in the medical domain.

To conclude, the results of the research indicate that DenseNet201, is capable of detecting patients infected with COVID 19 at a high speed through chest x rays. Hence, the proposed model will provide an instant method of screening chest diseases reliably.

3.2.20.2 Critical analysis of the research item

Strengths:

- The DenseNet201 model achieves high accuracy and speed, aiding in the detection of the COVID-19 virus, which might save many lives through quick diagnosis, especially during a pandemic.
- The proposed model is scalable and accessible as it utilizes cloud technology, making it practical for use in hospitals and clinics due to its cost-effectiveness.

Weaknesses:

- The size of the dataset used is limited in scope, as the study primarily focuses on COVID-19 detection with only generalized insights towards other respiratory diseases.
- Another concern is the DenseNet201 model's dependency on the quality of imaging; the performance of the model may decline with variations in the quality or standards of the images included in the training dataset.

3.2.20.3 Relationship to the proposed research work

DenseNet201 in the detection of multiple respiratory diseases. The scope of the paper overlaps with our project as one of the diseases we aim to identify is Covid 19. Moreover, the paper also highlights the importance of speed in diagnosis of life threatening diseases.

3.3 Literature Review Summary Table

Table 3.1: Summary of Literature Review

Author	**Method**	**Results**	**Limitations**
Viswanathan et al. [1]	Scoping review of chatbots in medical fields	Different applications and benefits of chatbots in healthcare were identified	Existing publications were reviewed only
Effah et al. [2]	Random Forest and XGBoost along with other ensemble ML models	RF (accuracy 92.0, precision 91.3, recall 96.0, f1-Score 93.6) XGBoost (accuracy 90.8, precision 92.6, recall 92.3, f1-score 92.4)	Relies on imbalanced datasets, limited by specific biomarkers
Vo Trong et al. [3]	Convolutional Block Attention and Wide Dense Net - CBAMWDnet for tuberculosis detection in chest x-rays	Accuracy: 98.80%, Sensitivity: 94.28%, Precision: 98.50%, Specificity: 95.7%, F1 Score: 96.35%	Biases and variations in imaging conditions not addressed
Sanghvi et al. [4]	Deep learning approach for classification	98.6% accuracy	DenseNet201 proven to be very slow and inefficient
Etemadi et al. [5]	Classified HRS into five types: collaborative, content, knowledge, context, hybrid	Identified 17 factors for HRS evaluation; highlighted need for scalable HRS framework	Early stage maturity of HRS, lack of standardization, cold start issues not fully addressed

Author	**Method**	**Results**	**Limitations**
Kabir et al. [6]	Knowledge distillation framework	Accuracy: 0.97, Precision: 0.94, Recall: 0.97	Dependent on large datasets, varied performance across different datasets
Khan et al. [7]	Pneumonia detection using chest X-ray	Comprehensive analysis of available public datasets, highlighted the importance of handling class imbalances	Limited focus on real-world limitations, insufficient analysis of machine learning methods;
Ahmed et al. [8]	CNN for diagnosis of pneumonia, COVID-19, and tuberculosis from chest X-rays	Accuracy 99.66% for Pneumonia, 98.10% for TB, 96.27% for COVID-19 using pre-processed images and multi-classification	Imbalanced COVID-19 dataset affected accuracy; lack of independent datasets for validation
Rahman et al. [9]	Use of nine CNNs for tuberculosis detection using chest X-rays	DenseNet201 achieved the highest accuracy, sensitivity, and precision	Public datasets may lack diversity, lower accuracy compared to similar studies
Tripathi et al. [10]	Survey of deep learning in medical image analysis	Comprehensive overview of deep learning applications in medical imaging	Rapid pace of field development may quickly date findings

Author	Method	Results	Limitations
Ulas et al. [11]	Computer-aided detection (CAD) for lung infections	Comprehensive review of CAD techniques for lung disease detection	Theoretical framework without real dataset testing, dependent on high image quality
Kawsher et al. [12]	Custom deep neural network model	Highest accuracy compared to similar studies	Small COVID-19 dataset, limitations in DNN model, needs testing with external datasets.
Luca et al. [13]	Three-phase deep learning for pneumonia, COVID-19, and area localization	0.99 accuracy, 2.5s detection time	Dataset size, institutional bias
Fethyaseid et al. [14]	Xception deep learning model for multi-class lung disease classification from chest X-rays	97.3% accuracy, 97.2% sensitivity, 99.4% specificity	Limited dataset, variability in image quality across institutions
Latheesh et al. [15]	VGG19, Resnet50V2, Densenet201 (CNN Models) analyzed X ray images for disease detection	Resnet50V2 showed the highest accuracy with F1 scores of 0.98 (Pneumonia), 0.92 (Tuberculosis), and 0.97 (COVID-19)	Limited dataset diversity and model complexity may impact generalizability and real time deployment

Author	**Method**	**Results**	**Limitations**
Karaddi et al. [16]	AlexNet, Darknet-19, Darknet-53, Densenet-201, Googlenet, InceptionResnetV2, MobilenetV2, Resnet-18) to chest x rays	Densenet-201 achieved 97.2% accuracy with 94.28% sensitivity and 97.92% specificity	Misdiagnosis risk due to overlapping features and reliance on dataset quality
Fozia et al. [17]	Fine-tuned GPT-3 and OPT-350m for automatic medical report generation from CT scans	Achieved high performance in report accuracy	May misinterpret data due to limited semantic understanding
Gumilar et al. [18]	Analyzed AI chatbot responses across four regions and three platforms in 24 hours	Variations in responses by location (p ¡ 0.001), with Bing Nigeria showing the best performance	Responses vary due to demographic differences
Mani V et al. [19]	Random Forest algorithm for symptom-based disease prediction and hospital recommendations	Accurate predictions with reduced time, high efficiency	Not a substitute for medical practices, dependence on user input accuracy
Kumar et al. [20]	DenseNet201 on a cloud platform to classify COVID-19 from chest x-rays	Achieved 99.24% accuracy in 7.47 minutes	Dependent on dataset quality, real-life performance and efficiency not fully tested

3.4 Conclusion

In a nutshell, we have researched and reviewed around 20 articles, research papers and journals highlighting the importance of pulmonary diseases and the need for urgent yet accurate diagnosis in healthcare. These studies emphasize the use of AI in this field showing splendid accuracy rates. The deep learning models, most relevantly CNN models play a remarkable role in detecting and predicting respiratory diseases such as pneumonia, TB and covid-19 from CXRs. Researches indicates that integration of AI and its promising features such as recommendation systems and chatbots in medical field is needed for escalate the efficacy of health sector. The reviewed articles discussed a diverse range of techniques including CNN models, CapsNet, GAN, VGG-16, STN, DNN etc. These models were discussed in detail, compared and indicated higher accuracy rates. The performance of these models were also taken into account by using using performance evaluation metrics such as specificity, accuracy and loss. However, we have seen some limitations in the studies and solutions proposed that mainly includes limited data set sizes, the potential biases, their accuracies limited to certain diseases only, missing rare conditions and failing to predict early stage diseases .

As our project - RespiraSense, is an effort to contribute to this field, understanding of the problem statement and insights gained from these researches proved a valuable source of information that will influence our methodological decisions and help us make a reliable respiratory diagnostic tool with an emphasize on higher accuracy rates. Our main goal for this project is to make a tool that supports the health warriors make informed decisions and for patients to easily manage and track their respiratory health. We hope to build a robust pulmonary diagnostic tool that can help save patients lives so that they can look forward to a happy and healthy life.

Chapter 4 Software Requirement Specifications

This section outlines all modules of requirements and design for our project. It describes the features of our project highlighting the functional requirements, quality attributes, non-functional requirements, related assumptions, usecase scenarios, hardware and software requirements, user interface design (GUI) and analysis of the risks that are associated with our project.

4.1 List of Features

Following list of features will be available in RespiraSense:

1. Secure user registration and login functionality for both patients and doctors.
2. Compatibility for uploading lungs scans datasets like X-rays etc for both patients and doctors.
3. Lung disease prediction and suggestions classifying scans in normal, Pneumonia, Covid and Tuberculosis for doctors and detailed reports for patients and the need to seek medical guidance.
4. Chatbot feature that helps user get any form of information about their disease or condition.
5. Patients can look for nearest hospitals and doctors during emergencies.

4.2 Functional Requirements

Following is the list of functional requirements that shall be in our project:

- The user (patients and doctors) shall be able to register by creating an account.
- The user (patients and doctors) shall be able to login to their account(s) by providing their credentials.
- The user (patients and doctors) shall be able to logout from their account(s).
- The user (patients and doctors) shall be able to upload lung scans.
- For patients, the system shall apply a machine learning algorithm to determine the scan's identity and categorize it as normal or aberrant, directing the patient to seek medical attention.
- For doctors, the system shall implement a machine learning algorithm to identify and classify the scan as either normal or abnormal and predict various lung conditions in case of anomalies (e.g., Pneumonia, COVID-19, Tuberculosis).
- The system shall provide a diagnostic result for doctors.

- The system shall display possible recommendations to the patients based on their lung conditions.
- The system shall provide the patient with the facility to locate the nearest hospitals in case of emergency.
- The system shall provide the patient with the facility to store lab reports to maintain their lung's history and track the progression of their disease.

4.3 Quality Attributes

Our project aims to incorporate and meet the following quality standards. These fundamental quality attributes help ensure project performance and ensure seamless operation.

4.3.1 Reliability

Reliability is one of the most crucial quality attributes to ensure reliable medical assistance. We need to make sure that it predicts right results for the scans uploaded and guides the user efficiently. The software product needs to guide user and predict the results in any condition. The software product will be made to help users rely on our app to help gain correct insights about their lung conditions.

4.3.2 Maintainability

RespiraSense ensures sustainability in the longer run due to the use of trained models for lung scans and analyse them with proper care. This ensures that the system remains easy to update or switch to the newer technologies, extend its functionality to incorporate more new features, and manage its overall performance overtime. Moreover, we will follow the best coding practices and include proper and detailed documentation to ensure long term sustainability making future advancements easier and more manageable.

4.3.3 Usability

Our project aims to focus on usability making sure that our platform is open for all, offers a user-friendly and intuitive environment for our users (both patients and doctors). We aim to ensure simple and smooth flow of actions, offering easy access and clear navigation that helps users interpret the results. We are also offering chatbot feature and to locate and navigate to nearest hospitals is just at their fingertips. Our platform offers consistent user interface, easy for novice users to help adapt to our system, accessible actions with minimal effort.

4.3.4 Correctness

As for medical context, correctness is an essential quality attribute ensuring consistent and accurate prediction and detection of the lung disease avoiding unreliable results. We ensure data integrity and focus on conformance with our functional requirements, Incorporating the correctness quality standard is made to provide users a sense of surety that they can rely on our system.

4.4 Non-Functional Requirements

4.4.1 Availability

- The system shall be available 24/7 for the users and giving responses to their requests anytime anywhere in no time.
- The system shall provide real time access to information and to locate nearest hospitals in case of emergency.

4.4.2 Reusability

- There will be separate modules based on different features enabling reusability of code.
- The system aims to maximize the efficiency and should work consistently without failing to meet its expectations hereby trying to minimize the redundancy.
- The system should incorporate small, independent and reusable modules allowing easy integration.

4.4.3 Robustness

- The system shall be able to tackle any sudden unexpected condition gracefully without any failure.
- The system shall be able to manage errors and handle them efficiently to improve project performance.

4.4.4 Security Requirements

Security is a top-notch priority of our system due to the given nature of healthcare scans and data.

- The system shall incorporate secure authentication mechanisms to ensure user authorization and authenticity.
- The system shall provide secure and seamless file uploading feature that protects the user scans

from malicious attacks.

- The system shall not provide user's information with anyone to ensure compliance with healthcare standards and rules.

4.4.5 Performance

- The system shall be able to full fill user's requests providing timely responses 24/7.

4.5 Assumptions

The following assumptions have been made for this system:

- Users are assumed to possess a basic understanding of website navigation and usage.
- Users will access the application via modern web browsers (Google Chrome or Microsoft Edge).
- A stable internet connection is available at all times.
- Users are presumed to have access to a device capable of running web applications.
- Team members have the necessary skills to implement the project successfully.

4.6 Use Cases

4.6.1 User Registration

Name	User Registration		
Actors	User, System		
Summary	The user fills in personal details to create an account within the system.		
Pre-Conditions	No existing account for the provided email or username.		
Post-Conditions	The The creation of the account is successful and the login page is displayed to the user.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to the registration page.	2	The system prompts for account creation details (Name, Email, Password).
2	The user enters valid details.	4	The system validates the input and creates an account for the user.

4.6.2 User Login

Name	User Login		
Actors	User, System		
Summary	The user logs into the system using their email and password.		
Pre-Conditions	The user must have a valid account.		
Post-Conditions	The user is logged into the system successfully.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to the login page.	2	The system prompts for credentials.
2	The user enters valid credentials.	4	The system verifies the credentials and logs in the user.

4.6.3 User Logout

Name	User Logout		
Actors	User, System		
Summary	The user logs out of the system.		
Pre-Conditions	The user must be logged into the system with valid credentials.		
Post-Conditions	The user is logged out and redirected to the login page.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user clicks on logout button.	2	The system processes the user logout request.
2		4	The system logs out the user and redirects user to login page.

4.6.4 Edit Profile

Name	Edit Profile		
Actors	User, System		
Summary	The user updates their profile information.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The user updates their profile information.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user clicks on the edit profile button.	2	The system displays a screen to edit profile details.
2	The user edits the desired fields	3	The system validates the entered information for errors.
3	The user click the confirm button.	4	The system updates the profile in the database.
5		6	The system confirms the update and displays a success message.

4.6.5 Add Patient

Name	Add Patient		
Actors	Doctor, System		
Summary	The user adds a new patient.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The new patient is successfully added.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user selects the option to add a new patient.	2	The system displays patient information
2	The doctor fills in the patient details	3	The system validates the entered information.
3	The doctor clicks Add.	4	The system adds new patient to database.

4.6.6 Add Lab Report

Name	Add Lab Report		
Actors	Patient, System		
Summary	The user adds a new lab report to the system.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The patient adds a new lab report in the system.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to Lab Reports from the side menu.	2	The system shows available reports.
2		3	The system shows add report button.
3	The user clicks on add new report button.	4	
5	The user chooses file from his machine.	6	
7	The user pressed the upload button.	8	The system saves the report.

4.6.7 View Lab Report

Name	View Lab Report		
Actors	Patient, System		
Summary	The user views list of uploaded lab reports.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The system displays the requested lab report to the user.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to Lab Reports from the side menu.	2	The system shows available reports.
2		3	The system shows view button for each.
3	The user clicks on view report button.	4	The system processes request.
5		6	The system displays report.

4.6.8 Delete Lab Report

Name	Delete Lab Report		
Actors	Patient, System		
Summary	The user deletes a lab report from the list of lab reports.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The system deletes the requested lab report from the system.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to Lab Reports from the side menu.	2	The system shows available reports.
2		3	The system shows delete button for each.
3	The user clicks on delete report button.	4	The system processes request.
5		6	The system deletes report.

4.6.9 Image Upload for Disease Detection

Name	Image Upload for Disease Detection		
Actors	User, System		
Summary	The user uploads an image for disease detection.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The system processes the image for analysis.		
Special Requirements	The image must be of acceptable quality and resolution.		
Basic Flow			
Actor Action		**System Response**	
1	The user opens the upload screen.	2	The system prompts the user to upload an image for analysis.
2	The user uploads the image.	4	The system processes the image for disease detection.

4.6.10 Disease Detection

Name	Disease Detection		
Actors	Doctor, System		
Summary	The user starts a diagnosis, and the AI tool determines lung disease.		
Pre-Conditions	The user is logged into the system and has relevant medical image.		
Post-Conditions	The AI tool provides a diagnosis for the lung disease.		
Special Requirements	Accurate and quick classification of disease		
Basic Flow			
Actor Action		**System Response**	
1	The user clicks on the Diagnose button	2	The system runs an analysis on the relevant image.
2		3	The AI tool analyzes the image to determine the presence of lung disease.
3	The user may ask follow-up questions.	4	Diagnosis results are displayed

4.6.11 Appointment Booking

Name	Booking an Appointment		
Actors	User, System, Hospital		
Summary	The user schedules an appointment with a doctor/hospital.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The appointment is successfully booked.		
Special Requirements	All details must be provided, and slot availability is required.		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to the appointments page.	2	The system displays available dates and times.
2	The user selects a date and time.	3	The system checks the availability of the selected slot.
3	The user confirms the appointment details.	4	The system books the appointment and sends a confirmation to the user.

4.6.12 Appointment Cancellation

Name	Appointment Cancellation		
Actors	Patient, System		
Summary	The user cancels an existing appointment.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The appointment is successfully cancelled.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to the appointments page.	2	The system displays upcoming appointments.
2	The user selects the appointment to cancel.	3	The system prompts the user to confirm the cancellation.
3	The user confirms the cancellation.	4	The system cancels the appointment and updates the appointment list.

4.6.13 Chatbot Interaction

Name	Chatbot Interaction		
Actors	Patient, System		
Summary	The user interacts with the chatbot for assistance.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The user receives information from the chatbot.		
Special Requirements	The chatbot must understand user queries accurately.		
Basic Flow			
Actor Action		**System Response**	
1	The user prompts a message to the chatbot.	2	The chatbot respond asking how it can assist.
2	The user writes a query.	3	The chatbot processes the input and provides a relevant response.
3	The user may ask follow-up questions.	4	The chatbot continues the conversation based on the user's input.
5	The user ends the conversation.	6	The chatbot offers further assistance if needed.

4.6.14 View Patients Under Observation

Name	View Patients Under Observation		
Actors	Doctor, System		
Summary	The user views a list of patients currently under his/her observation.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The system displays list of patients under observation.		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to Patients from the side menu.	2	System gets patients under observation.
2		3	The system displays the list of patients to the doctor.

4.6.15 Hospital Direction

Name	Hospital Directions		
Actors	Patient, System		
Summary	The user receives directions to the hospital.		
Pre-Conditions	The user is logged into the system.		
Post-Conditions	The user is redirected to Google Maps with directions.		
Special Requirements	The directions must be updated and accurate.		
Basic Flow			
Actor Action		**System Response**	
1	The user selects the option to get directions.	2	The system starts search for the nearest location.
2		3	Google Maps is opened with directions to the nearest hospital.

4.7 Hardware and Software Requirements

This section outlines the hardware and software requirements needed to build and use the project.

4.7.1 Hardware Requirements

The hardware requirements for RespiraSense will require the following specifications:

- **Processor:** Minimum Intel Core i5 or an AMD Ryzen 5 series
- **RAM:** Minimum 8GB
- **Graphics Card:** Minimum 4GB VRAM
- **Storage:** User Preference
- **Display:** User Preference
- **Network Connectivity:** Reliable and fast internet connection

4.7.2 Software Requirements

The software requirements for RespiraSense will require the following specifications:

- **Integrated Development Environment:** Microsoft Visual Studio Code
- **Operating System:** Compatible with Windows 8, 10, 11
- **Application Development:** React.js, Express.js, Node.js, Flask
- **Database:** MongoDB
- **Machine Learning:** TensorFlow, Keras

4.8 Graphical User Interface

The GUI dumps of each screen, with reference to the functionality allowed and intended user are given in this section starting from the next page.

Figure 4.1: Login Screen

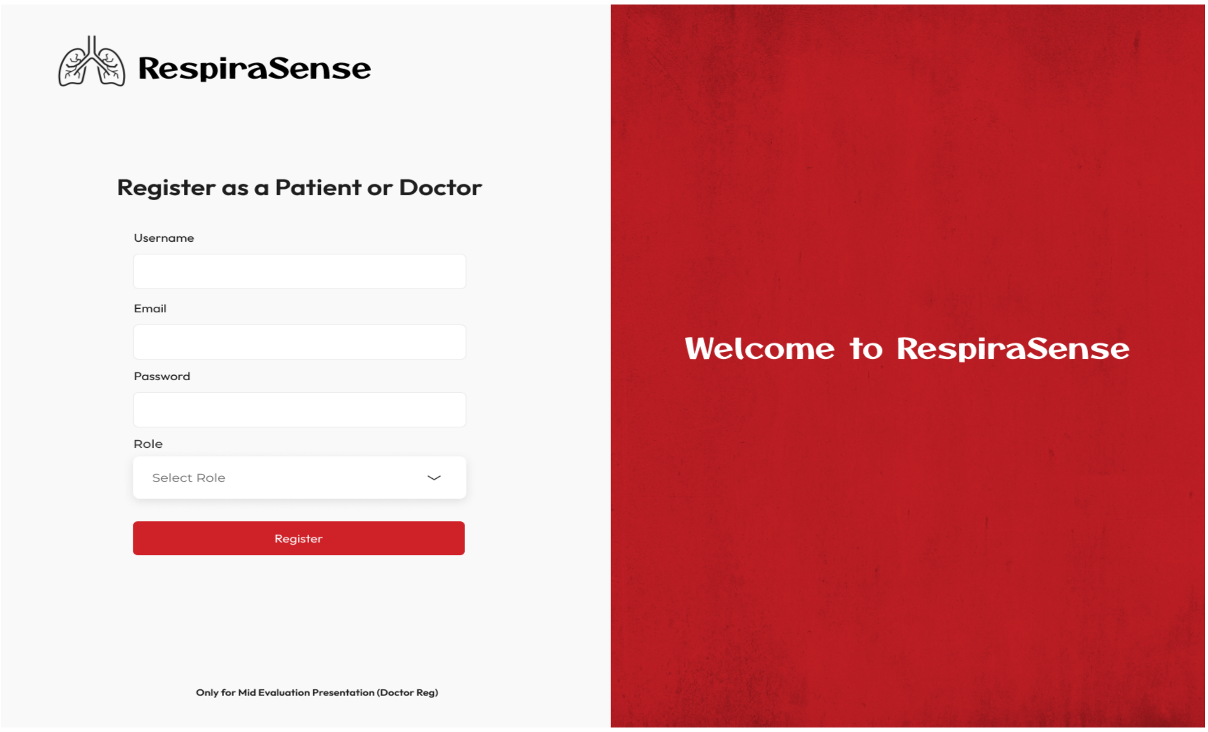

Figure 4.2: Registration Screen

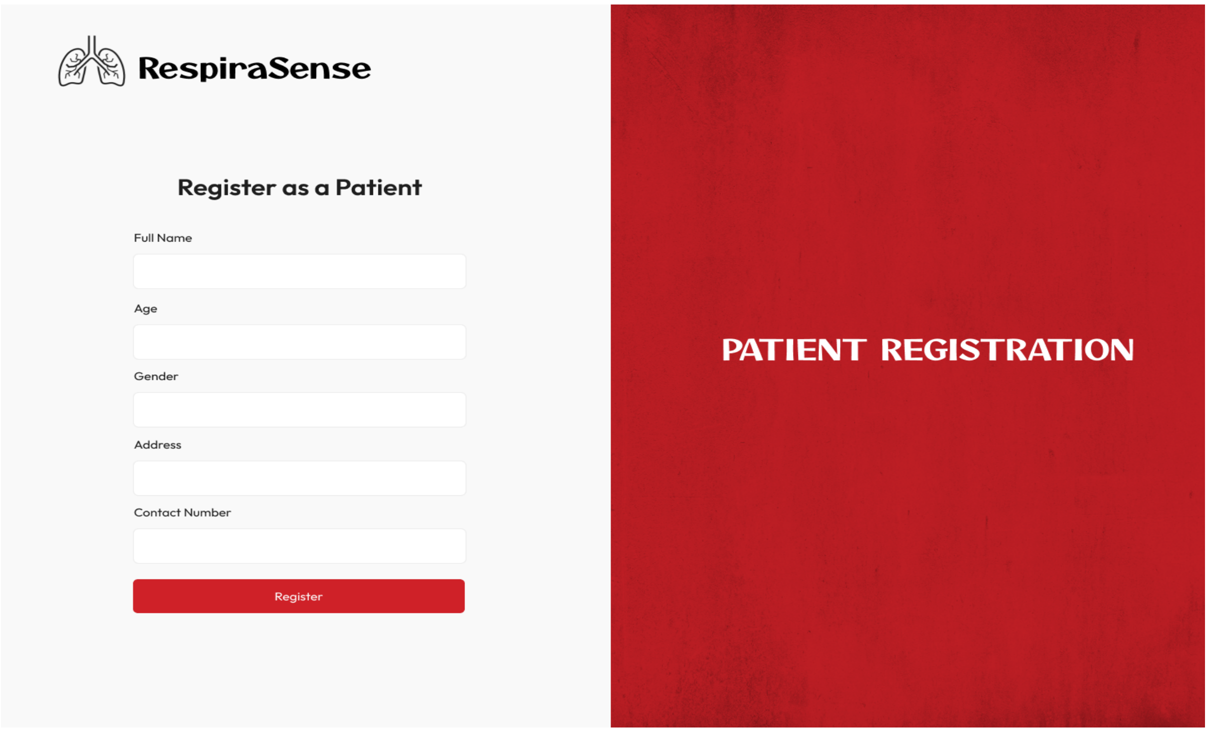

Figure 4.3: Patient Registration Screen

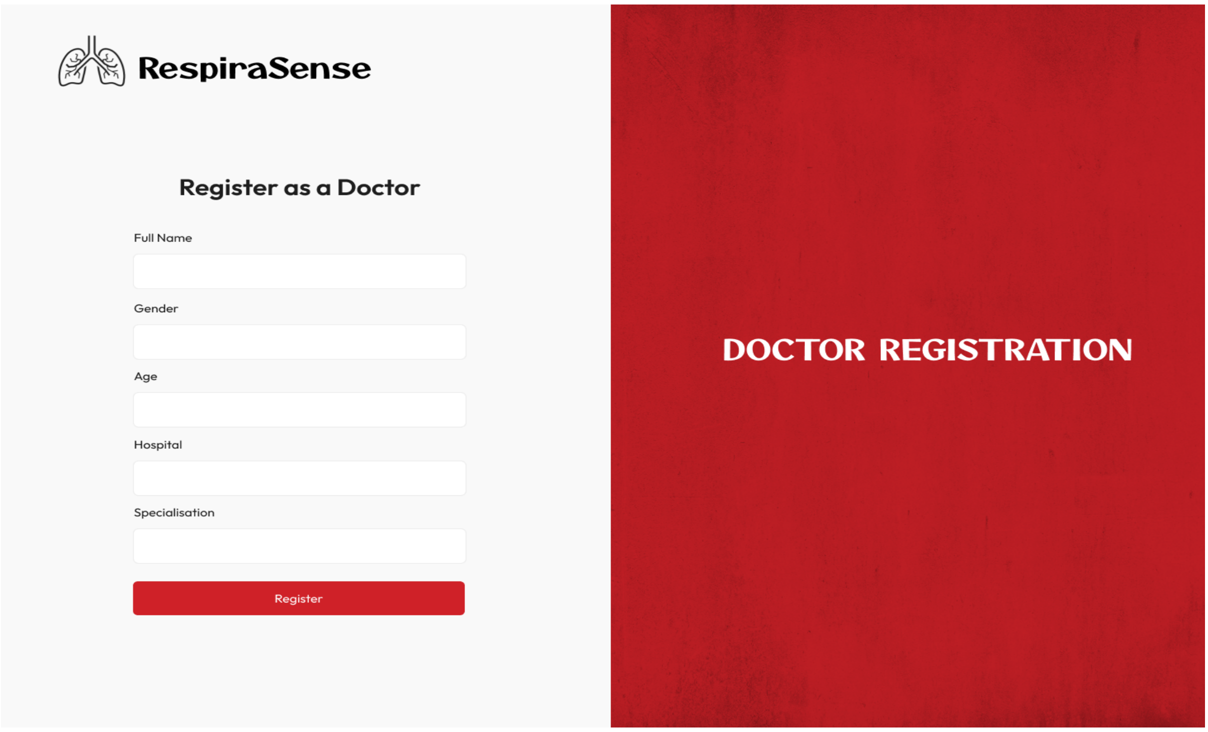

Figure 4.4: Doctor Registration Screen

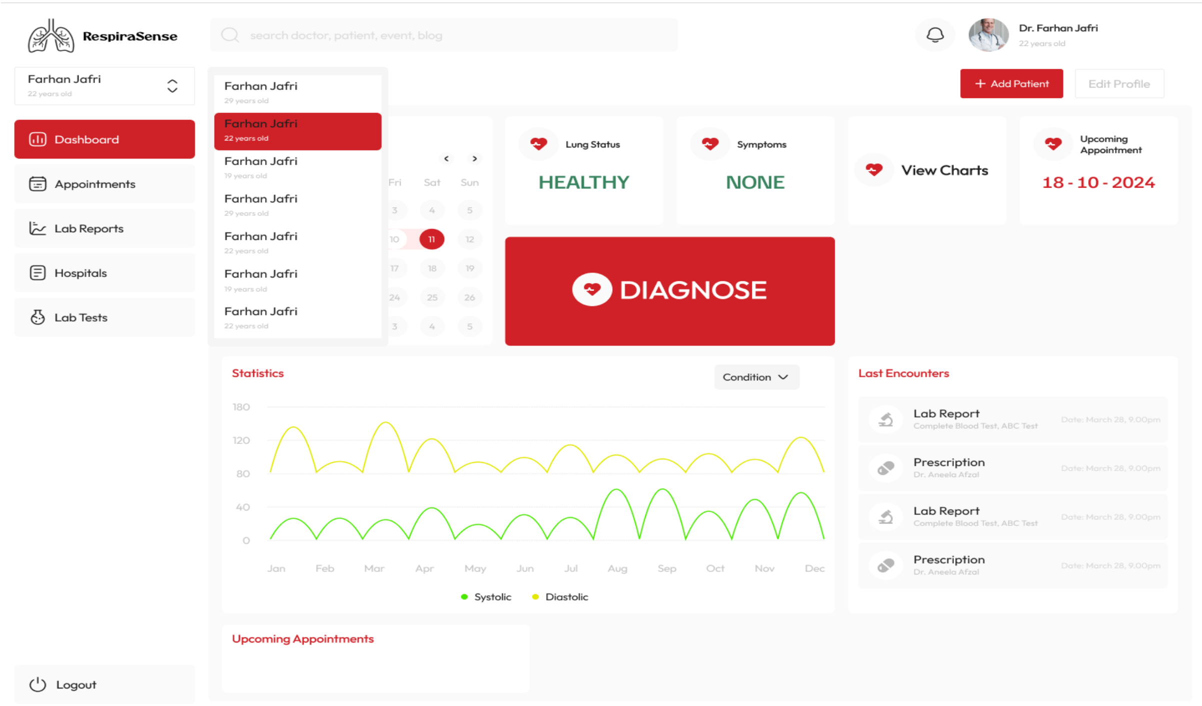

Figure 4.5: Doctor Dashboard Screen

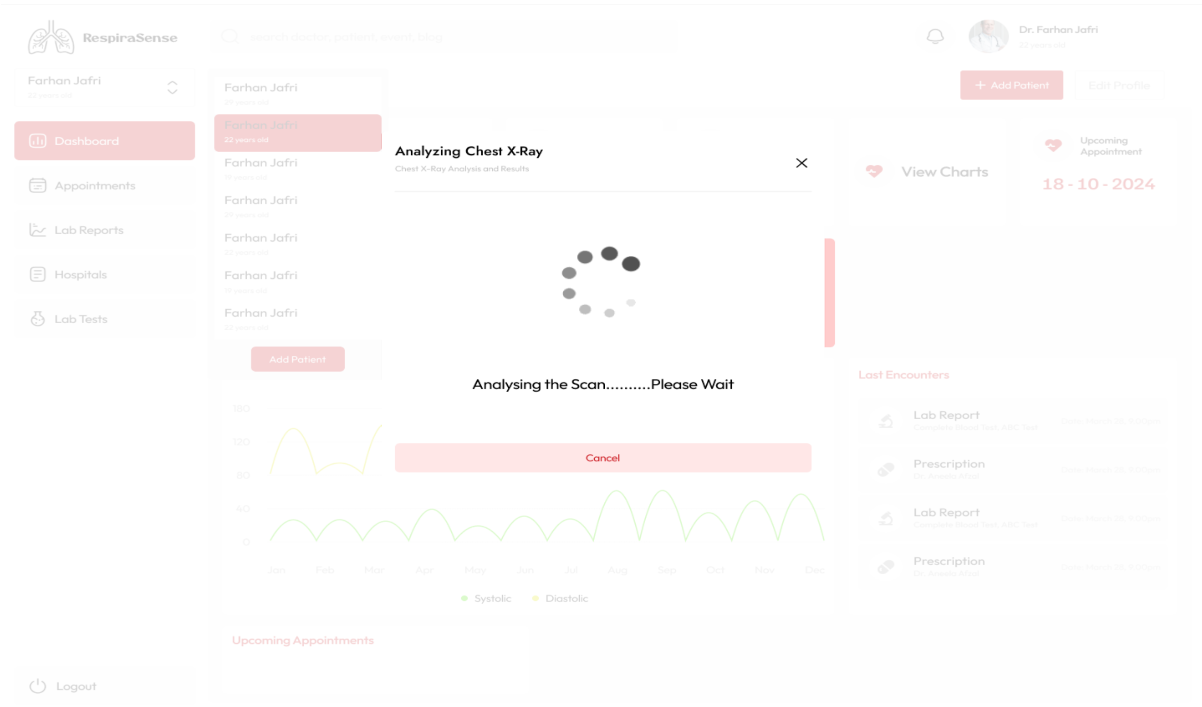

Figure 4.6: Analyzing X-Ray Screen

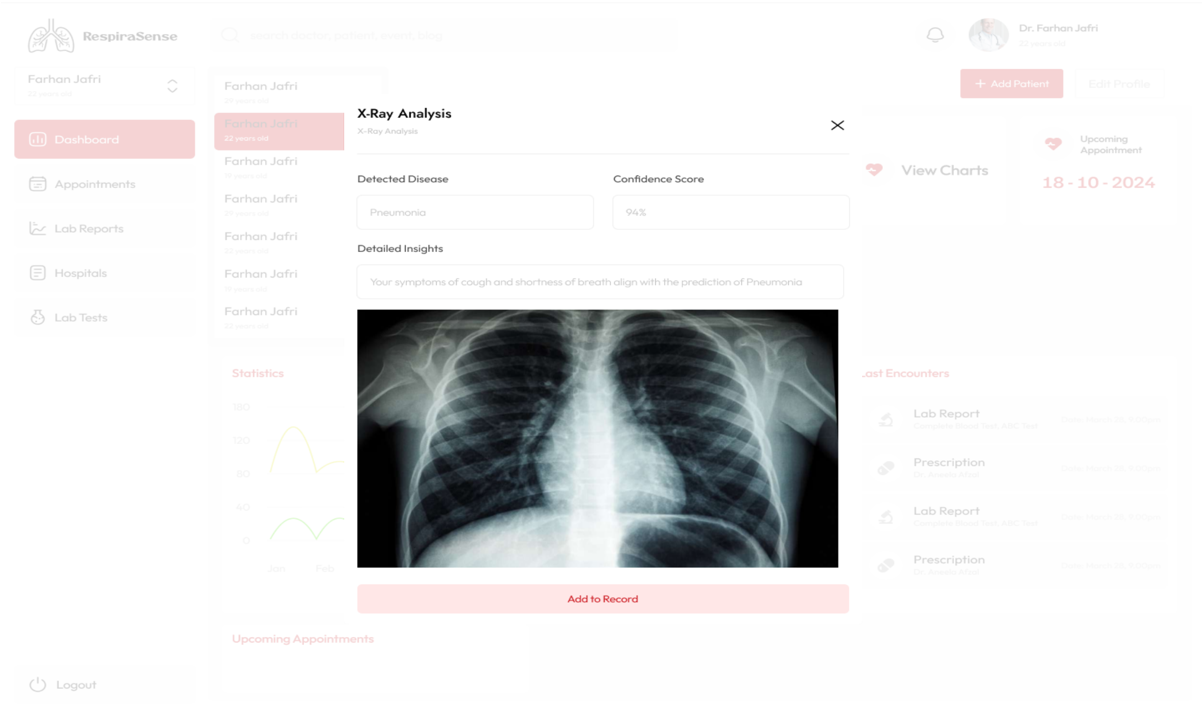

Figure 4.7: Detection Tool Result Screen

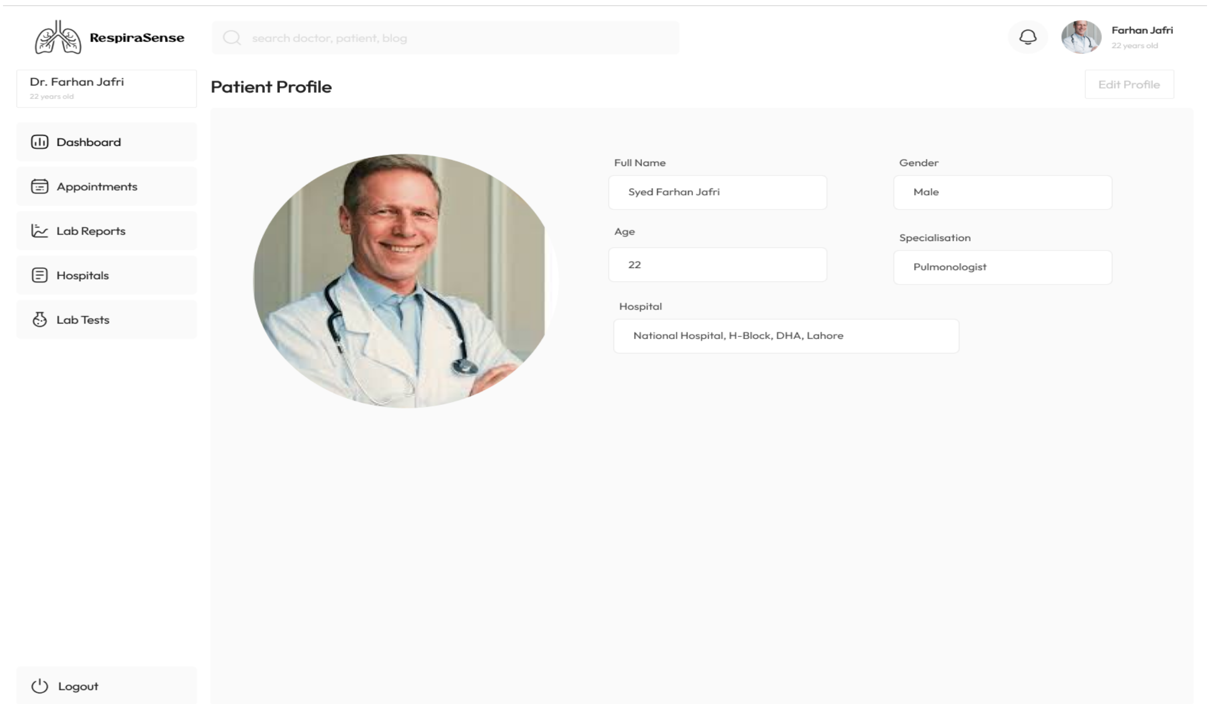

Figure 4.8: Doctor Profile Screen

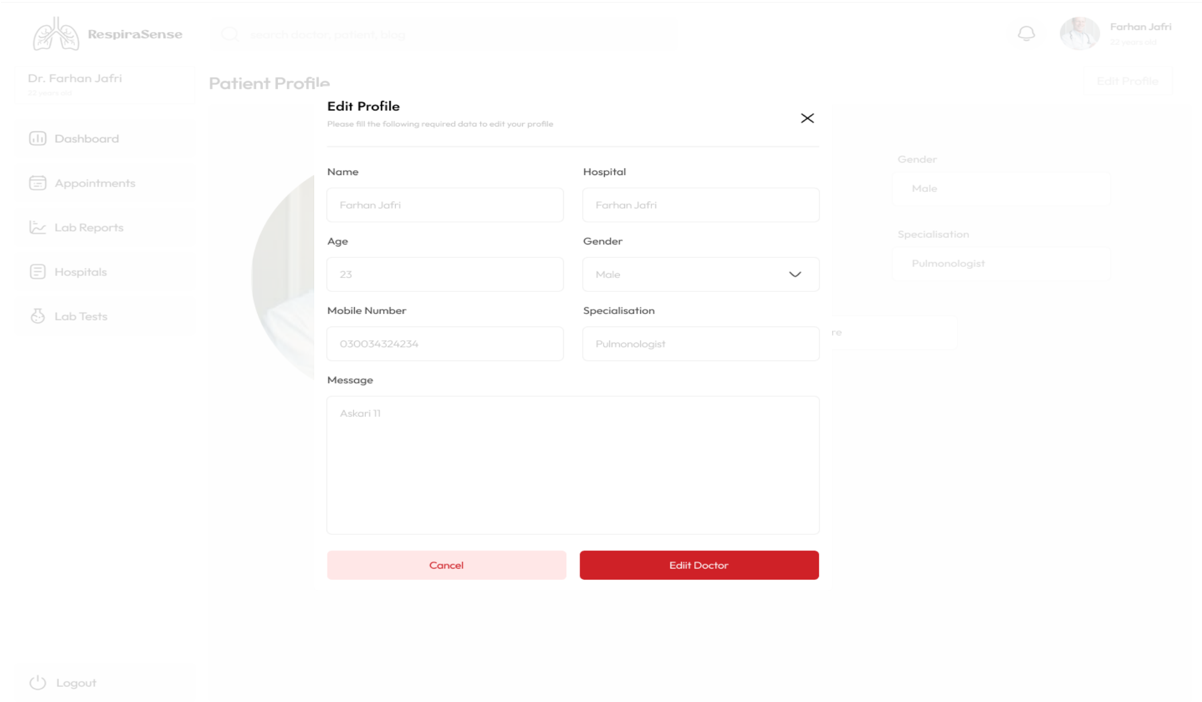

Figure 4.9: Edit Doctor Profile Screen

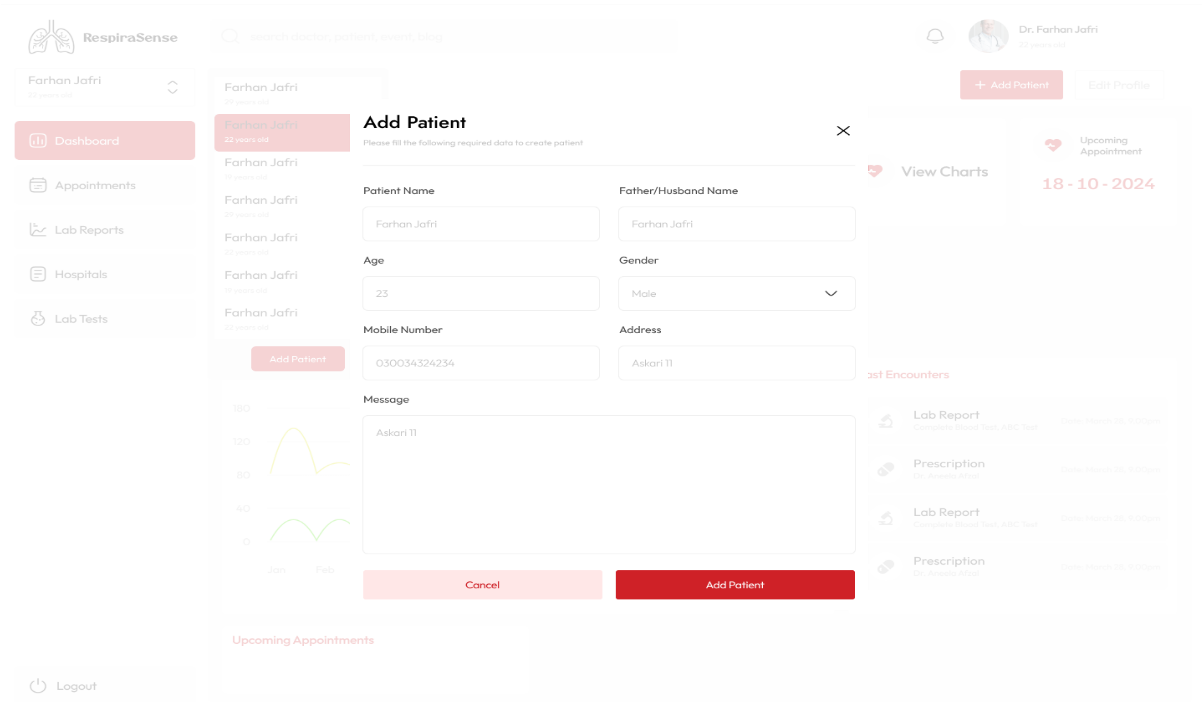

Figure 4.10: Add Patient Screen

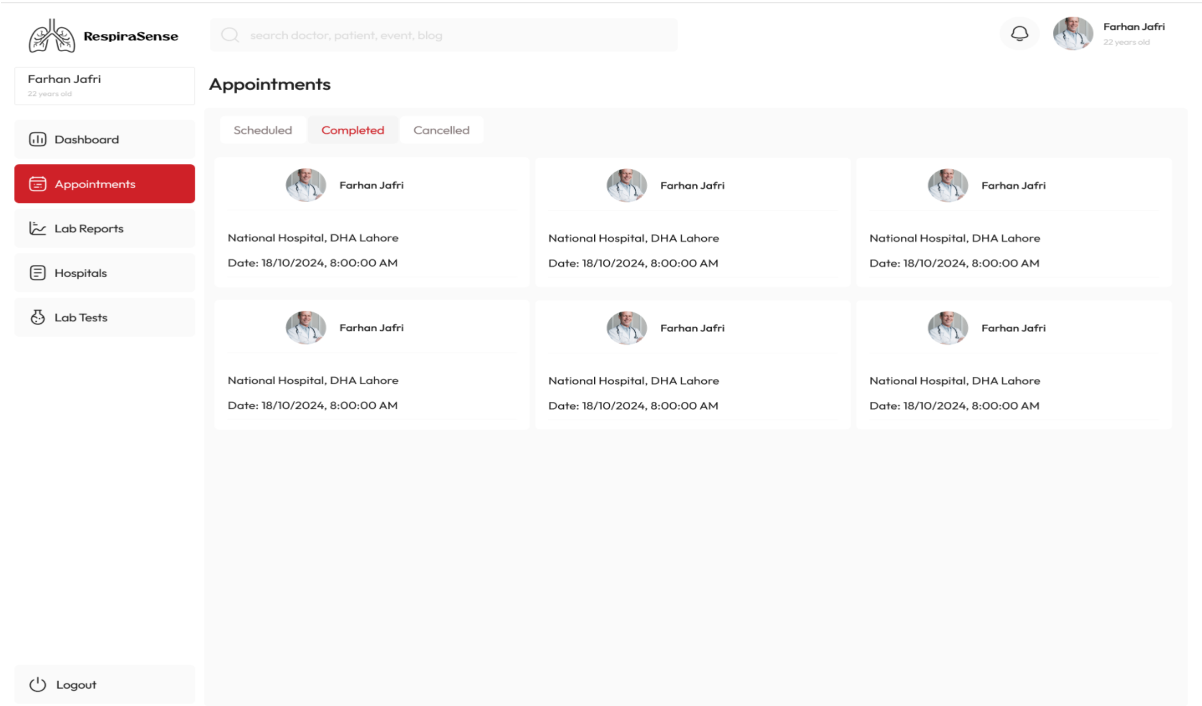

Figure 4.11: Doctor's Completed Appointments Screen

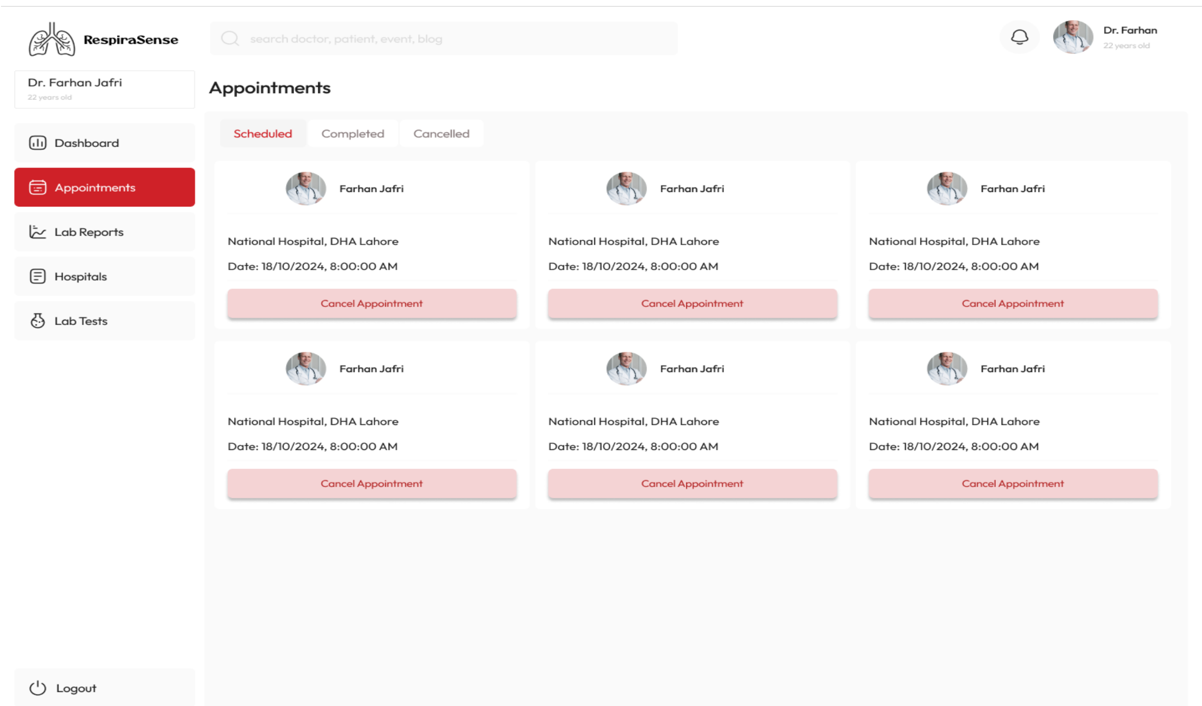

Figure 4.12: Doctor's Scheduled Appointments Screen

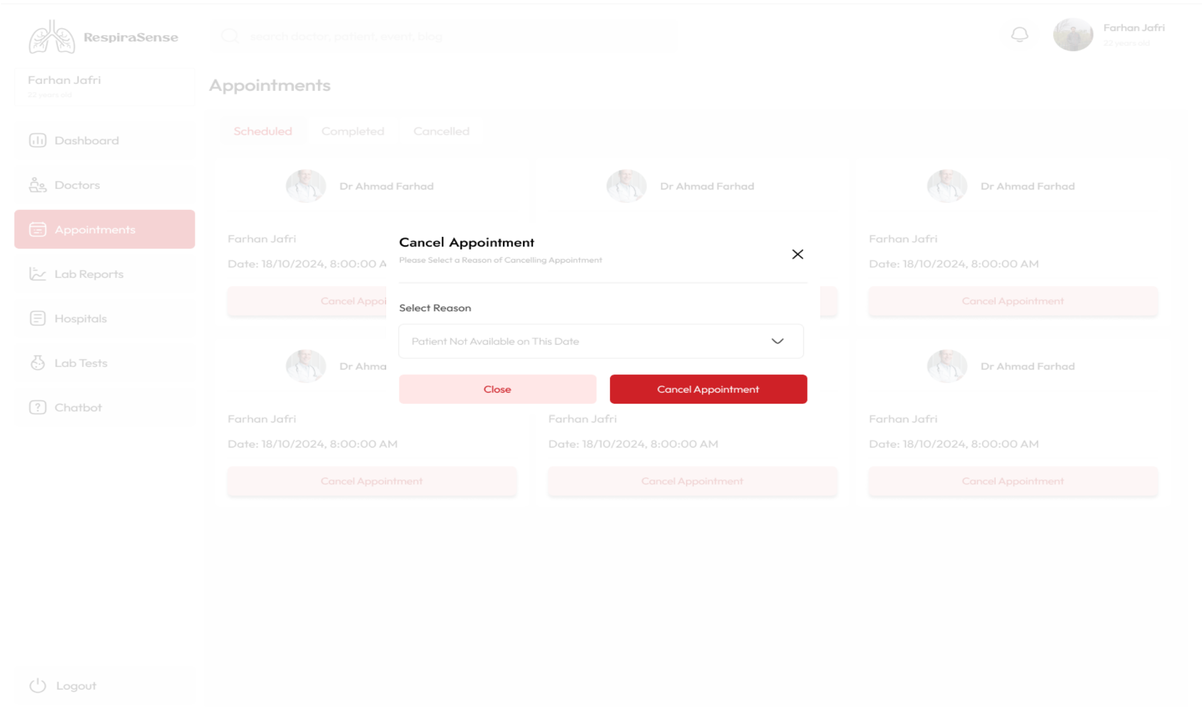

Figure 4.13: Doctor's Appointment Cancellation Confirmation Screen

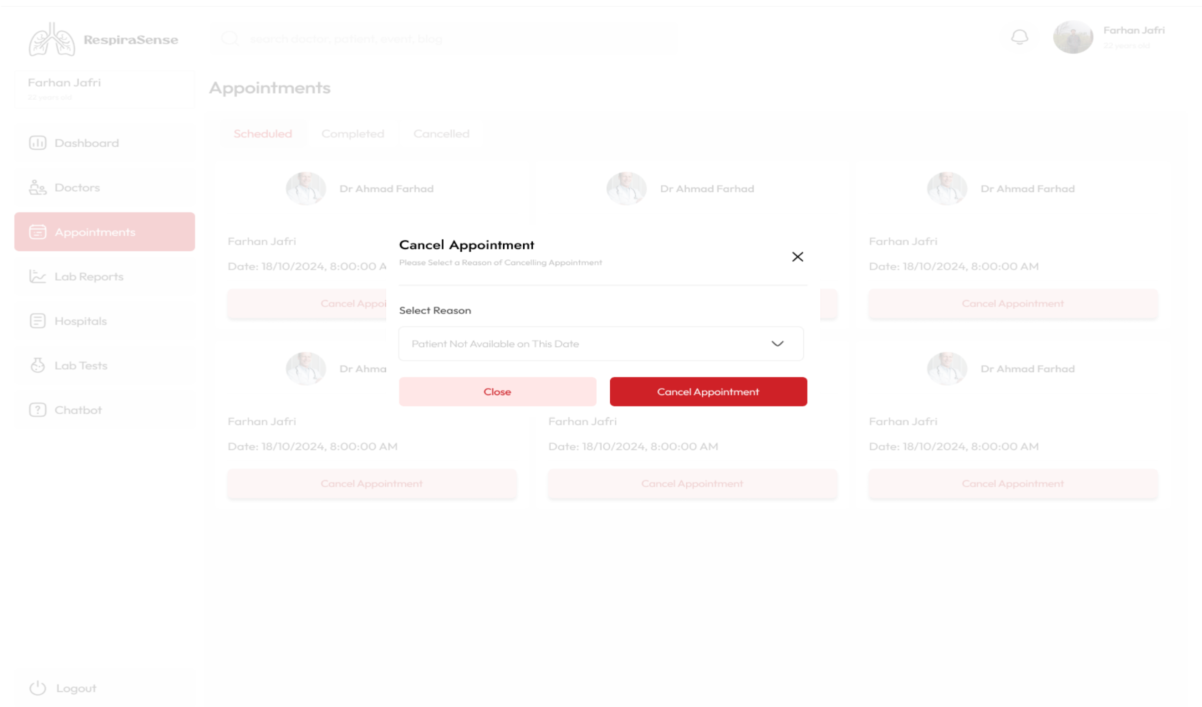

Figure 4.14: Doctor's Cancelled Appointments Screen

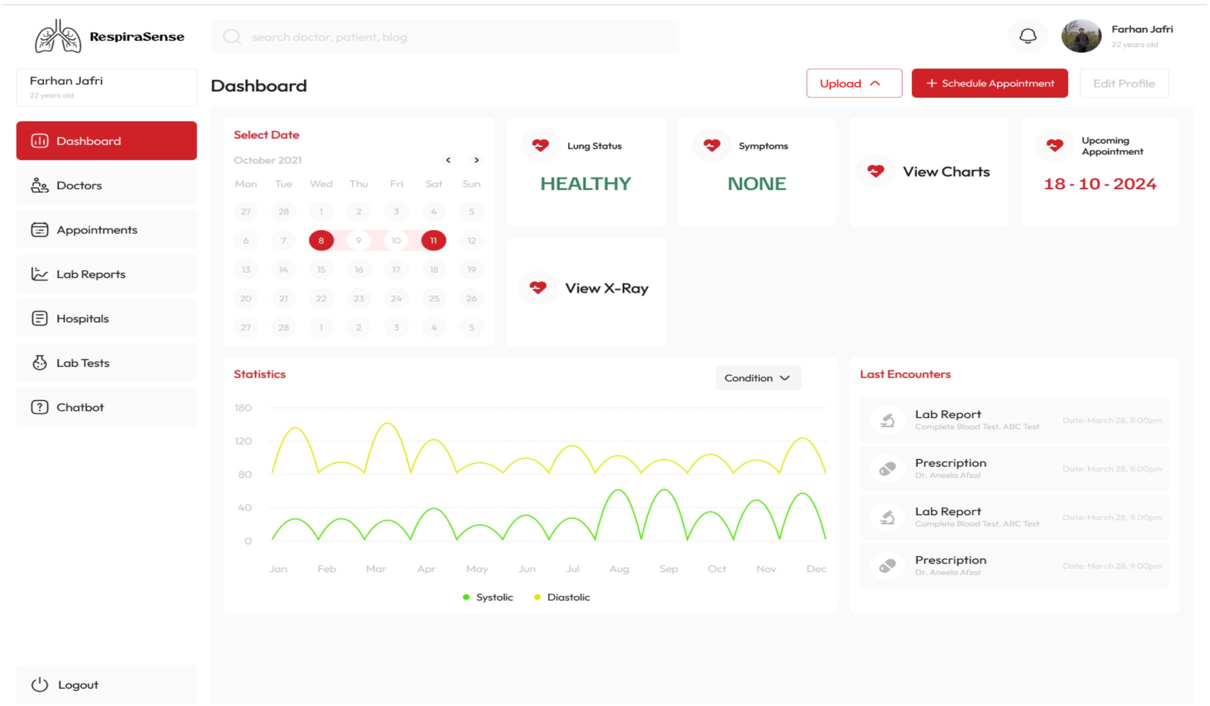

Figure 4.15: Patient Dashboard Screen

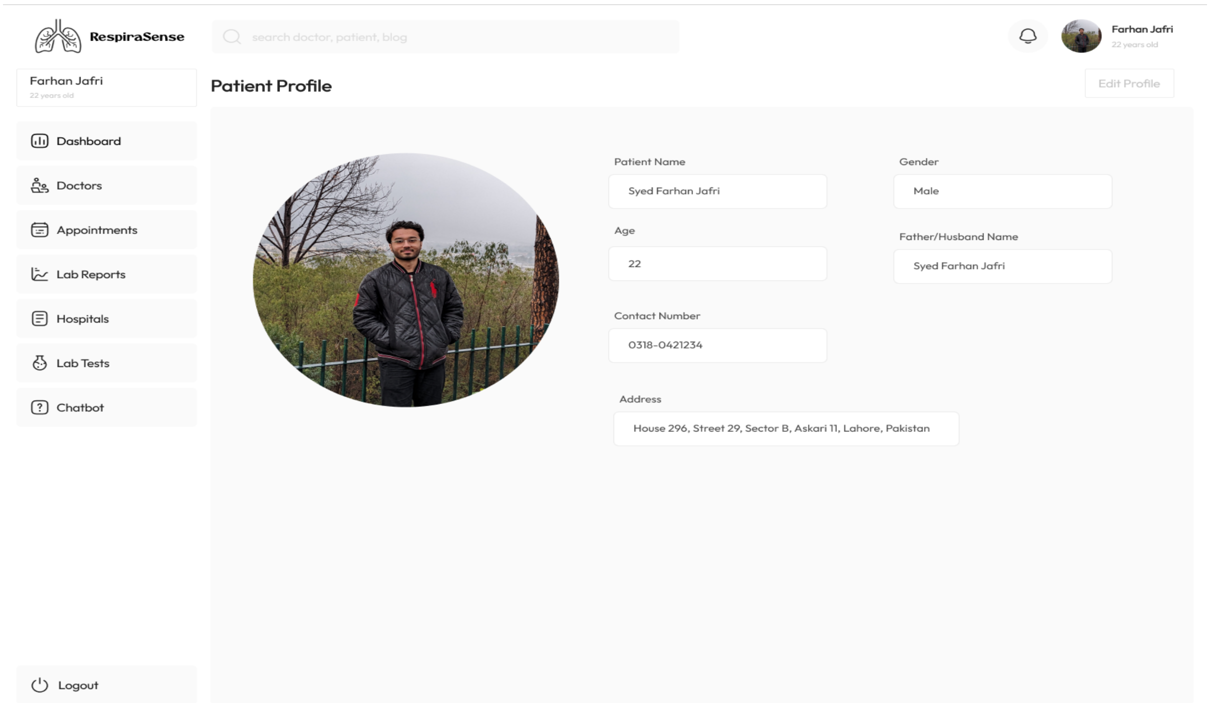

Figure 4.16: Patient Profile Screen

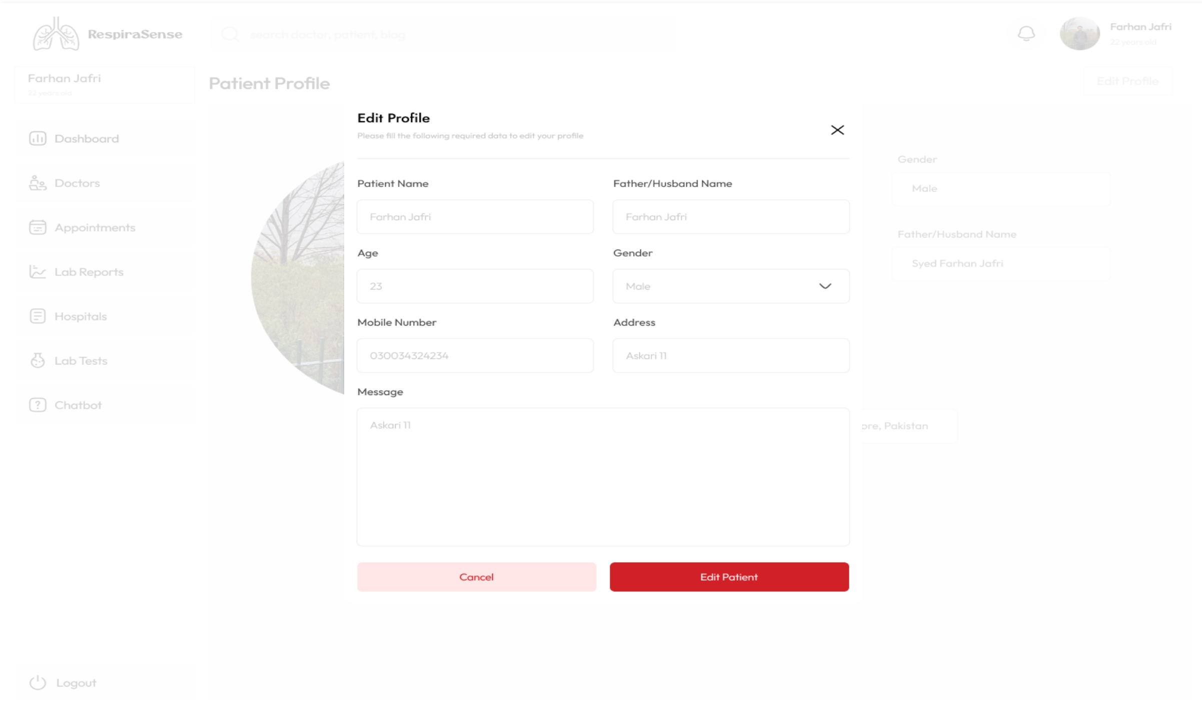

Figure 4.17: Edit Patient Profile Screen

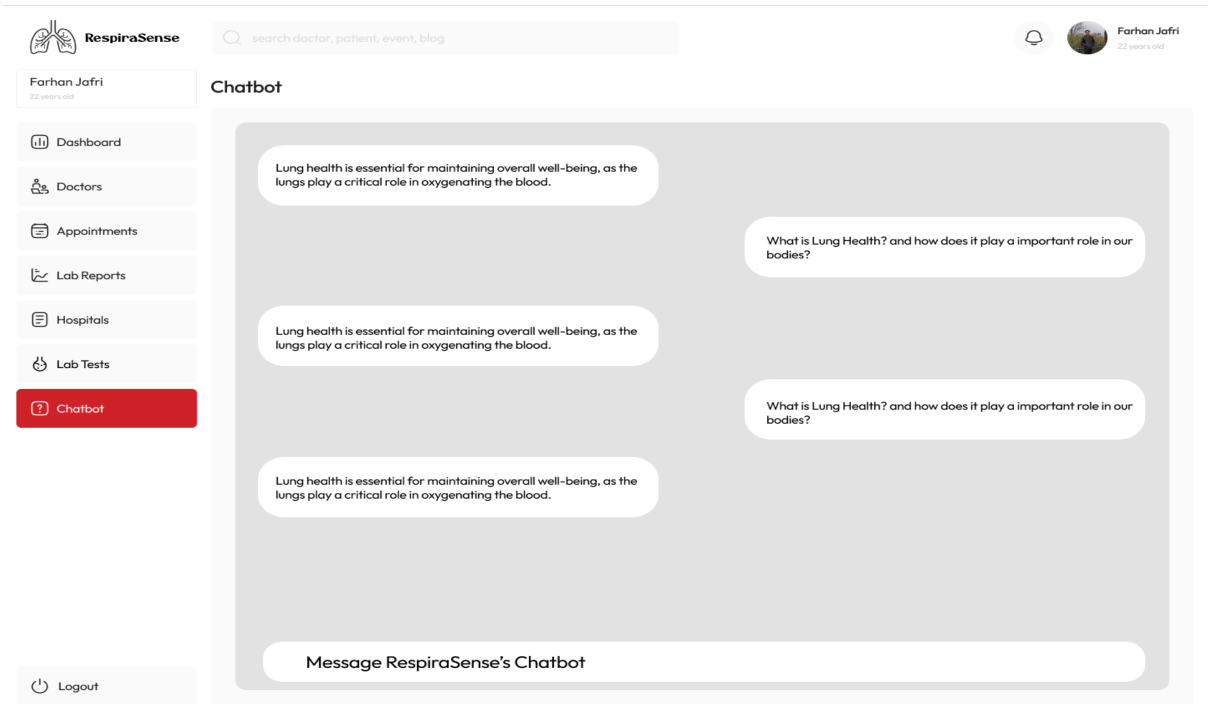

Figure 4.18: Chatbot Screen

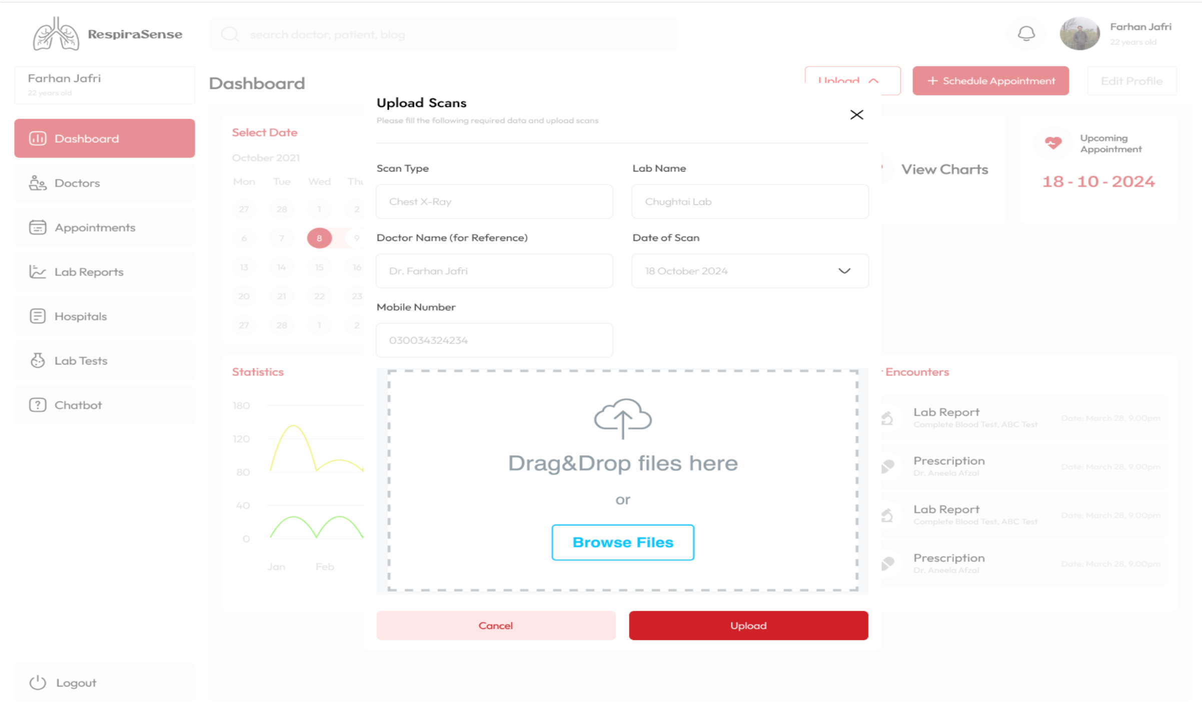

Figure 4.19: Upload Scan Screen

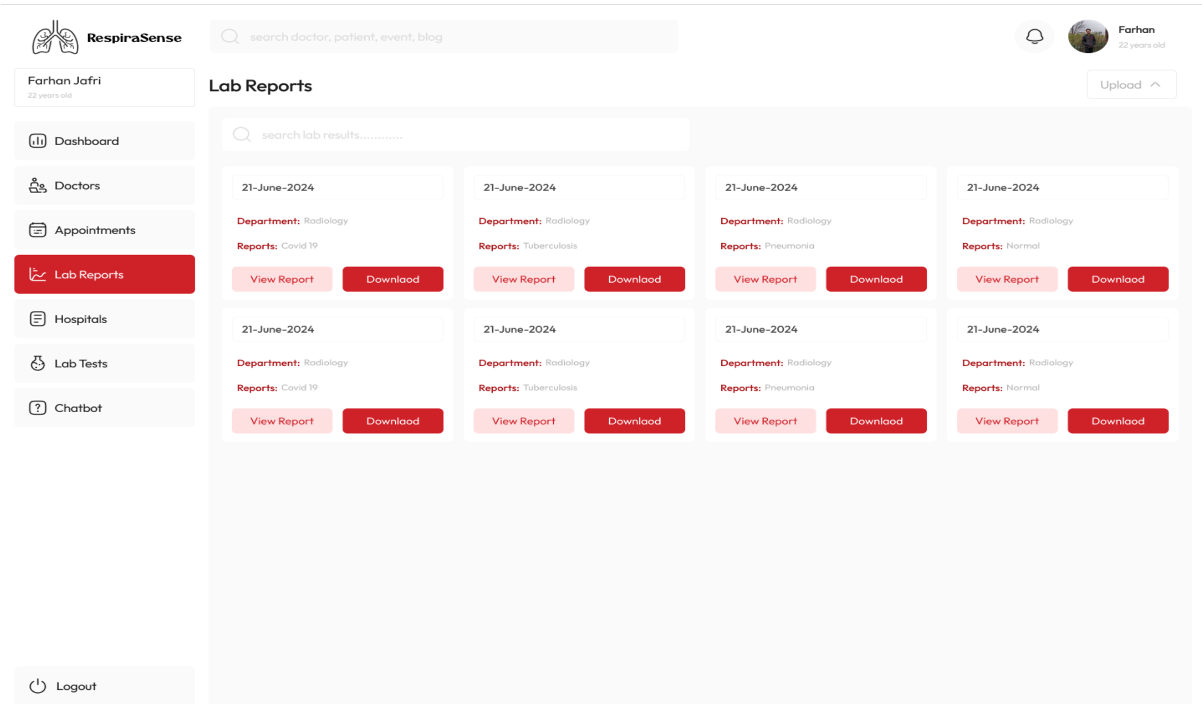

Figure 4.20: Patient Lab Reports Screen

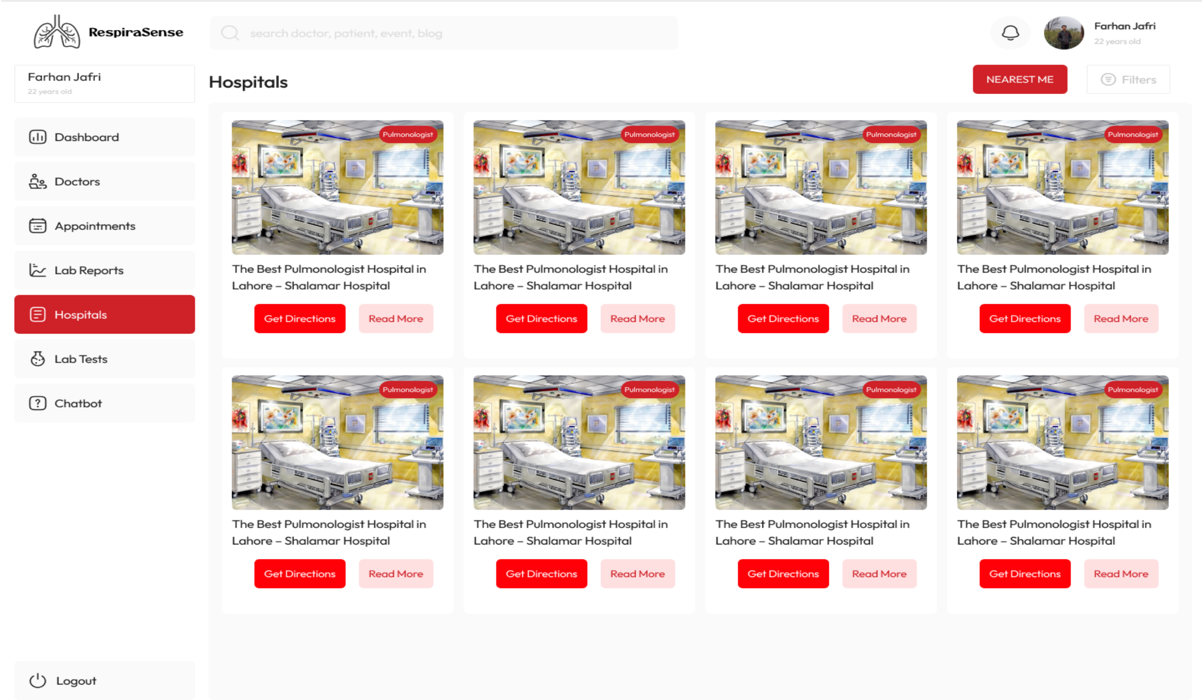

Figure 4.21: Hospitals Screen

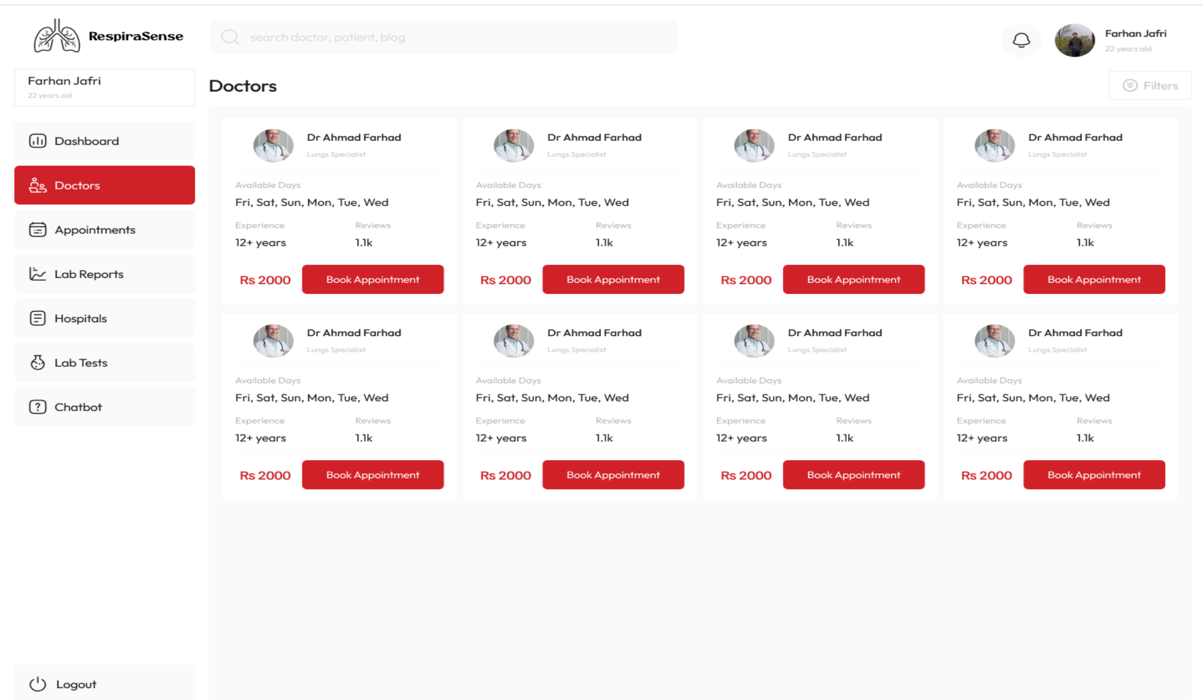

Figure 4.22: Doctors Available Screen

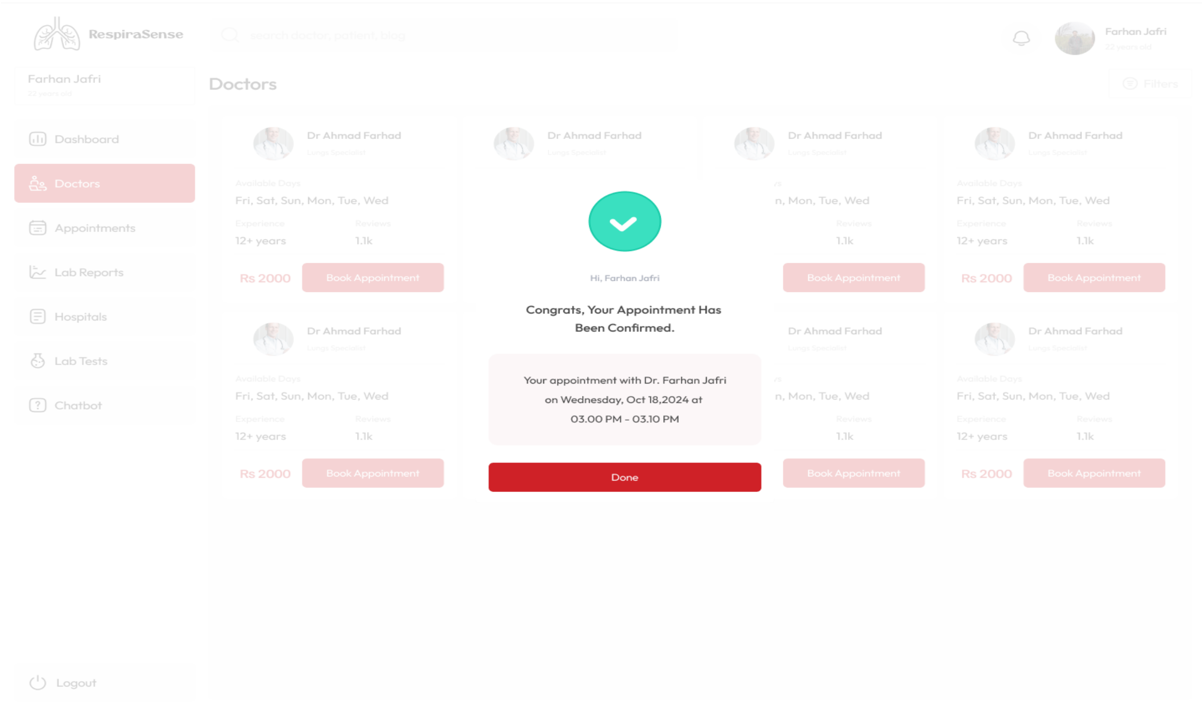

Figure 4.23: Appointment Confirmation Screen

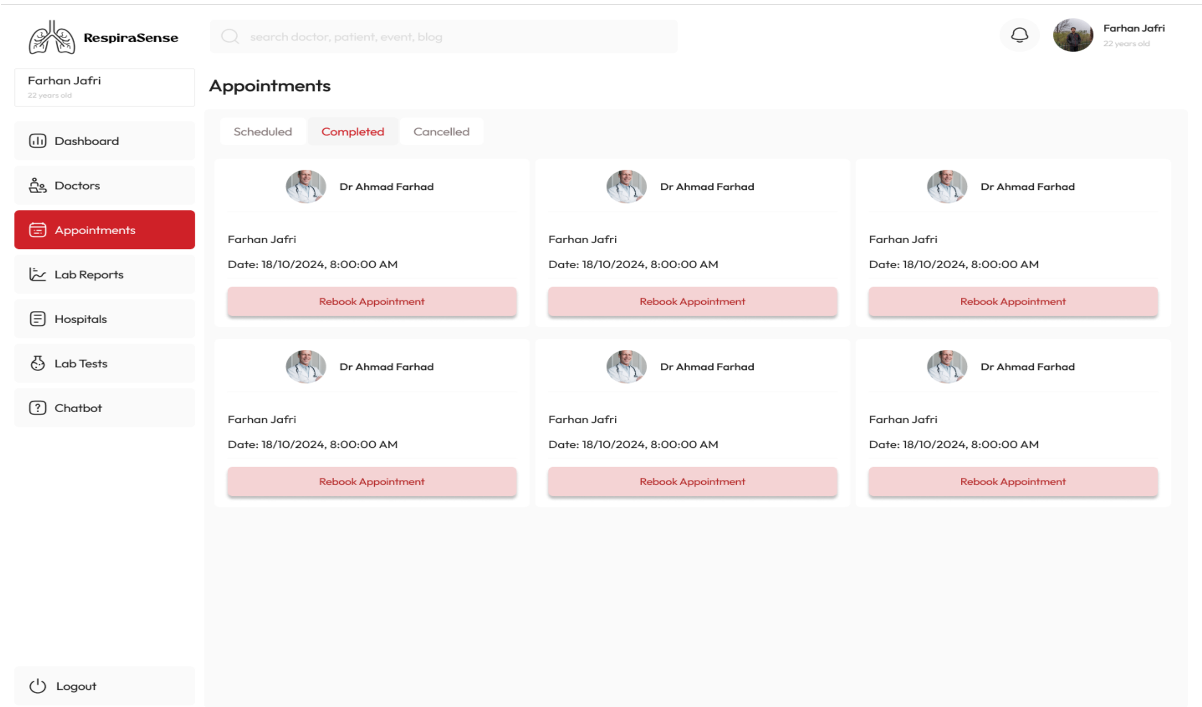

Figure 4.24: Completed Appointments Screen

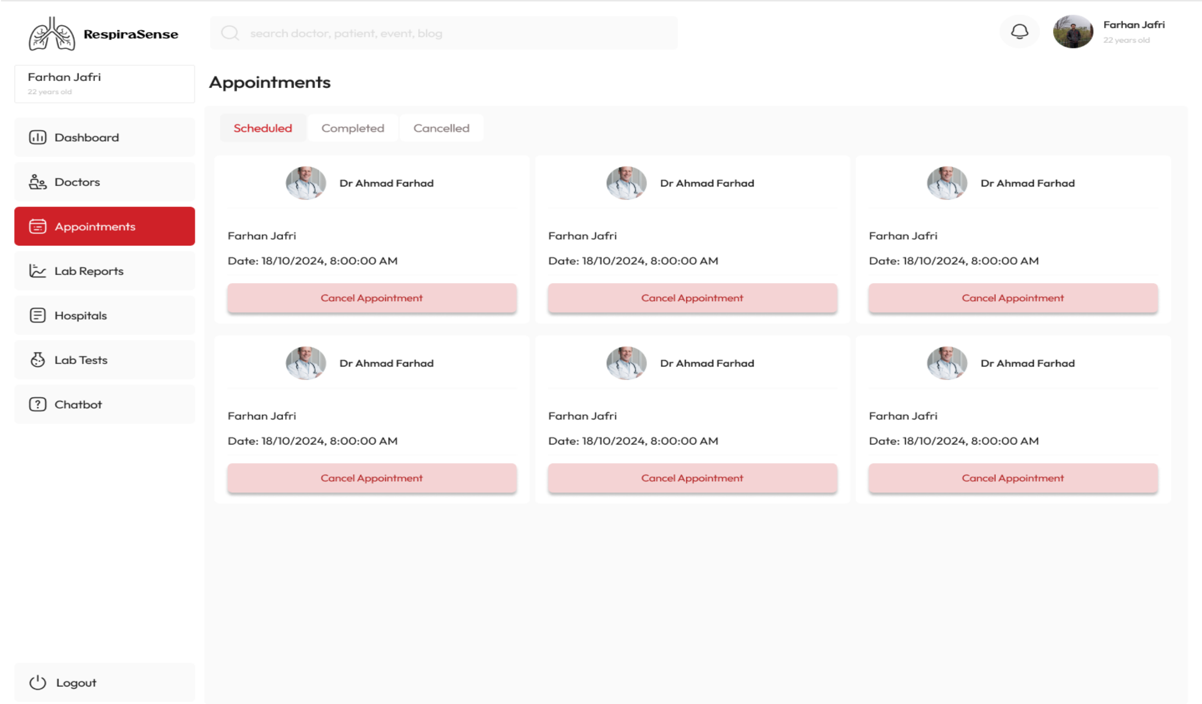

Figure 4.25: Scheduled Appointments Screen

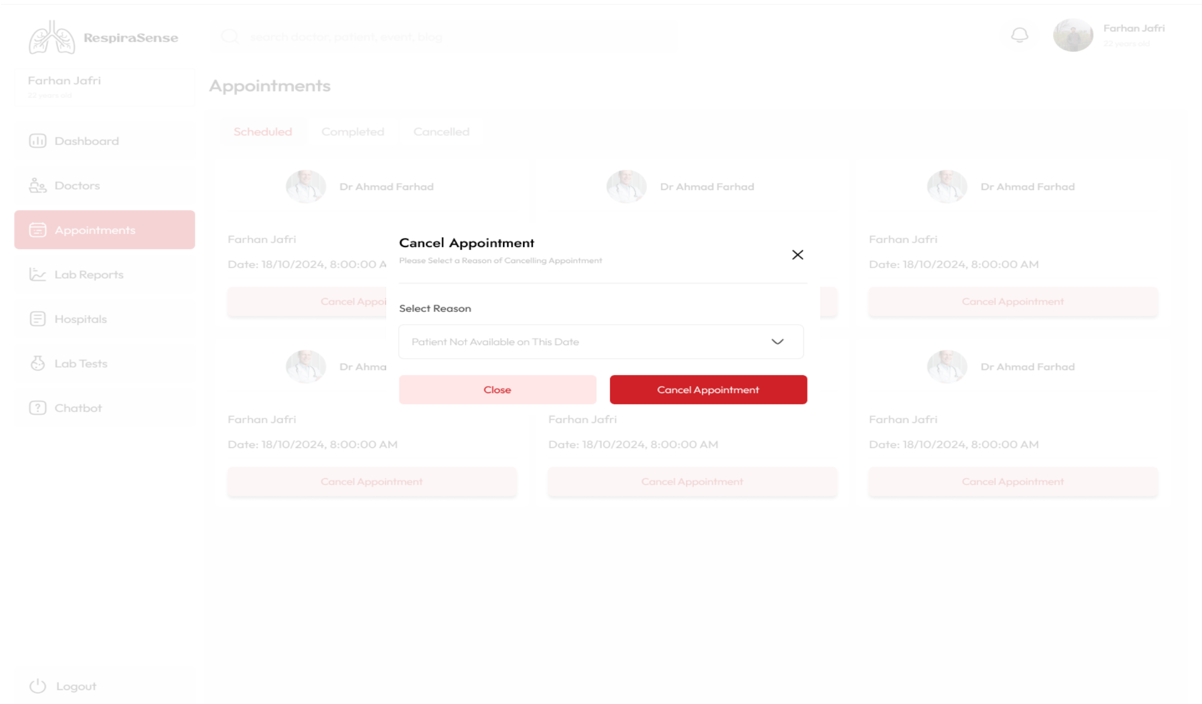

Figure 4.26: Appointment Cancellation Confirmation Screen

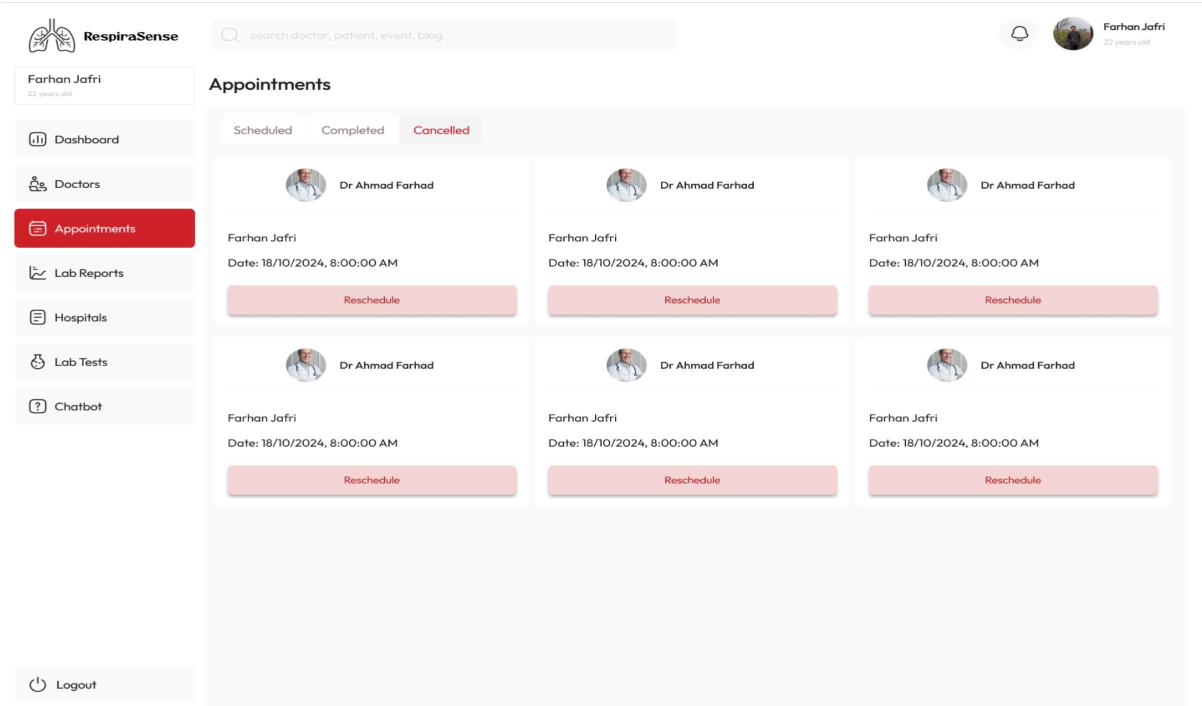

Figure 4.27: Cancelled Appointments Screen

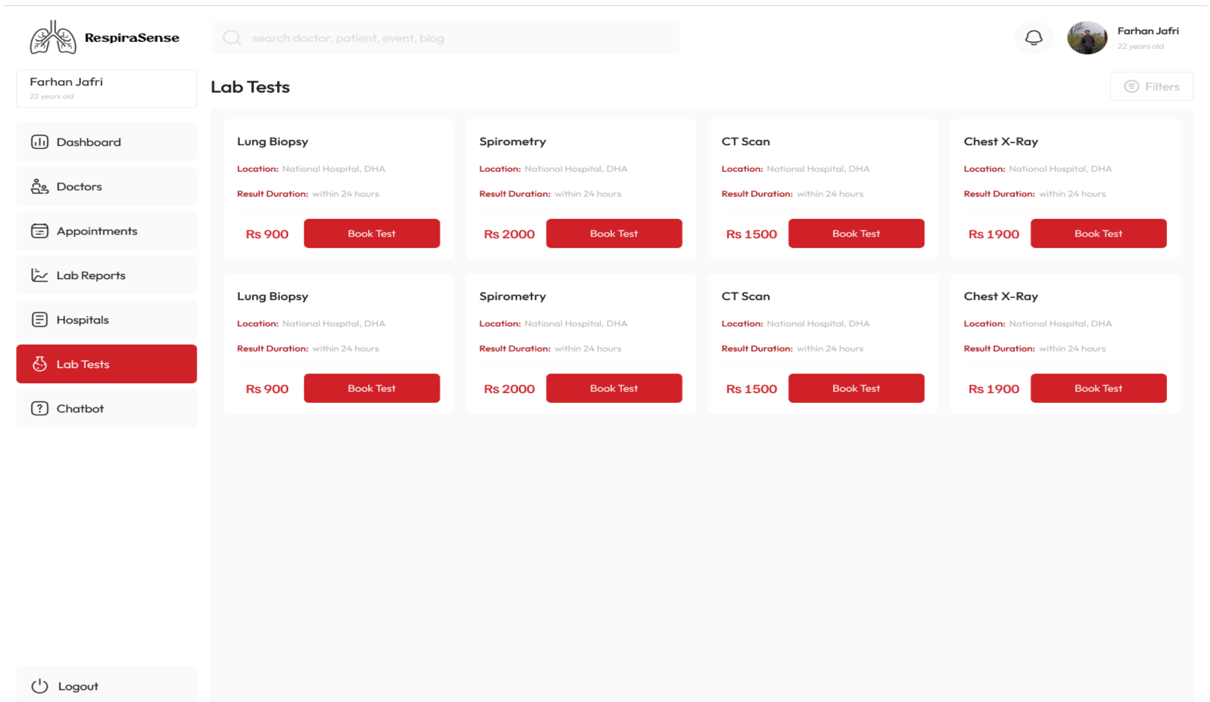

Figure 4.28: Lab Tests Screen

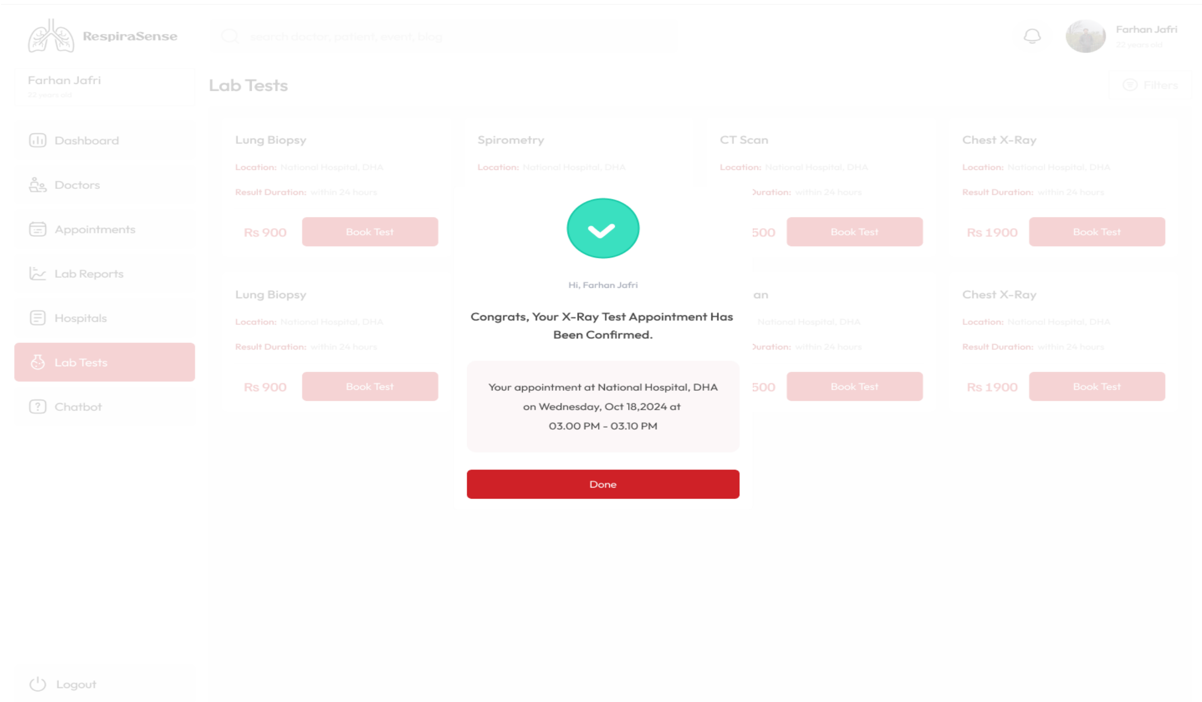

Figure 4.29: Lab Tests Confirmation Screen

4.9 Database Design

4.9.1 ER Diagram

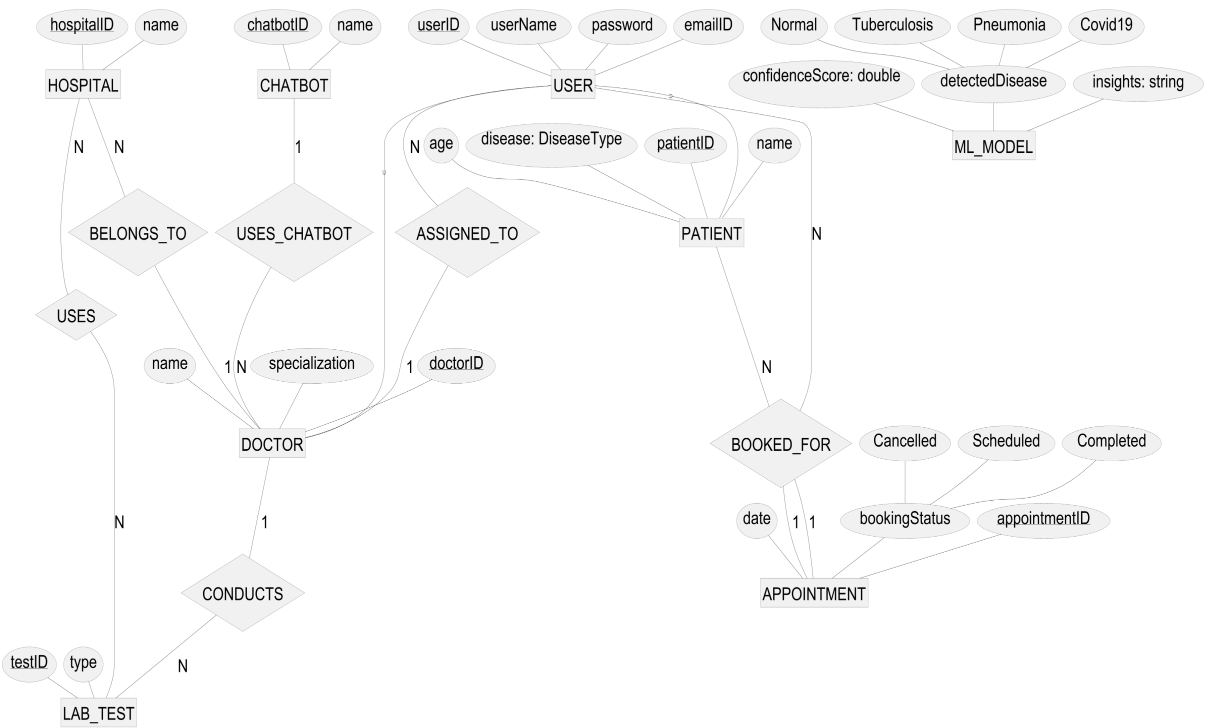

Figure 4.30: Entity Relation Diagram

4.9.2 Data Dictionary

Table 4.1: Data Dictionary

Entity	Attribute	Data Type	Nullable	Relationship To	Relationship Type
USER	userID	Number	No	-	-
	userName	Varchar(50)	No	-	Username for login
	password	Varchar(50)	No	-	Password for login
	emailID	Varchar(50)	No	-	Email of the user
PATIENT	patientID	Number	No	-	-
	name	Varchar(50)	No	-	Name of the patient
	age	Number	No	-	Age of the patient
	disease	Varchar(50)	No	-	Disease type
	userID	Number (Foreign Key)	No	USER	N to 1
DOCTOR	doctorID	Number	No	-	-
	name	Varchar(50)	No	-	Name of the doctor
	specialization	Varchar(50)	No	-	Doctor's specialization
	hospitalID	Number (Foreign Key)	No	HOSPITAL	N to 1
HOSPITAL	hospitalID	Number	No	-	-
	name	Varchar(50)	No	-	Name of the hospital
LAB_TEST	testID	Number	No	-	-
	type	Varchar(50)	No	-	Type of lab test
	doctorID	Number (Foreign Key)	No	DOCTOR	N to 1
APPOINTMENT	appointmentID	Number	No	-	-
	date	Date	No	-	Date of the appointment
	bookingStatus	Varchar(50)	No	-	Status: Cancelled, Scheduled, Completed
	patientID	Number (Foreign Key)	No	PATIENT	N to 1
	doctorID	Number (Foreign Key)	No	DOCTOR	N to 1
ML_MODEL	detectedDisease	Varchar(50)	No	-	Detected disease: Tuberculosis, Pneumonia, Covid19, Normal.
	confidenceScore	Double	No	-	Confidence score of disease detection
	insights	Varchar(255)	No	-	Insights about the detected disease
CHATBOT	chatbotID	Number	No	-	-
	name	Varchar(50)	No	-	Name of the chatbot

4.10 Risk Analysis

The following are some of the risks that could be encountered during the project:

4.10.1 Model Accuracy

There is a risk that the AI model may produce inaccurate results, such as false positives or negatives, especially when tested with x-rays from many different sources. This could lead to incorrect diagnosis, affecting doctor and patient trust in our product.

4.10.2 Liability in Case of Incorrect Diagnoses

In a case of a misdiagnosis by the AI, there could be legal repercussions. Ensuring clear disclaimers and requiring professional validation of AI-generated results is crucial to avoiding liability issues.

4.10.3 System Performance

The system must handle large volumes of medical image data and support multiple users simultaneously. Poor performance or slow image processing times could negatively affect the user experience.

4.10.4 Data Privacy and Security

Security breaches or vulnerabilities could expose patient information, leading to potential misuse of personal health data.

Chapter 5 Proposed Approach and Methodology

This section outlines the proposed Approach and Methodology for RespiraSense. It presents a detailed overview of the extensive dataset handling techniques that will be employed as well as how the various functions of RespiraSense will be implemented. Namely; disease detection, doctor recommendation system, and the symptom checking chatbot. This systematic approach ensures a thorough understanding of the system's design and functionality, paving the way for its successful implementation.

5.1 Disease Detection

This section of the methodology chapter is concerned with the implementation details of our disease detection module. It will be used to identify tuberculosis, Covid-19, viral pneumonia, and bacterial pneumonia, or to categorize the presented chest x-rays as normal.

5.1.1 Data Collection

We have selected datasets which are publicly available on Kaggle. The dataset contains images for Bacterial Pneumonia, Viral Pneumonia, Tuberculosis, COVID 19 and normal lungs.

There are 1205 photos in the training set, 403 images in the testing set, and 401 images in the validation set for bacterial pneumonia. For COVID-19, there are three sets of images: 1218 in the training set, 407 in the testing set, and 406 in the validation set. There are 1207 photos in the training set, 404 in the testing set, and 402 in the validation set for the Normal Lungs category. There are 1220 photos in the tuberculosis category for training, 408 for testing, and 406 for validation. Finally, there are 1204 photos in the training set, 403 pictures in the testing set, and 401 photographs in the validation set for the Viral Pneumonia category.

5.1.2 Data Preprocessing

The dataset undergoes a series of preprocessing steps. Initially, the images are rescaled so that the pixel values are normalized from a range of 0 to 255 to 0 to 1. Secondly, to improve the model's generalization; width shifts, height shifts and zooms are applied. Moreover, to comply with the DenseNet201 model, the images are resized to uniform 224x224 dimensions. Keras ImageDataGenerator can be used to organize the images into a 4D matrix form. Lastly, the final step involves labeling each image to ensure that they are organized and categorized properly for the next stages of analysis.

5.1.3 Classification

We will classify the lung images into the 5 distinct classes as mentioned above by utilizing a pre trained DenseNet201 model for transfer learning.

5.1.4 Model Details

The model which will be used is a CNN, more specifically DenseNet201 as proposed by Sanghvi et al.(2022) in their research article on respiratory diseases classification. The main reason for selecting this model is because it uses memory efficiently and has high computing power. This is important when it comes to working with large datasets like ours. DenseNet201 will be employed for transfer learning, a method in which a model that has previously been trained to solve one issue is utilized to educate it to solve another that is comparable. Moreover, we can add custom layers to adapt the network for our project. Additionally, TensorFlow framework will be used for implementation, training and testing the model.

5.2 Doctor Recommendation System

We will be implementing a system designed to suggest the best pick doctor to the patients according to the disease they were diagnosed with and their location.

5.2.1 Algorithm

For the implementation of the recommendation system we will implement a ML based matchmaking model. It will make use of patient medical condition, proximity and popularity of the doctor. Moreover, we will use content based filtering to match the right patient needs with the right doctors' expertise.

5.3 Chatbot

We will be implementing a chatbot that will engage in conversation with the users to gather information about their symptoms. Based on this information it will provide information about potential conditions.

5.3.1 Technique

For our healthcare or symptom checking chatbot, we shall make use of the OpenAI API as proposed by Viswanathan et al. (2024) in their review of ChatBots and their medical applications. The API Key for the project can be obtained for free from the OpenAI website and be integrated into our application. Once it has been added to the code, the application will be able to return responses from OpenAI.

The major reason for using this is that the advanced language model of OpenAI allows for contextual conversations. This is crucial for the user focused design of RespiraSense. Secondly, ChatGPT powered by OpenAI managed to pass the USMLE. This makes the diagnostic accuracy a powerful feature.

Chapter 6 High-Level and Low-Level Design

The high and low level design of RespiraSense are explored in further detail in this chapter. System architecture and flow of functionalities is shown visually using diagrams. Detailed discussions on architecture, strategy, and policy are provided.

6.1 System Overview

RespiraSense uses AI to diagnose lung problems with simplicity, with the goal of completely changing the healthcare sector. Our system software comprises the following key modules:

6.1.1 User Profile Management

The system allows both patients and doctors to create and manage their profiles. Patients can update their personal details and medical history, while doctors can showcase their qualifications, and professional details. Secure user authentication ensures privacy and data protection.

6.1.2 Disease Detection

This module facilitates the seamless upload of chest X-rays for disease detection. Patients and doctors can upload X-rays with ease, add relevant details such as scan dates and symptoms. The system then uses the AI model to analyze the scans, providing a detailed report with disease predictions and confidence scores for conditions such as Pneumonia, COVID-19, and Tuberculosis.

6.1.3 Diagnostic Reports and Visualizations

The system is capable of generating detailed diagnostic reports that include the AI's predictions, and severity of the detected conditions. These reports offer visual representations, such as charts and graphs.

6.1.4 Hospitals/Doctor Search and Recommendation System

Patients can use this module to search for doctors and hospitals based on their location which is closest to them or the most approved/recommended by previous patients. The integrated map service allows patients to locate and navigate to the nearest clinics. This feature is particularly useful in emergencies, providing real-time recommendations and navigation.

6.1.5 Appointment and Lab Tests Scheduling

The appointment and lab test scheduling module streamlines the process of booking appointments and scheduling lab tests for patients. This feature allows patients to easily select a healthcare provider, view their availability, and book appointments that fit their schedules.

6.1.6 Chatbot for Health Assistance

The chatbot is designed to assist patients in tracking symptoms and receiving relevant health information. It provides a user-friendly interface for ease in use. The chatbot also provides tips on breathing exercises and relaxation techniques.

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6.2 Design Considerations

This section outlines various considerations that need to be taken into account before devising a complete design solution. A range of issues, assumptions, dependencies, and constraints to ensure a smooth user experience are addressed.

6.2.1 Assumptions and Dependencies

The following are the assumptions and dependencies associated with the project:

6.2.1.1 Hardware and Software Related

- Devices capable of handling high-resolution image uploads (e.g., chest X-rays) are used.
- Standard web browsers (e.g., Chrome, Edge) are used.
- Appropriate server hardware capable of handling GPU-intensive tasks, as defined in hardware requirements is installed in the system.

6.2.1.2 Operating System

- The system is designed on Windows, and is expected to run on Windows only. requirements is installed in the system.

6.2.1.3 End-user characteristics

- Users should have a reliable Internet connection.
- Users should have basic knowledge of using the application.
- Users should possess the latest devices with up-to-date browser versions.
- Doctors are assumed to understand medical images and diagnostic reports

6.2.2 General Constraints

Our project aims to provide an easy-to-use platform for doctors and patients to be able to detect and handle respiratory diseases before they get out of hand. However, there are certain limitations and constraints that will significantly impact the design of the system's software. These constraints include:

6.2.2.1 Hardware and Software Environment

- The user is assumed to have an OS better than Windows 10 or equal.
- Stable and reliable internet connection
- RAM greater than 8GB.
- CPU equal or better than an Intel i5 CPU.
- A GPU consisting of a 4GB VRAM or better.

6.2.2.2 End-User Environment

- Doctors and patients have a basic understanding of how to use web applications.
- A simplified user interface for non technical users.
- Doctors and patients have the understanding of reading reports.
- Doctors have the ability to make informed decisions on their own.

6.2.2.3 Availability or Volatility of Resources

- Must have a computer, a browser, and a stable internet connection.
- Users are assumed to have necessary resources to run the application.

6.2.2.4 Standards Compliance

- Microsoft Visual Studio Code IDE for development.

- JS Libraries installed already.

6.2.2.5 Interface/Protocol Requirements

- Intuitive and easy to navigate for both patients and doctors.
- Frontend to be developed in React.
- Ease in reading reports and results of predictions.

6.2.2.6 Data Repository and Distribution Requirements

- Medical images and reports must be stored securely, with access restricted to unauthorized users.
- Database to be developed primarily in MongoDB.

6.2.2.7 Performance Requirements

- The system must be able to handle multiple concurrent users, especially in emergency situations or peak usage times.
- Ability to process multiple scan uploads simultaneously without significant delays.
- Predict diseases with great accuracy and quickly.

6.2.3 Goals and Guidelines

The goals and guidelines of our system are included below:

6.2.3.1 Efficiency

The system should be fast and accurate for AI-driven disease detection, ensuring that both patients and doctors receive actionable diagnostic results without unnecessary delays.

6.2.3.2 User Experience

Our system will be user friendly, ensuring that even non-technical users can navigate through the system without difficulty. Clear navigation menus, and easy to read diagnostic reports are important to ensure a user friendly experience.

6.2.3.3 Security

Encryption technologies must be used to secure patient data, including multi-factor authentication (MFA) for authorised user access.

6.2.3.4 Scalability

RespiraSense must be able to scale seamlessly without compromising on performance or security, as the system expands and more users start to use the application.

6.2.4 Development Methods

An Agile Scrum methodology will be used. The project is divided into 1-2 week sprints, allowing the team to iteratively build features. Each sprint includes a clear set of goals, and a sprint review is conducted at the end of each cycle to discuss the work, review the progress, and schedule the rest of the work.

Trello is used as the primary tool for project management. Each feature and task is organized on Trello boards, allowing the team to:

- Break down tasks into manageable components.
- Track the progress of each task, from ”To Do” to ”In Progress” and ”Completed.”
- Set deadlines for specific tasks to ensure that sprints remain on schedule.
- Assigning of tasks to different members of the group to ensure collaboration and timely completion of work.

6.3 System Architecture

This section provides an overview of the system's architecture, describing how the overall functionality is divided into different subsystems. The architecture follows a multi-layered approach, ensuring modularity, scalability, and ease of maintenance. The system is primarily divided into four layers: Presentation Layer, Business Logic Layer, AI Diagnostic Layer, and Data Persistence Layer as shown in Figure 6.1 on the next page. Each layer interacts with the others to deliver the complete functionality of the system.

6.3.1 Subsystem Architecture

The individual subsystem which need to be explained in more detail are discussed in this subsection. Their primary responsibilities, interactions, and contributions to the overall functionality of the system are discussed.

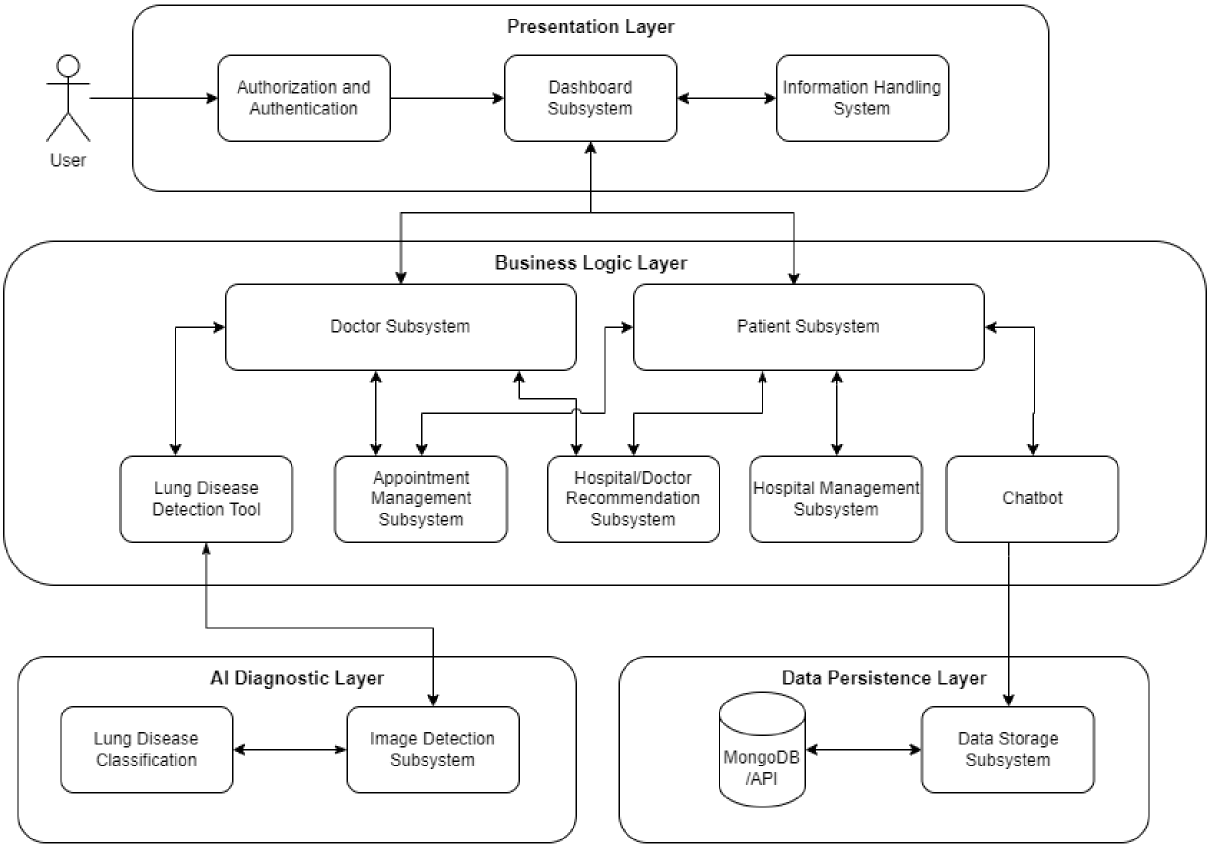

Figure 6.1: Architecture Diagram

6.3.1.1 Lung Disease Detection Tool

This system is responsible for detecting lung diseases such as Pneumonia, Tuberculosis, Covid-19 and also normal lungs by analyzing medical images (such as X-rays).

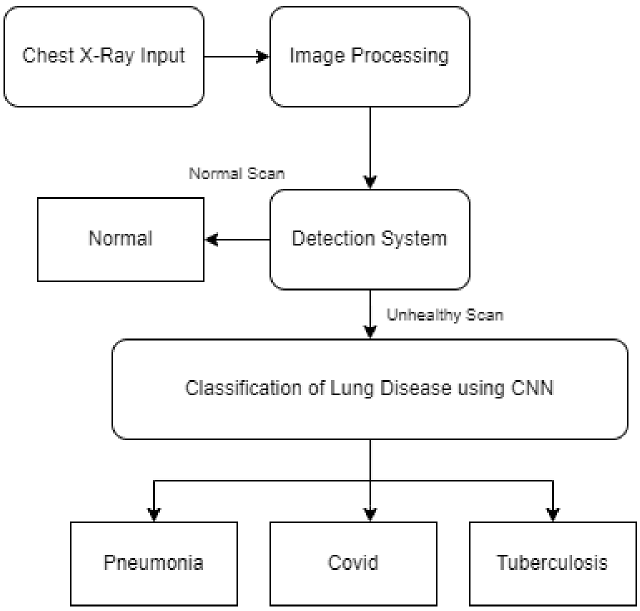

Figure 6.2: Architecture of Lung Disease Detection Tool

6.3.1.2 Appointment Management Subsystem

This subsystem manages the scheduling and coordination of appointments between patients and doctors. This is responsible for the scheduling of appointments and ensuring the availability of doctors, managing rescheduling and cancellations based on user requests and also sending reminders to patients and doctors regarding upcoming appointments. Flask is used to handle the microservices architecture for managing hospital resources and appointment schedules. MongoDB is ideal for managing complex data structures like hospital resource availability, patient data, and appointment details due to its scalability and flexibility.

6.3.1.3 Chatbot

The chatbot system will provides support to patients and users to help answer common questions and other question they may have related to their disease or health condition. The OpenAI API will be implemented for seamless integration with the system.

6.3.1.4 Hospital/Doctor Recommendation System

This system suggests the nearest hospital to their location or address and/or appropriate doctors to patients based on the medical condition and severity. RESTful APIs are employed to fetch data related to doctors' specialties, availability, location, and patient preferences. The API-based approach allows seamless communication between the system and other modules in it.

6.4 Architectural Strategies

RespiraSense makes use of various strategies to shape its architecture, they are as follows:

6.4.1 Technology Stack

We opted for the MERN stack (MongoDB, Express.js, React.js, and Node.js) for the development of the web application. This is to make sure that the application is extremely responsive, scalable, and easy to maintain. The MERN stack allows the system to handle large volumes of data, support a modern user interface, and manage backend logic efficiently. The MERN stack was chosen for its end-to-end JavaScript support, simplifying development by allowing both frontend and backend to be managed with a single language.

6.4.2 AI Model Integration

The main purpose of the system relies on AI for diagnosing lung diseases from chest X-rays. We decided to use TensorFlow with Keras as the framework for building the Convolutional Neural Network (CNN) models used for image classification. This choice was made based on TensorFlow's flexibility, strong community support, and ability to scale across different hardware environments (CPU, GPU). TensorFlow is highly optimized for deep learning tasks like image classification, which is critical for processing chest X-rays. Its compatibility with various platforms ensures that future scalability and deployment needs are met without a need for many changes.

6.5 Class Diagram

The class diagram of the system is given below.

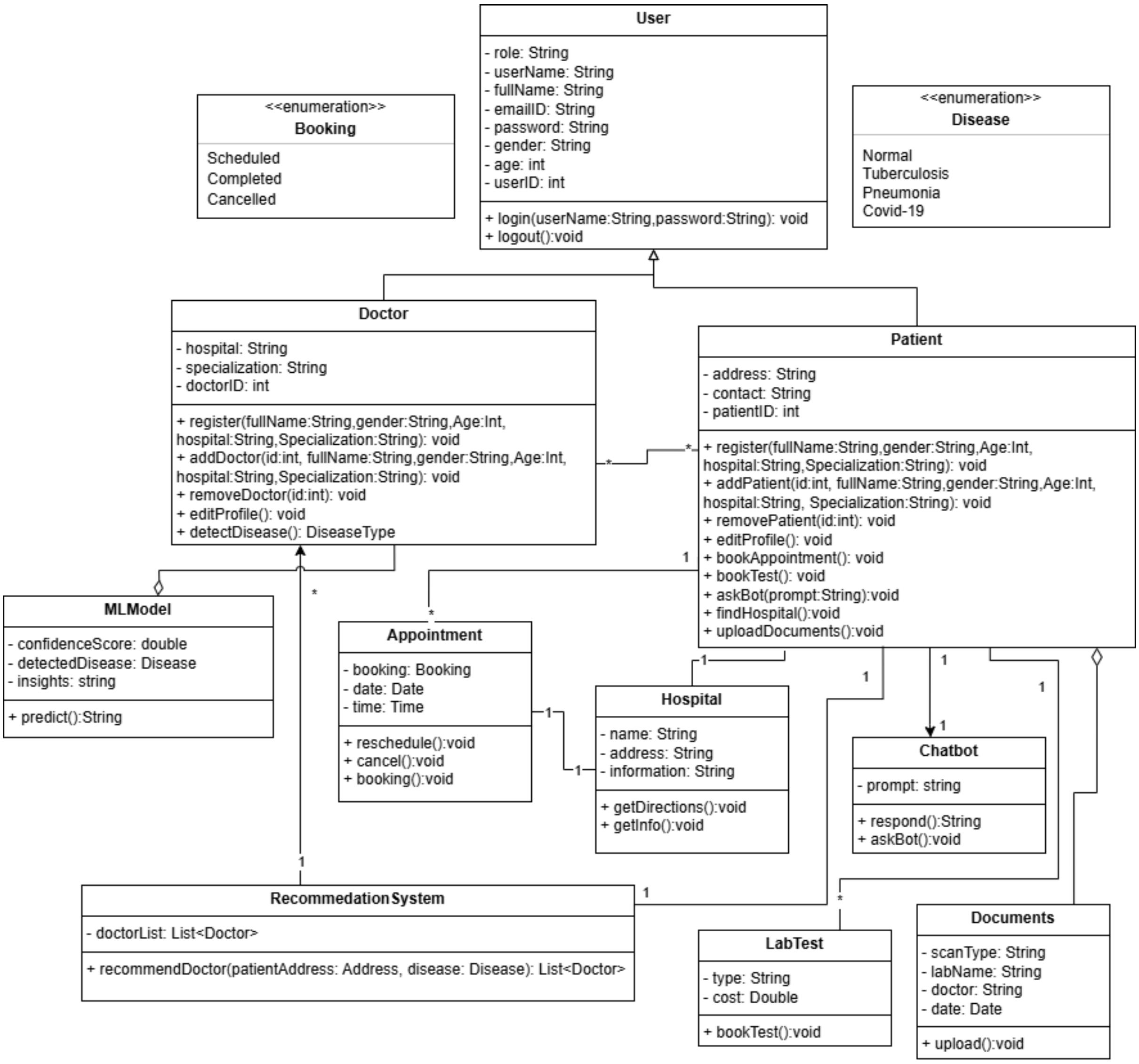

Figure 6.3: Class Diagram

6.6 Policies and Tactics

6.6.1 Tools to be Used

Several tools, and external libraries are of key importance to the RespiraSense project:

- MERN stack (MongoDB, Express.js, React.js, Node.js) - Technology stack of the application
- OpenAI chatbot API to be used.
- TensorFlow and Keras for machine learning algorithm.
- Dataset of chest X-rays to be taken from Kaggle.

6.6.2 Coding Guidelines and Conventions

To maintain consistency and readability of the code JavaScript Coding Standards such as ES6+ syntax is used throughout the project. Variables, classes, and methods follow clear and descriptive naming conventions.

6.6.3 Interface Design and Protocols

The front-end is fully responsive, ensuring accessibility across a range of desktops and laptops. The user interface (UI) is defined by its' simplicity, relevant color schemes, and an intuitive design, ensuring that users can easily navigate and interact with the platform.

6.6.4 System Testing Policies

A comprehensive and extensive testing approach is used, which includes both white box and black box testing. Every aspect is rigorously tested, ensuring that the application functions smoothly and without errors.

Chapter 7 Implementation and Test Cases

In this chapter, the current prototype of RespiraSense is described in detail. By developing a workable frontend at the user-side, the implementation phase of the project has been initiated which has enabled some of the fundamental functionalities of our system. Furthermore, this chapter introduces an overview of the team's development until now, including backend modules and technical specifications.

Content of this chapter is likely to change and may differ when other modules are eventually added.

7.1 Implementation

In the process of implementing the project, our team has put in efforts to research different tools and utilities that will help us as we go further developing our application. We considered a wide array of technologies and APIs while building RespiraSense and improving it.

Below is a discussion on the implementation specifics of the work completed so far.

7.1.1 Disease Classification Model Development

The data was processed in a Kaggle environment since it is efficient with large datasets and supports integrated GPUs. The data was split into training (6,054 images), validation (2,016 images), and test (2,025 images) for five classes.

For data preprocessing, ImageDataGenerator was used to apply width and height shifts, zooming, and rescaling to the training set. The test and validation sets were rescaled for the sole purpose of normalizing pixel values to [0,1] range. All the images were resized to 224×224 pixels to offer consistent input size.

DenseNet201 as the base model was employed with pre-training over ImageNet. Manually loaded pre-trained weights and the base model were frozen in layers to retain learned features. A classification head with a custom configuration involving dropout layers to offer regularization and fully connected layers to learn features was introduced.

It was trained using Adam optimizer and categorical cross-entropy loss. It was trained for 100 epochs, with ModelCheckpoint being used to save the best model according to validation accuracy. ReduceLROnPlateau was used to reduce the learning rate dynamically when validation accuracy plateaued.

7.1.2 Model Integration into the Application

To integrate the trained classification model into the application, a Flask-based API was implemented to handle model inference and output predictions. The trained DenseNet201 model was exported as a

.hdf5 file and loaded into the API to utilize in real time predictions. The API was designed to receive image uploads, preprocess them to resize to 224×224 pixels and normalize pixel values, then pass them through the model for classification. argmax was utilized to make the predictions to get the class with the highest confidence score. Class index mapping was utilized to give human-readable disease labels back.

The API handled requests efficiently using Flask's request-handling feature, ensuring smooth image processing and response generation. IThe compatibility of the Flask server with the MERN app was tested with "curl" commands on GitBash, verifying model accuracy and inference speed optimization for real-time applications.

7.1.3 Frontend Development

The frontend has been done in React with TypeScript for a modern, responsive, and user friendly interface. It includes features such as a lab report upload system, a personalized user dashboard to manage reports and health data, appointment scheduling and cancellation feature, and the additional "Happenings" section that keeps the users updated on the latest health related news and updates.

Frontend development has paid much attention to usability and accessibility. The design is user friendly with features well planned to minimize user interactions.

7.1.4 Backend Development

The frontend has been done in React with TypeScript for a modern, responsive, and user friendly inter face. It includes features such as a lab report upload system, a personalized user dashboard to manage reports and health data, appointment scheduling and cancellation feature, and the additional "Happenings" section that keeps the users updated on the latest health related news and updates using the News API, that is a public API to download news articles and media. Frontend development has paid much attention to usability and accessibility. The design is user friendly with features well planned to minimize user interactions.

Furthermore, Flask manages model inference for disease classification, ensuring smooth image processing and integration. The OpenAI API drives the symptom-checking chatbot, giving users real-time medical insights.

7.1.5 Chatbot Module and Fine-Tuning

The chatbot feature provides an interface for the users to talk about symptoms and be medically guided. Frontend as well as backend development of the chatbot has been completed along with seamless integration with the rest of the application. The chatbot is based on the OpenAI API so that it can make smart and medially appropriate responses. Fine-tuning has also been performed so that the chatbot becomes an expert in responding to medical questions more accurately.

7.1.5.1 Dataset Acquisition and Preparation

For the tuning of the chatbot, a specific dataset was oreoared. The medical query dataset was gathered from Kaggle and converted into a format compatible with OpenAI. The non medical query dataset was generated to help the model differentiate between relevant and irrelevant queries i.e to provide it with example of irrelevant queries and their response. These datasets are then pre processed for fine tuning by transforming the data into .jsonl format. To assure the accuracy, a validation phase is implemented during which the dataset removes inconsistencies as well as any issues in terms of formatting.

7.1.5.2 Fine-Tuning Process and Implementation

The fine-tuning procedure started with the dataset preparation and its conversion into.jsonl format for training. The data was uploaded to OpenAI using a Node.js script through an HTTP POST request to the /files endpoint with its purpose set to ”fine-tune”.

Upon uploading, a fine tuning task was triggered with a POST request to the /fine_tuning/jobs endpoint, aimed at gpt-4o-mini-2024-07-18. This tailored the model to prioritize interactions related to healthcare while eliminating noisy queries. Progress of the job was tracked using OpenAI’s Playground to receive precise responses.

The model was then fine-tuned and deployed in the RespiraSense MERN application by configuring the Node.js backend to make calls to OpenAI’s API. Specialized API endpoints process patient input, evaluate model output, and provide appropriate medical advice through the RespiraBot chatbot. Thus, improving patient-doctor interactions.

7.2 Conclusion

The RespiraSense implementation phase has been effective in merging core functionalities such as disease classification, symptom checking chatbot, and ease of user interaction. The MERN stack provides a scalable and interactive environment, and Flask facilitates model inference for easy real-time prediction. The OpenAI tuned chatbot boosts healthcare interactions by suppressing irrelevant questions and providing correct answers. Continued enhancements, such as further optimizations and new features, will keep the system evolving, making it a solid, effective, and accessible healthcare solution for users.

Chapter 8 Experimental Results and Discussion

This chapter highlights the experiments conducted till now and their results. This chapter also highlights the hardware used and the model details.

8.1 Evaluation Metrics

The evaluation measures used to assess the model's performance are described in depth in this section.

8.1.1 Accuracy

The accuracy of a model determines how accurate its predictions are. It assesses the proportion of accurate predictions to all of the model's predictions.

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{TN}+\text{FN}}$$

8.1.2 Precision

Another indicator for assessing a model's performance is precision. It shows the caliber of the model's accurate predictions. It may be expressed mathematically as the ratio of genuine positives to all of the model's positive predictions.

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}$$

8.1.3 Recall

Recall, which characterizes the actual number of true positives the model detected, is the next assessment metric employed. In other words, recall is calculated by dividing the total number of true positives by the number of real positives. It assesses the model's accuracy in identifying the positive class.

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}}$$

8.1.4 F-1 Score

The F1 score evaluates the model's overall performance by looking at its accuracy and recall. It is defined as the harmonic mean of the model's accuracy and is mathematically expressed using the following formula:

$$F1\text{-}Score = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

8.2 Experimentation Setup

The experiments were performed using the DenseNet201-based model of deep learning, set up in a Kaggle environment accessed through a local laptop. The computational powers of the Kaggle environment, including a GPU P100 accelerator, were used during training and testing to speed the model's training process and efficiency. The dataset that was used was 10,000 labeled chest X-rays for tuberculosis, pneumonia, and COVID-19 classification, sourced from Kaggle and preprocessed within the same environment as mentioned before. This setup made sure that the model could be evaluated robustly within an optimized computational setting.

8.3 Results

A thorough summary of the findings from our investigation is given in this section. It highlights the main conclusions and results from our study, providing a thorough grasp of the ramifications and importance of these discoveries.

8.3.1 Disease Classification

An outline of the disease classification model and the outcomes of extensive testing of the model are given in this part.

8.3.1.1 DenseNet201 Model Approach

The pictures of chest X-rays were classified correctly into five categories of illnesses: COVID-19, pneumonia, and TB, based on the deep learning network DenseNet201. For the training, 10,000 labeled chest X-rays were used, and the data was split into training, validation, and test sets comprising 6054, 2016, and 2025 pictures, respectively. For the classification challenge, the pre trained DenseNet201 model was fine-tuned using manually acquired weights from TensorFlow's source.

8.3.1.2 Performance Metrics

A thorough overview of the outcomes obtained from the model evaluation procedure is given in the confusion matrix that follows. It summarizes the model's performance indicators and provides a clear illustration of its accuracy and predictive power.

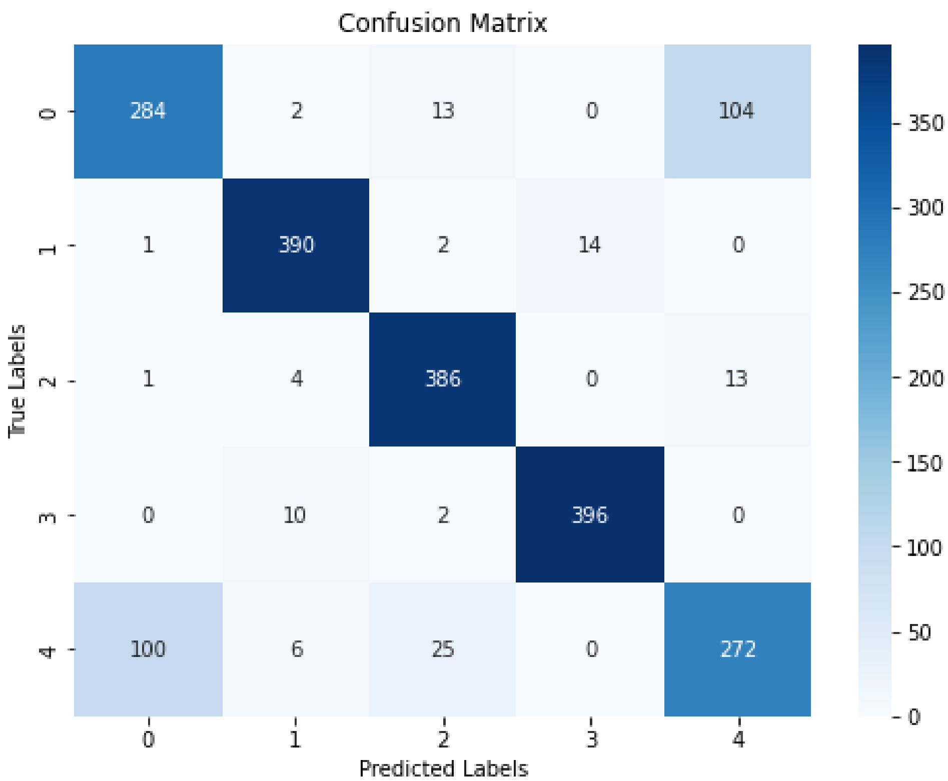

Figure 8.1: Confusion Matrix for Test Results on DenseNet201

The model achieved the following performance metrics on the test dataset:

Accuracy: 85.33%

Precision: 0.8504

Recall: 0.8533

F1 Score: 0.8516

8.3.2 Chatbot Fine Tuning Results

The fine-tuning of the RespiraBot model was successful with gpt-4o-mini-2024-07-18 as the base model. It was trained on 831,201 tokens during three epochs and a batch size of 11 and resulted in a training loss of 0.0000, indicating good learning. The last model, ft:gpt-4o-mini-2024-07-18:personal::AdEGOWH3, was tested and verified to provide precise medical answers and correctly exclude unrelated questions as in the image for example comparison. This enhanced the chatbot's performance within the RespiraSense application.

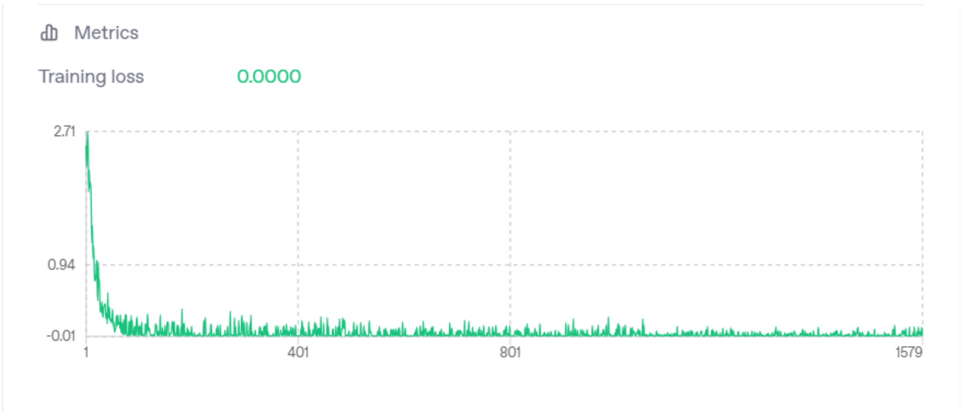

Figure 8.2: Training Loss Curve for the Fine-Tuned Chatbot Model

A comparison of the simple base model Gpt-4o-mini and the finetuned model are given below. These were obtained by running the prompts in the OpenAI fine tuned model 'Playground' environment:

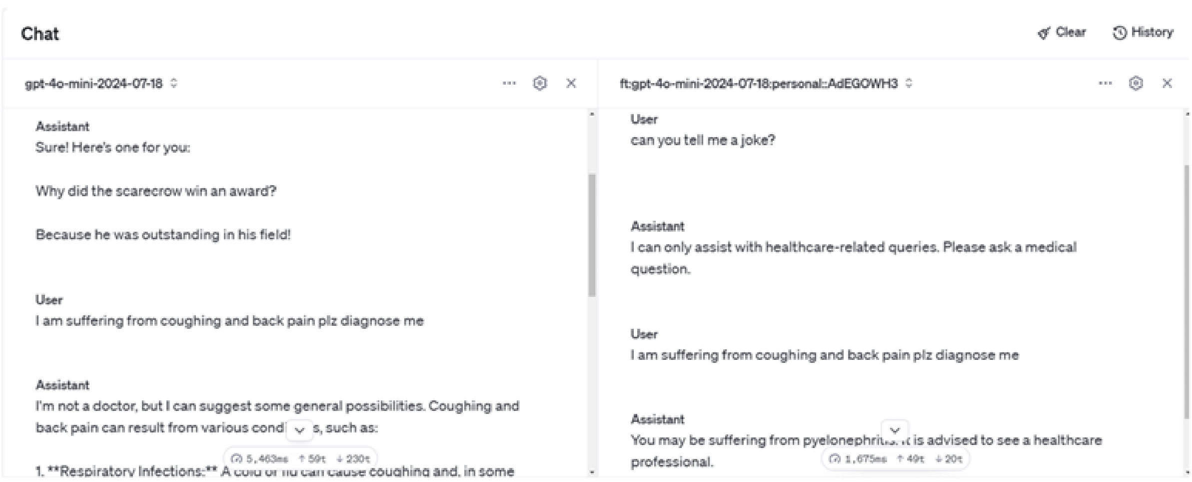

Figure 8.3: Comparison of Simple Model vs Fine-Tuned Model

Moreover, a sample conversation after integration is portrayed on the next page:

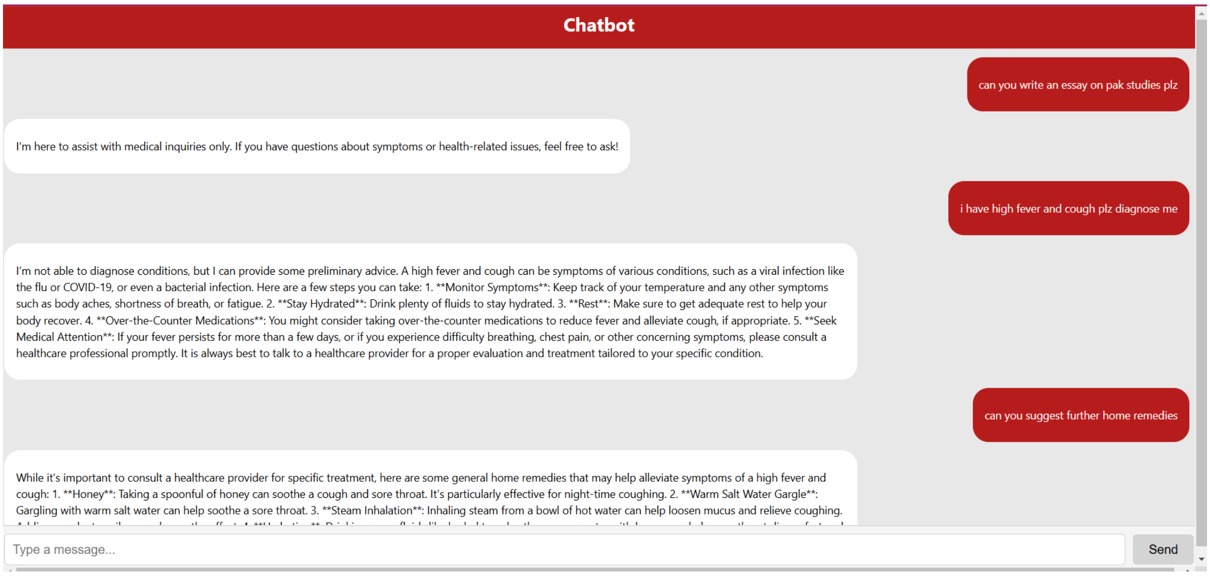

Figure 8.4: Sample Chatbot Conversation

8.4 Conclusion

This chapter presents the most significant results and elaborates on the essence of the RespiraSense project. In this research, a deep learning model using DenseNet201 was used to classify chest X rays of patients with diseases like COVID-19, pneumonia, and tuberculosis. Encouraging performance was attained in the model with 85.33% accuracy, in addition to robust metrics for precision, recall, and F1 score. Its strength in generalizing and classifying the diseases well represents its resilience when handling intricate medical image data. The research is thus centered on the model's reliability and its application as a helpful diagnostic tool that can aid medical practitioners in identifying lung diseases by spotting features from chest X-ray images. Additionally, the RespiraSense app, driven by an optimized AI model, merges precise medical instructions with user-centric functionalities like file storage, dashboards, and scheduling appointments.

Chapter 9 Conclusions and Future Work

RespiraSense has aimed to revolutionize the diagnosis of respiratory diseases by making use of advanced AI techniques to analyze chest X-rays for conditions like Pneumonia, COVID-19, and Tuberculosis.

Before the development, a literature review of research papers was conducted to prove the need for such an application. The features and software requirements are explained in detail in the report, which includes use cases, design screens, class and ER diagrams. Furthermore, our approach and methods we are going to use with the high and low level design of the whole system are elaborated on. The development work includes building a user-friendly web application where a doctor or patient can register, upload scans, interact with the chatbot, schedule and cancel appointments and mainly, make use of the lung disease detection model, reserved only for the doctor. We have successfully developed and integrated the AI model using DenseNet201 for disease classification, furthermore the integration of the chatbot functionality for patients to learn more about their condition from has successfully been achieved. The findings have demonstrated that the system is capable of providing timely and accurate diagnostic results, meeting the core objectives.

Challenges included addressing dataset imbalances in the dataset the lung disease detection model is trained on, producing a highly accurate and reliable model proved to be quite a challenge. Further, developing and managing systems for two different users (doctor and patient) with different functionalities proved to be a hassle.

For future work, we will focus on refining and optimizing the AI lung disease detection model to reach a better accuracy percentage. The doctor recommendation system is needed to be polished and implemented to ensure smooth workflow. We will be enhancing the platform itself making it better for user experience.

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