A

PROJECT REPORT

ON

"Diagnosing respiratory conditions via lung sound using CNN and LSTM"

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY ,
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE OF

BACHELOR OF ENGINEERING

(COMPUTER ENGINEERING)

SUBMITTED BY

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UNDER THE GUIDENCE OF
Prof. Shah S. N.

DEPARTMENT OF COMPUTER ENGINEERING
SSPM's Sharadchandra Pawar College of Engineering and Technology
Someshwarnagar, Baramati-412306

AY 2024-2025

CERTIFICATE

This is to certify that the Project Entitled

"Diagnosing respiratory conditions via lung sound using CNN and LSTM"

Submitted by

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is a record of bonafide work carried out by her/him in the department of Computer Engineering, SSPM's Sharadchandra Pawer College of Engineering and Technology Someshwarnagar, Baramati-412306 under the guidance and supervision of **Prof. Shah S. N.** in partial fulfilment of requirements for the award of Degree of **Bachelors of Computer Engineering** as prescribed by the S. P. Pune University, in the academic year 2024-2025.

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Prof. Shah.S.N.
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Prof. Shah.S.N.
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Dr.Deokar S.A.
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Signature of External Examiner

Place: Someshwarnagar

Date: / / 2025.

Certificate by Guide

This is to certify that **Mr. Pawar Rohit Balaso, Ms. Raut Aditi Shivaji, Ms. Jadhav Sneha Nitin,** has completed the dissertation work under my guidance and supervision and that, I have verified the work for its originality in documentation, problem statement, implementation and results presented in the dissertation. Any reproduction of other necessary work is with the prior permission and has given due ownership and included in the references.

Place:**Someshwarnagar, Baramati** Signature of Guide

Date: **(Prof. Shah S.N.)**

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ABSTRACT

In order to analyze respiratory sounds on a computer, we developed a cost-effective and easy-to-use Algorithm that can be used with any device. We employed two types of machine learning algorithms; Gammatone cepstrum coefficients features in a Convolutional Neural Network and Since using GTCC and STFC features with a CNN-LSTM algorithm. We prepared four data sets for CNN-LSTM algorithm to classify respiratory audio:healthy versus pathological classification; rale, rhonchus, and normal sound classification; singular respiratory sound type classification; and audio type classification with all sound types.
Keywords- Respiratory Sound Analysis, Breathing Sound Classification, Gammatone Cepstrum Coefficients (GTCC), Short-Time Fourier Coefficients (STFC), CNN (Convolutional Neural Networks) LSTM (Long Short-Term Memory),Machine Learning, Healthcare Applications.

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Chapter 1

INTRODUCTION

Respiratory diseases are leading causes of death and disability in the world. The poorest regions of the world had the greatest disease burden. Ageing and risk factors includ- ing smoking, environmental pollution, and body weight also play a key role, say the researchers. Chronic respiratory diseases pose a major public health problem and about 65 million people suffer from chronic obstructive pulmonary disease and with an esti- mated 3.91 million deaths in 2017 which accounts for 7 of all deaths worldwide and its third leading cause of death. Between 1990 and 2017, the number of deaths due to chronic respiratory diseases increased by 18, from 3.32 million in 1990 to 3.91 million in 2017. About 334 million people suffer from asthma, the most common chronic disease of childhood affecting 14 of all children globally. Respiratory diseases like Pneumonia kills millions of people annually and is a leading cause of death among children under 5 years old. Over 10 million people develop tuberculosis (TB) and 1.4 million die from it each year, making it the most common lethal infectious disease. Lung cancer kills 1.6 million people each year and is the deadliest cancer. Globally, 4 million people die prematurely from chronic respiratory disease. Res- piratory diseases make up five of the 30 most common causes of death: COPD is third; lower respiratory tract infection is fourth; tracheal, bronchial and lung cancer is sixth; TB is twelfth; and asthma is twenty-eighth . Altogether, more than 1 billion people suffer from either acute or chronic respiratory conditions. The stark reality is that each year, 4 million people die prematurely from chronic respiratory disease . Infants and young children are particularly susceptible. A total of 9 million children under 5 years old die annually, and pneumonia is the world's leading killer of these children . People often take breathing and our respiratory health for granted, but the lung is a

vital organ that is vulnerable to airborne infection and injury. Respiratory system diseases affect people's social, economic and health life significantly. Social deprivation was the most important factor affecting rates of death and disability, with the highest rates seen in the poorest regions of the world. Lower mortality was seen in more affluent countries, reflecting better access to health services and improved treatments. So, treatment of lung diseases, which are the most common cause of death in the world, is of great importance in the medical field. For these reasons, a lot of research are going on for early diagnosis and intervention in respiratory diseases. In order to accurately identify health problem regarding this information requires experience and time, but according to the World Health Organization (WHO) statistics [3], 45 of the WHO Member States report to have less than 1 physician per 1000 population, the WHO ratio recommendation. Considering these statistics into account, to study individually and diagnose every patient by a health specialist who are already overbooked, mistakes can happen. This is why finding new ways to help doctors to save time is a priority. Hence, automatic and reliable tools can help in diagnosing more people and it can also help specialists to make less mistakes due to the work overload.

1.1 Overview

Respiratory conditions, such as asthma, pneumonia, bronchitis, and chronic obstructive pulmonary disease (COPD), are significant health concerns worldwide. Early detection and accurate diagnosis of these conditions are critical for effective treatment and improved patient outcomes. Traditionally, diagnosis involves physical examination, medical imaging, and sometimes invasive tests. However, advances in machine learning, particularly convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), have opened new avenues for diagnosing respiratory conditions non-invasively using lung sound analysis. Lung sounds, or breath sounds, are the noises generated by airflow through the respiratory system. Abnormal lung sounds such as wheezing, crackles, and rhonchi can be indicative of underlying respiratory issues.

1.2 Motivation

As rapid growth of respiratory diseases is witnessed around the world, medical research field has gained interest in integrating potential audio signal analysis based technique. From the past few decades, computer science constantly improving the ability to analyze media data automatically and with the help of diagnosis tools we are able to process image and/or audio information. Hence, Computer science could help nursing staff or doctors for diagnosis by proposing faster and reliable tools and by giving customizable tools for medical monitoring to the

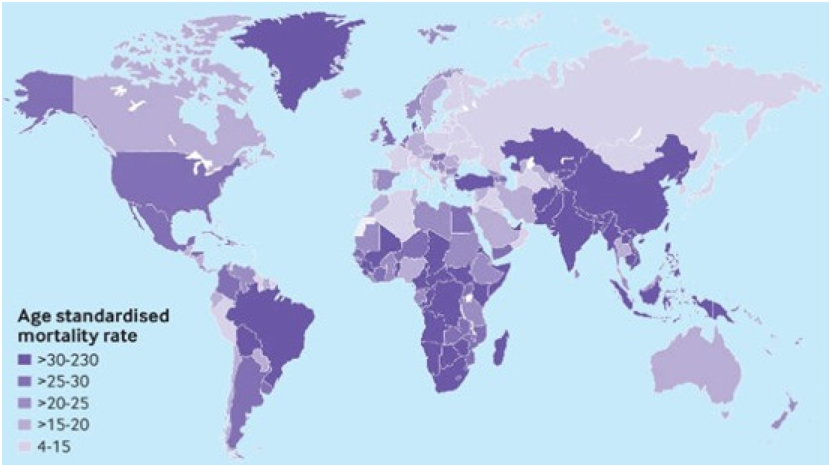


Figure 1.1: Global age standardized mortality rate per 100000 people of chronic obstructive pulmonary disease for both sexes in 195 countries and territories in 2017

patient. Like in other application domains, audio signal analysis tools can potentially help in analyzing respiratory sounds to detect problems in the respiratory tract. Audio analysis aids in timely diagnosis of respiratory ailments more effortlessly in the early stages of a respiratory dysfunction. Apart from respiratory check-ups, every cardiac assessment also includes an audio auscultation in which one the medical specialist listens to sounds from the patient body with different tools like stethoscope or sonography. This shows how important sound analysis is for heart and lungs disease detection. recognizing abnormalities, which can be due to not calibrating the instrument and/or due to noisy environment, is very high using this method As lung and heart diseases remains the leading cause of death globally, there are many studies about lung and heart sound identification. Since then, there are lots of improvements, for processing records taken in noisy environments. Furthermore, new kinds of methods drastically improve the domain, as machine learning and deep learning. These approaches contribute a lot to computer vision, or audio analysis. This gives more relevant information from respiratory sounds extracted and contribute to reducing the time for diagnosis, consequently increasing treatment efficiency. Thus, an automated algorithm developed to recognize abnormalities in respiratory sounds may be of great relevance to clinical diagnosis. Also researchers are looking in to combining speech and signal processing tools techniques with image analysis-based tools techniques can also help doctors predict or guess about the presence of respiratory diseases based on verbal communication before they even start with the X-ray screening or other procedures. Machine learning has proven to be an effective technique in recent years and machine learning algorithms have been successfully used in a large number of applications. The development of computerized lung sound analysis has attracted many researchers in recent years, which has led to the implementation of machine learning algorithms for the diagnosis of lung sound. In our research we have used machine learning techniques in computer-based lung sound analysis. A brief description of the types of lung sounds and their characteristics is provided. We examined specific lung sounds/disorders, the number of subjects, the signal processing and classification methods and the outcome of the analyses of lung sounds using machine learning methods that have been performed by previous researchers. Before diagnosing disease based on their types, it is important to first ensure that whether a person has any lung infection. True positive case can then be pushed for further processing, such as diagnosis. In this research, we developed an automated tool to distinguish healthy respiratory sound from and non-healthy ones that come from respiratory infection carrying patients, where GTCC-based features are employed. Using over 6800 clips, we obtained the highest accuracy of 99.22. A brief description on the previous works is also included and in conclusion, the review provides recommendations for further improvements.

Respiratory sounds may be acquired by the easy and non-invasive auscultation procedure. Auscultation is an effective technique in which physicians evaluate and diagnose the disease after using a stethoscope for lung disease. This method is inexpensive and easy as it does not require internal intervention into the human body. However, traditional stethoscopes may be exposed to external noise sounds and cannot filter the audio frequencies of the body in auscultation and cannot create permanent recordings in monitoring of the disease course. Also, there is a possibility of untrained physicians incorrectly

1.3 Problem Definition and Objectives

1.3.1 Problem Definition

- Respiratory diseases like asthma, pneumonia, and COPD often go undiagnosed in their early stages due to limitations in traditional diagnostic methods, which can be costly, invasive, and inaccessible. Additionally, manual analysis of lung sounds is prone to human error and subjectivity. The problem is to develop an automated, non-invasive, cost-effective diagnostic tool that uses machine learning techniques (CNNs and LSTMs) to accurately analyze lung sounds, detect abnormalities, and provide early, reliable diagnoses of respiratory conditions, especially in resource-limited settings.

1.3.2 Objectives

- Develop a Cost-Effective and Accurate System: Create a system for classifying lung sounds that is affordable, precise and requires minimal computational resources.
- Automate Respiratory Sound Analysis:Address the increasing demand for automated tools due to the high global burden of respiratory diseases, improving accessibility and efficiency in diagnosing respiratory conditions.
- Medical professionals looking to quickly assess respiratory conditions in clinical and remote settings.
- Training datasets and improving machine learning models for more accurate respiratory sound classification

1.4 Project Scope and Limitations

1.4.1 Project Scope

The proposed system the scope is to develop an automated system for diagnosing respiratory conditions using lung sound analysis, leveraging deep learning techniques, specifically Convolutional Neural Networks (CNNs) for feature extraction and Long Short-Term Memory (LSTM) networks for temporal analysis. The system will classify common respiratory conditions such as asthma, pneumonia, and bronchitis based on audio recordings of lung sounds, utilizing preprocessed features like Mel-frequency cepstral coefficients (MFCCs) or spectrograms. The project will encompass data collection, preprocessing, model development, evaluation, and the creation of a user-friendly application for real-time diagnosis. The goal is to provide a reliable, efficient tool that can assist healthcare professionals in diagnosing respiratory diseases quickly and accurately, with a focus on optimizing model performance, ensuring generalization, and exploring deployment options for practical medical use.

1.4.2 Limitations

Dependency

Without Internet Connection project will not work.

1.5 Methodologies of Problem solving

Respiratory conditions are diagnosed through spirometry and lung auscultation. Spirometry is measuring the volume of air mobilized in respiration. Even though, this method is one of the most commonly available lung function tests and well validated for the diagnosis and monitoring of upper and lower airway abnormalities , it is limited to patient's cooperation and therefore, is error prone. Moreover, traditional spirometers are normally used only in clinical settings due to their high cost and required calibration along with challenges in patient guiding. Auscultation is other technique which involves listening to the internal human body sounds with the aid of a stethoscope and typically performed on the anterior and posterior chest. From past few years, it has been an effective tool to understand lung disorders and possible abnormalities. However, this process is limited to physicians as they are well trained. For various reasons like faulty instrument or noisy environment, false positives can happen. Therefore, it opens a door to develop computerized lung sound analysis tools/techniques, where automation is the integral part.

Chapter 2

LITERATURE REVIEW

A literature research with respect to the previously published literature is the initial stage of any project. A series of comprehensive market survey of publications in a specific field of study is conducted before a suitable problem solving method is finalized. It is seen as an essential task as it will ensure that a thorough understanding of a project is gained and subsequently lays a solid foundation on our future task.

All the research done will serve as a yardstick and reference to our project. After a complete literature review is finished, we are supposed to be able to write in such a way that shows we have a feel for the area, know what the important issues are and their relevance to our work. We should have known what can be neglected and we have the anticipation of the outcome. To summarize all the above, the direction of a project is determined and indeed this is the objective of literature review.

1. Investigating into segmentation methods for diagnosis of respiratory diseases using adventitious respiratory sounds
Author: Liqun Wu and Ling Li
Description:
Respiratory condition has received a great amount of attention nowadays since respiratory diseases recently be come the globally leading causes of death. Traditionally, stethoscope is applied in early diagnosis but it requires clinician with extensive training experience to provide accurate diagnosis. Accordingly, a subjective and fast diagnosing solution of res piratory diseases is highly demanded. Adventitious respiratory sounds (ARSs), such as crackle, are mainly concerned during diagnosis since they are indication of various respiratory dis eases. Therefore, the characteristics of crackle are informative and valuable regarding to develop a computerised approach for pathology-based diagnosis. In this work, we propose a frame work combining random forest classifier and Empirical Mode Decomposition (EMD) method focusing on a multi-classification task of identifying subjects in 6 respi-

ratory conditions (healthy, bronchiectasis, bronchiolitis, COPD, pneumonia and URTI). Specifically, 14 combinations of respiratory sound segments were compared and we found segmentation plays an important role in classifying different respiratory conditions. The classifier with best performance (accuracy = 0.88, precision = 0.91, recall = 0.87, specificity = 0.91, F1-score = 0.81) was trained with features extracted from the combination of early inspiratory phase and entire inspiratory phase. To our best knowledge, we are the first to address the challenging multi-classification problem.

2. Respiratory Sound Database for the Development of Automated Classification

Author: B. M. Rocha1, D. Filos, L. Mendes, I. Vogiatzis, E. Perantoni, E. Kaimakamis, P. Natsiavas, A. Oliveira3,4, C. Jácome3, A. Marques3,4, R. P. Paiva1, I. Chouvarda2, P. Carvalho1, N. Maglaveras2

Description:

The automatic analysis of respiratory sounds has been a field of great research interest during the last decades. Automated classification of respiratory sounds has the potential to detect abnormalities in the early stages of a respiratory dysfunction and thus enhance the effectiveness of decision making. However, the existence of a publically available large database, in which new algorithms can be implemented, evaluated, and compared, is still lacking and is vital for further developments in the field. In the context of the International Conference on Biomedical and Health Informatics (ICBHI), the first scientific challenge was organized with the main goal of developing algorithms able to characterize respiratory sound recordings derived from clinical and non-clinical environments. The database was created by two research teams in Portugal and in Greece, and it includes 920 recordings acquired from 126 subjects. A total of 6898 respiration cycles were recorded. The cycles were annotated by respiratory experts as including crackles, wheezes, a combination of them, or no adventitious respiratory sounds. The recordings were collected using heterogeneous equipment and their duration ranged from 10s to 90s. The chest locations from which the recordings were acquired was also provided. Noise levels in some respiration cycles were high, which simulated real life conditions and made the classification process more challenging.

3. Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning

Author: Yoonjoo Kim, YunKyong Hyon, Sung Soo Jung, Sunju Lee, Geon Yoo, Chaeuk Chung Taeyoung Ha **Description:**

Auscultation has been essential part of the physical examination; this is non-invasive, real-time, and very informative. Detection of abnormal respiratory sounds with a stethoscope is important in diagnosing respiratory diseases and providing first aid. However, accurate interpretation of respiratory sounds requires clinician's considerable expertise, so trainees such as interns and residents sometimes misidentify respiratory sounds. To overcome such limitations, we tried to develop an automated classification of breath sounds. We utilized deep learning convolutional neural network (CNN) to categorize 1918 respiratory sounds (normal, crackles, wheezes, rhonchi) recorded in the clinical setting. We developed the predictive model for respiratory sound classification combining pretrained image feature extractor of series, respiratory sound, and CNN classifier. It detected abnormal sounds with an accuracy of 86.5 and the area under the ROC curve (AUC) of 0.93. It further classified abnormal lung sounds into crackles, wheezes, or rhonchi with an overall accuracy of 85.7 and a mean AUC of 0.92. On the other hand, as a result of respiratory sound classification by different groups showed varying degree in terms of accuracy; the overall accuracies were 60.3 for medical students, 53.4 for interns, 68.8 for residents, and 80.1 for fellows. Our deep learning-based classification would be able to complement the inaccuracies of clinicians' auscultation, and it may aid in the rapid diagnosis and appropriate treatment of respiratory diseases

4. Performance evaluation of lung sounds classification using deep learning under variable parameters
Author: Zhaoping Wang and Zhiqiang Sun
Description:
It is desired to apply deep learning models (DLMs) to assist physicians in distinguish ing abnormal/normal lung sounds as quickly as possible. The performance of DLMs depends on feature-related and model-related parameters heavily. In this paper, the relationship between performance and feature-related parameters of a DLM, i.e., convolutional neural network (CNN) is analyzed through experiments. ICBHI 2017 is selected as the lung sounds dataset. The sensitivity analysis of classification perfor mance of the DLM on three parameters, i.e., the length of lung sounds frame, overlap percentage (OP) of successive frames and feature type, is performed. An augmented and balanced dataset is acquired by the way of white noise addition, time stretching and pitch shifting. The spectrogram and mel frequency cepstrum coefficients of lung sounds are used as features to the CNN, respectively. The results of training and test show that there exists significant difference on performance among various parameter combinations. The parameter OP is performance sensitive. The higher OP, the better performance. It is concluded that for fixed sampling frequency 8 kHz, frame size 128, OP 75 and spectrogram feature is optimum under which the performance is rela tively better and no extra computation or storage resources are required.

5. Automated Detection of Pulmonary Diseases From Lung Sound Signals Using Fixed-Boundary-Based Empirical Wavelet Transforms.

Author: Rajesh Kumar Tripathy and Ram Bilas Pachori, Shaswati Dash, Adyasha Rath, Ganapati Panda

Description:

—In this letter, a promising method is proposed to automatically detect pulmonary diseases (PDs) from lung sound (LS) signals. The modes of the LS signal are evaluated using empirical wavelet transform with fixed boundary points. The time-domain (Shannon entropy) and frequency-domain (peak amplitude and peak frequency) features have been extracted from each mode. The classifiers, such as support vector machine, random forest, extreme gradient boosting, and light gradient boosting machine (LGBM), have been chosen to detect PDs using the features of LS signals automatically. The performance of the proposed method has been evaluated using LS signals obtained from a publicly available database. The detection accuracy values, such as 80.35, 83.27, 99.34, and 77.13 , have been obtained using the LGBM classifier with fivefold cross validation for normal versus asthma, normal versus pneumonia, normal versus chronic obstructive pulmonary disease (COPD), and normal versus pneumonia versus asthma versus COPD classification schemes. For the normal versus pneumonia versus asthma classification scheme, the proposed method has achieved an accuracy value of 84.76, which is higher than that of the existing approaches using LS signals.

Chapter 3

SOFTWARE REQUIREMENT SPECIFICATION

3.1 Introduction

Diagnosing respiratory conditions through lung sounds involves analyzing acoustic signals produced by breathing, such as wheezes, crackles, and rhonchi, which can indicate various respiratory diseases. Traditional methods for analyzing lung sounds rely on manual auscultation, but recent advancements leverage deep learning techniques to automate and enhance diagnosis.

1. User must require the Web Application.
2. Front End –HTML,CSS and Javascript
3. User has to Language– Python 3.8.

3.2 Functional Requirements

3.2.1 System feature

1. Admin - Add Users in the System with Permissions.
User should able to add new Users in the System, and Admin can give Permission for Activities as per Role.

2. User Login.
User should able to login into System after entering the correct password Successfully .

3.Enter Patient Name.
System should accept the patient name.

4. Choose the lung audio from System.
System should capture the lung audio file provided by the user .

5. Detect the accurate result .
System should provide the correct result .

3.2.2 User Interface

There would be efficient user interfaces. There would be a proper provision for the user to input the data and results extracted patterns.

3.2.3 Hardware Interfaces

Mobile Screen or Laptop Screen

3.2.4 Software Interfaces

Web Application

3.3 Non Functional Requirements

3.3.1 Performance Requirement

Performance requirements represent the bar to measure the performance, that is, they represent the benchmark for service measurement, usually defined through a description of the "target level of services", based on a performance indicators regime (KPIs).

3.3.2 Safety Requirement

The safety requirements are those requirements that are defined for the purpose of risk reduction. Like any other requirements, they may at first be specified at a high level, for example, simply as the need for the reduction of a given risk.

3.3.3 Security Requirement

A security requirement is a statement of needed security functionality that ensures one of many different security properties of software is being satisfied. Security requirements are derived from industry standards, applicable laws, and a history of past vulnerabilities. Security requirements define new features or additions to existing features to solve a specific security problem or eliminate a potential vulnerability.

3.3.4 Software Quality Attributes

Our software has many quality attribute that are given below:-

Adaptability: This software is adaptable by all users.

Availability: This software is freely available to all users. The availability of the software is easy for everyone.

Maintainability: After the deployment of the project if any error occurs then it can beeasily maintained by the software developer.

Reliability: The performance of the software is better which will increase the reliability of the Software.

3.4 System Requirements

3.4.1 Dataset Requirements

- Dataset Containg the lung audios of Multiple Peoples

3.4.2 Hardware Requirements

- Hard Disk: Greater than 500 GB,
- RAM : Greater than 4 GB,
- Processor : core i3 and above

3.4.3 Software Requirements

- Anaconda Navigator
- Visual Studio Code

3.5 Analysis Models: SDLC Model to be applied

We are using waterfall model for our project estimation. The Waterfall Model was the first Process Model to be introduced. It is also referred to as a linear-sequential life cycle model. It is very simple to understand and use. In a waterfall model, each phase must be completed before the next phase can begin and there is no overlapping in the phases.

The Waterfall model is the earliest SDLC approach that was used for software development. The waterfall Model illustrates the software development process in a linear sequential flow. This means that any phase in the development process begins only if the previous phase is complete. In this waterfall model, the phases do not overlap.

Waterfall Model - Design

Waterfall approach was first SDLC Model to be used widely in Software Engineering to ensure success of the project. In "The Waterfall" approach, the whole process of software development is divided into separate phases. In this Waterfall model, typically, the outcome of one phase acts as the input for the next phase sequentially. The following illustration is a representation of the different phases of the Waterfall Model.

1. Requirement gathering and analysis:
In this step of waterfall we identify what are various requirements are need for our project such are software and hardware required, database, and interfaces.

2. System Design:
In this system design phase we design the system which is easily understood for end user i.e. user friendly. We design some UML diagrams and data flow diagram to understand the system flow and system module and sequence of execution.

3. Implementation:
In implementation phase of our project we have implemented various module required of successfully getting expected outcome at the different module levels. With inputs from system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality which is referred to as Unit Testing.

4. Testing:
The different test cases are performed to test whether the project mod-

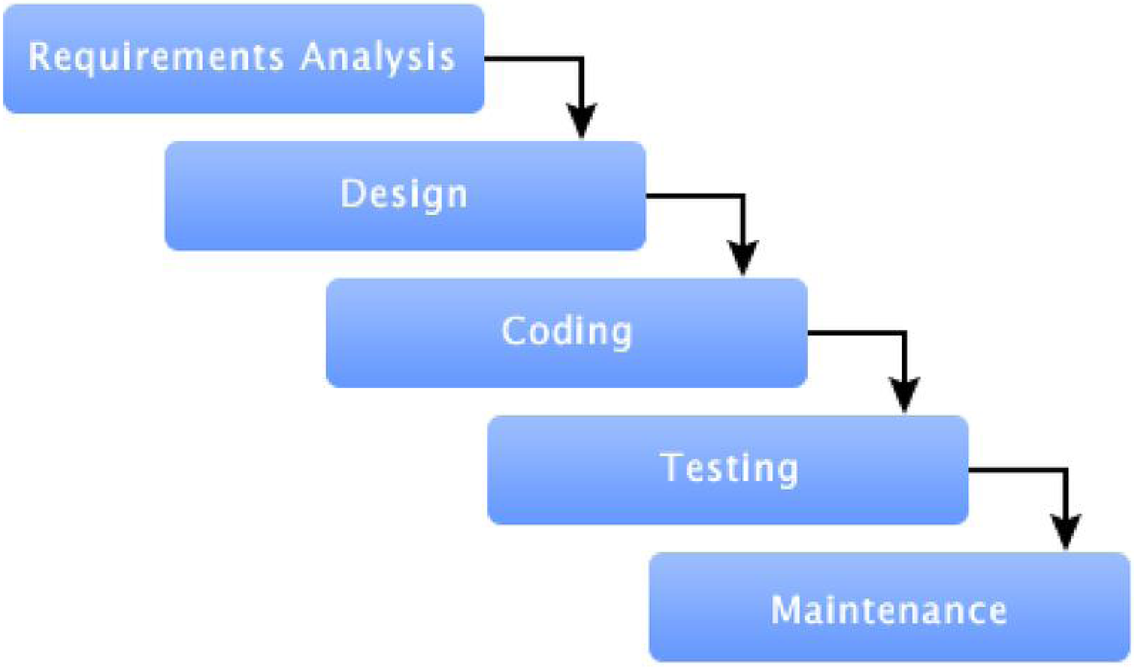


Figure 3.1: SDLC Model

ule are giving expected outcome in assumed time. All the units developed in the implementation phase are integrated into a system after testing of each unit. Post integration the entire system is tested for any faults and failures.

5. Deployment of System:

Once the functional and nonfunctional testing is done, the product is deployed in the customer environment or released into the market.

6. Maintenance:

There are some issues which come up in the client environment. To fix those issues patches are released. Also to enhance the product some better versions are released. Maintenance is done to deliver these changes in the customer environment. All these phases are cascaded to each other in which progress is seen as flowing steadily downwards like a waterfall through the phases. The next phase is started only after the defined set of goals are achieved for previous phase and it is signed off, so the name "Waterfall Model". In this model phases do not overlap.

3.6 System Implementation Plan

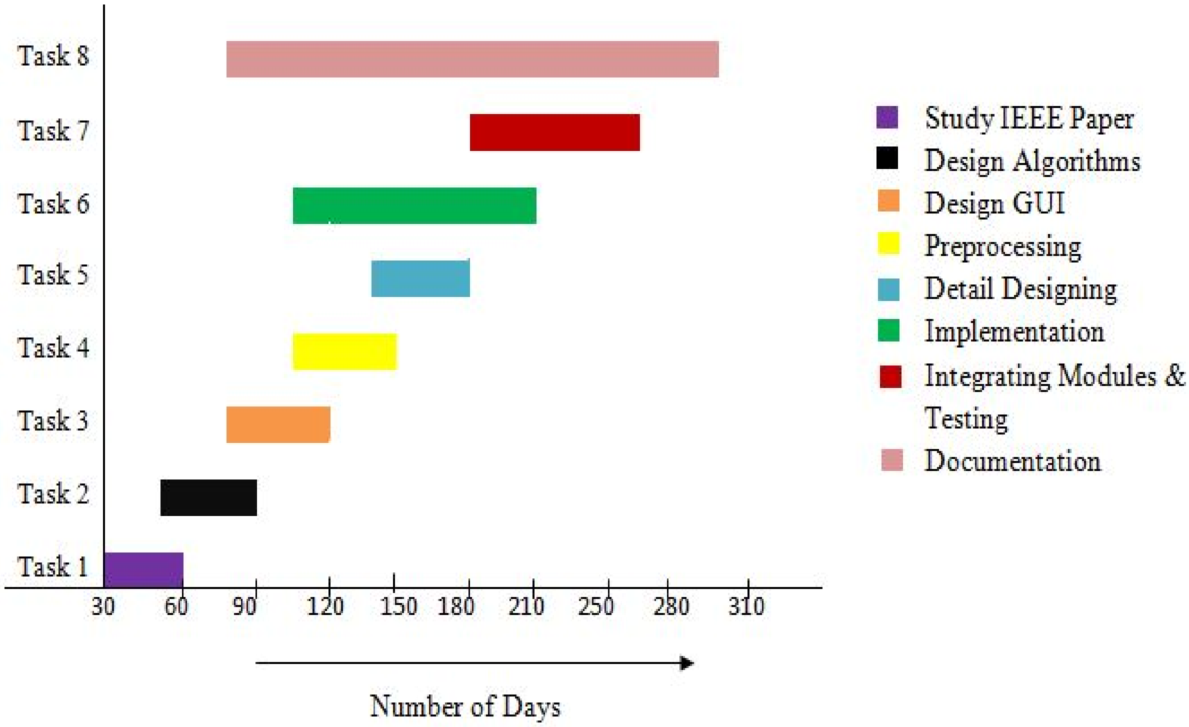


Figure 3.2: System Implementation Plan

Chapter 4

PROJECT PLAN

Sr. No.	Month Sheduled	Phase	Work Done
1	June-August	Topic Seraching	Topic Searched
2	August-September	Topic Selection	Topic Selected
3	August-September	Project Confirmation	Project Confirmed
4	August-September	Literature Survey	Literature Survey Done
5	September-October	Requirement Analysis	Requirement Analysis Done
6	September-October	Requirement Gathering	Requirements Gathered
7	November-December	Designing	Architecture Design
8	November-December	Designing Test	GUI Tested
9	November-December	Database Creation	Database Tested
10	January-February	Coding	Coded Different modules
11	January-February	Database And Module Connectivity	Connectivity Done
12	March	Testing of Project	Project Tested
13	April	Result Analysis	Result Analysis

4.1 Project Estimates

To estimate the required time and cost for the successful execution of this project, we used a combination of empirical analysis and the COCOMO model. The project involves stages such as data collection, preprocessing, model training using CNN-LSTM, evaluation, and documentation.

4.1.1 Reconciled Estimates

Cost and Time Estimation

Cost Estimate

The project cost can be found using any one of the following models:

- **COCOMO-1 Model:** Computes software development efforts as a function of program size expressed in estimated lines of code.
- **COCOMO-2 Model:** Computes software development efforts as a function of program size and a set of cost drivers that include subjective assessment of the product, hardware, personnel, and project attributes.
- **COCOMO-3 (Advanced) Model:** Incorporates all characteristics of the intermediate version with an assessment of cost driver impact on each step of the software engineering process.

Following is the application of the **basic COCOMO-2 model**:

- **Effort Equation:**

$$E = A(b) \times (KLOC)^{B(b)}$$

- **Development Time Equation:**

$$D = C(b) \times (E)^{D(b)}$$

  where:

  - E is the effort applied in person-months
  - D is the development time in months
  - $KLOC$ is the estimated number of delivered lines of code

This project is classified as a **Semi-detached software project**. The estimated lines of code is **9.072 KLOC**.

Applying the formulas:

$$E = 1.0 \times (9.072)^{1.22} = 11.60 \text{ person-months}$$

$$D = 2.5 \times 11.60 = 9.40 \text{ months}$$

Hence, according to the COCOMO-2 model, the time required for completion of the project is approximately **9.4 months**.

Cost of Project

The equation for calculating the project cost using COCOMO-2 is:

$$C = D \times C_p$$

Where:

- C = Cost of the project
- D = Duration in months = 9
- C_p = Cost incurred per person-month = Rs.3500/- (approx.)

$$C = 9 \times 3500 = Rs.31,500/-$$

Hence, the estimated cost of the project is approximately **Rs.31,500/-**
.

Time Estimates

Time estimation is the process of predicting the project duration based on effort and complexity. While it is not an exact science, it uses reliable models and estimation techniques.

The development time can be estimated using the following formula:

$$T_{dev} = b_1 \times Effort^{b_2}$$

Given:

- $b_1 = 2.5$, $b_2 = 0.38$
- $Effort = 5.04$ person-months (adjusted for project phases)

$$T_{dev} = 2.5 \times (5.04)^{0.38} = 4.788 \text{ months}$$

Hence, the predicted development time is approximately **4.79 months**.

4.2 Risk Management

1. In appropriate dataset -To overcome this risk we are trying to use well organized and complete dataset. 2. Security- To overcome and improving security we use multilevel security like access permissions of user.

4.2.1 Risk Identification

For risks identification, review of scope document, requirements specifications and schedule is done. Answers to questionnaire revealed some risks. Each risk is categorized as per the categories mentioned in . Please refer table for all the risks. You can refereed following risk identification questionnaire.

1. Have top software and customer managers formally committed to support the project?
   Ans- Not Applicable

2. Are end-users enthusiastically committed to the project and the system/product to be built?
   Ans- Not known at this time.

3. Are requirements fully understood by the software engineering team and its customers?
   Ans-yes

4. Have customers been involved fully in the definition of requirements?
   Ans-Not applicable
5. Do end-users have realistic expectations?
   Ans-Not applicable
6. Does the software engineering team have the right mix of skills?
   Ans-yes
7. Are project requirements stable? Ans-Not applicable
8. Is the number of people on the project team adequate to do the job? Ans-Not applicable

9. Do all customer/user constituencies agree on the importance of the project and on the requirements for the system/product to be built? Ans-Not applicable

4.2.2 Risk Analysis

The risks for the Project can be analyzed within the constraints of time and quality

ID	Risk Description	Probability	Impact		
			Schedule	Quality	Overall
1	Description 1	Low	Low	High	High
2	Description 2	Low	Low	High	High

Table 4.1: Risk Table

Probability	Value	Description
High	Probability of occurrence is	$> 75\%$
Medium	Probability of occurrence is	$26 - 75\%$
Low	Probability of occurrence is	$< 25\%$

Table 4.2: Risk Probability definitions

Impact	Value	Description
Very high	$> 10\%$	Schedule impact or Unacceptable quality
High	$5 - 10\%$	Schedule impact or Some parts of the project have low quality
Medium	$< 5\%$	Schedule impact or Barely noticeable degradation in quality Low Impact on schedule or Quality can be incorporated

Table 4.3: Risk Impact definitions [**?**]

4.3 Project Schedule

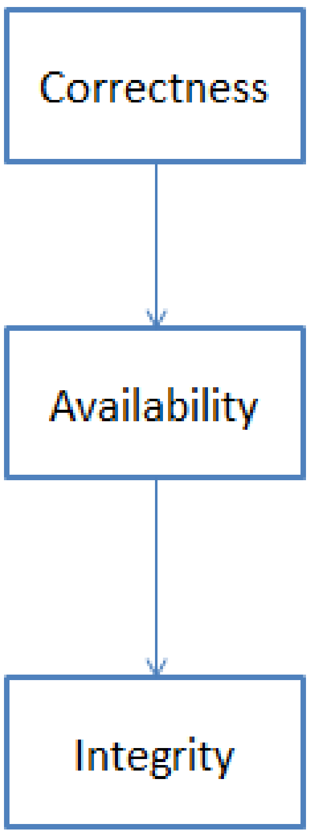
4.3.1 Project task set

Major Tasks in the Project stages are:

- Task 1:Availability
- Task 2: Correctness
- Task 3: Integrity

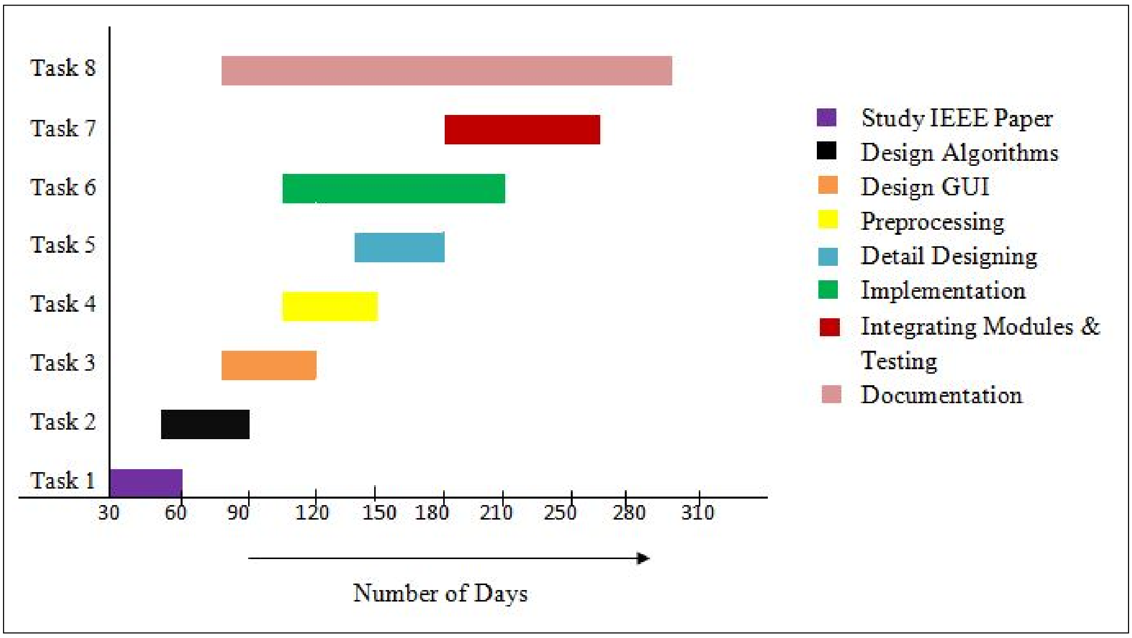
4.3.2 Task network

Project tasks and their dependencies are noted in this diagrammatic form.



4.3.3 Timeline Chart

A project timeline chart is presented. This may include a time line for the entire project. Above points should be covered in Project Planner as Annex C and you can mention here Please refer Annex C for the planner



4.4 Team Organization

Team organization refers to the structure, roles, and processes within a group of individuals working together towards a common goal. It involves determining how tasks are divided, who is responsible for what, how communication flows, and how decisions are made. Effective team organization can significantly impact productivity, collaboration, and overall success.

4.4.1 Team Structure

Group Member 1

Rohit Pawar

1. Report Completion

2. Logbook Completion
3. Workbook Completion
4. Presentation and Coding Completion
5. Testing

Group Member 2

Aditi Raut

1. Report Completion
2. Logbook Completion
3. Workbook Completion
4. Presentation and Coding Completion
5. Testing

Group Member 3

Sneha Jadhav

1. Report Completion
2. Logbook Completion
3. Workbook Completion
4. Presentation and Coding Completion
5. Testing

4.4.2 Management reporting and communication

Sr. No.	Month	Descreption
1	June	Descussion with guide regarding domain. Searching for IEEE paper for domain
2	July	Shortlisted of IEEE papers withn domain. Selection of IEEE paper
3	August	Deciding Project Name. Submission of Synopsis.
4	September	Requirement analysis. Designing of Model.
5	October	Report Preparation. Stage-1 report submission.
6	November	Design Remaining part of model.
7	December	Work on User Interface.
8	January	Work on Database
9	February	Main logic implementation
10	March	Whole modules Combine together.
11	April	Testing.

Chapter 5

SYSTEM DESIGN

The system for diagnosing respiratory conditions using lung sounds combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Lung sound data, such as wheezes, crackles, and normal breath sounds, is collected from publicly available datasets (e.g., PhysioNet or Kaggle). The raw audio is preprocessed into spectrograms (e.g., Mel-spectrograms), which are then fed into a CNN for feature extraction. The CNN identifies key frequency and time patterns, while the LSTM captures temporal dependencies in the sound sequences, essential for identifying events like wheezing or coughing.

The model is trained using labeled data and evaluated on metrics such as accuracy, precision, and recall. Hyperparameters like the number of CNN filters and LSTM units are optimized to improve performance. The system is implemented using deep learning frameworks like TensorFlow or Keras, with audio preprocessing handled by libraries such as Librosa. The resulting model can classify lung sounds into conditions like asthma or pneumonia.

5.1 Data Flow Diagram

A data Flow diagram (DFD) is used to depict the flow of data through an information system using a graphical representation that models process aspects. A DFD shows types of information given as input to and output from the system which will help to understand where the data will come from and go to, and where the data will be stored.DFDs can also be used for the visualization of data processing.

5.1.1 Level 0 Data Flow Diagram

DFD 1 Diagram shows our project at High Level, As Mentioned in the below Diagram We can get Idea of Our Flow of the Project.

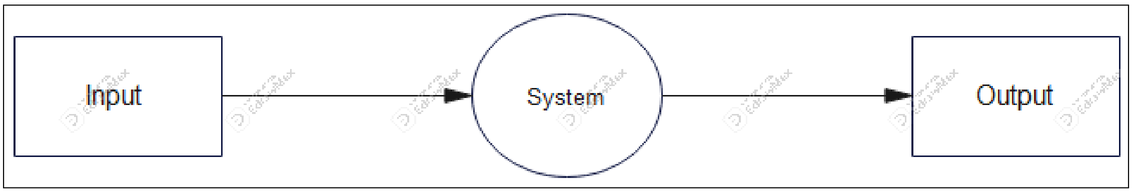


Figure 5.1: DFD level 0

5.1.2 Level 1 Data Flow Diagram

DFD 1 Diagram shows our project at Detail Level, As Mentioned in the below Diagram We can get Flow of Our the Project in Detail.

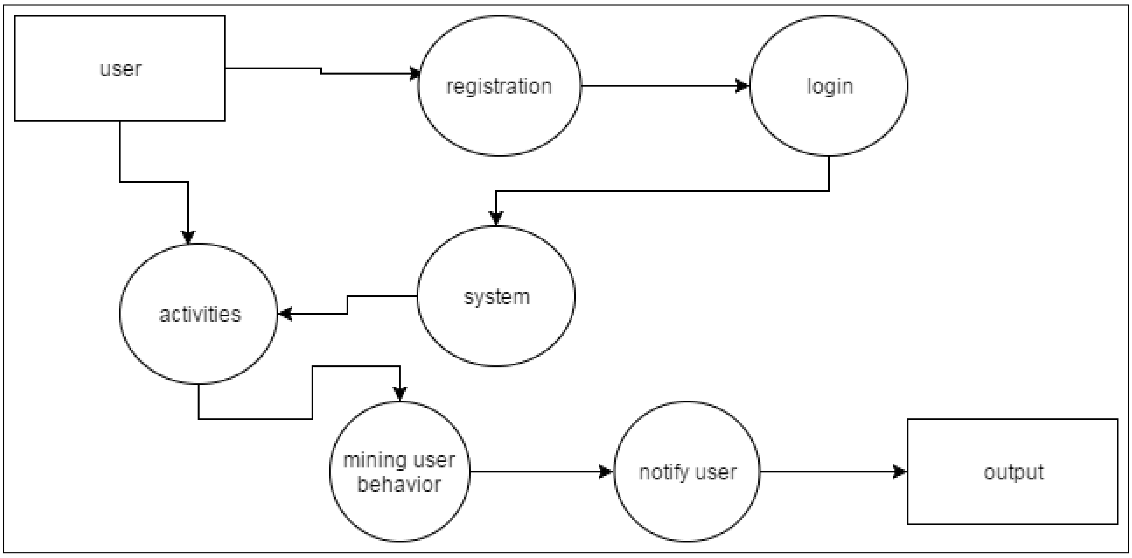


Figure 5.2: DFD level 1

5.1.3 Level 2 Data Flow Diagram

DFD 1 Diagram shows our project at Detail Level, As Mentioned in the below Diagram We can get Flow of Our the Project in Detail.

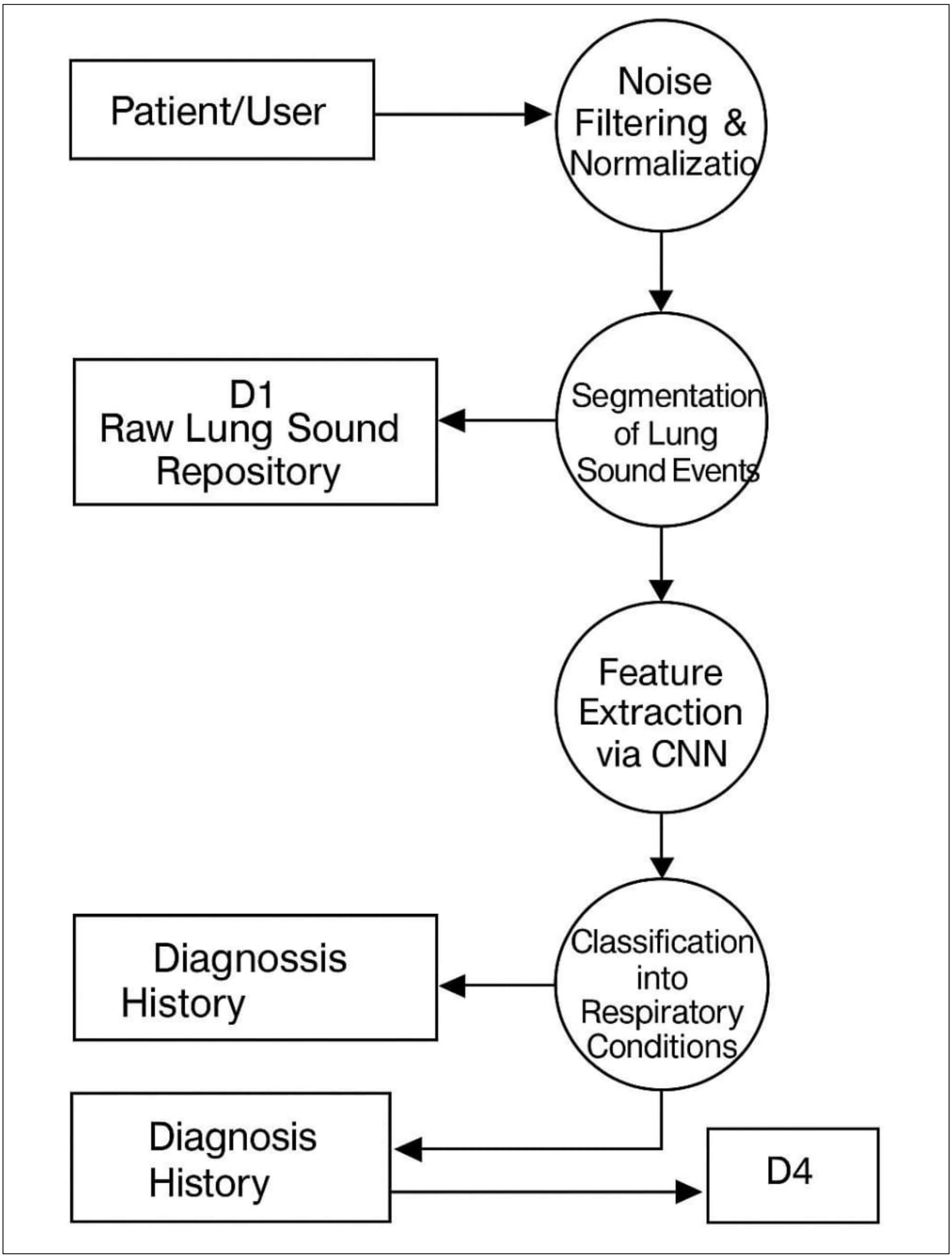


Figure 5.3: DFD level 2

5.2 UML Diagrams

5.2.1 Use-cases

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

So in below Diagram, We have represented how User will Intact with the system and which type type of actions he can Do and How System will React as per his action.

Use Case View

Use Case Diagram. Example is given below. In below Use Case Diagram We have shown how user will perform activities and how our system will response.The User interacts with the system by providing audio or labeled data, which triggers a chain of processes. Admin can manage user data and monitor the processes. The system performs data preprocessing, feature extraction, model training, and classification, providing results to the User. This setup allows the system to continuously improve its classification model with new data, enhancing its accuracy over time.

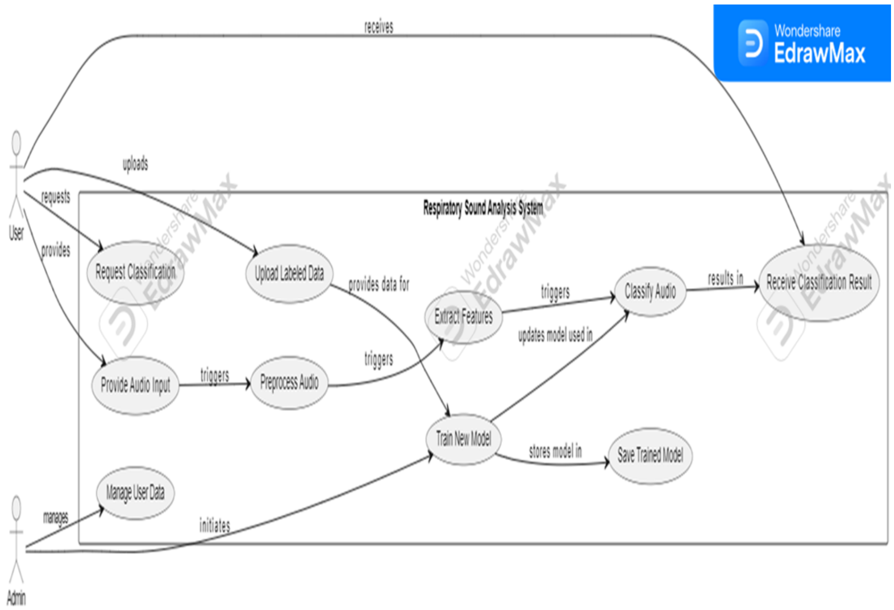


Figure 5.4: Use case diagram

Activity Diagram:

- Activity diagrams are graphical representations of work flows of step wise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step work flows of components in a system. An activity diagram shows the overall flow of control.

  In below Digram we mentioned the Activity Step by Stp. The diagram illustrates a looped process where the user can repeatedly upload audio, train models, and classify sounds. It shows decision points, such as whether training or classification is required, allowing for flexibility in the system's usage. The system uses extracted features for both model training and classification, optimizing the analysis of respiratory sounds. This structured process allows the system to handle multiple use cases, whether the user wants to classify new audio immediately or improve the model by training with labeled data.

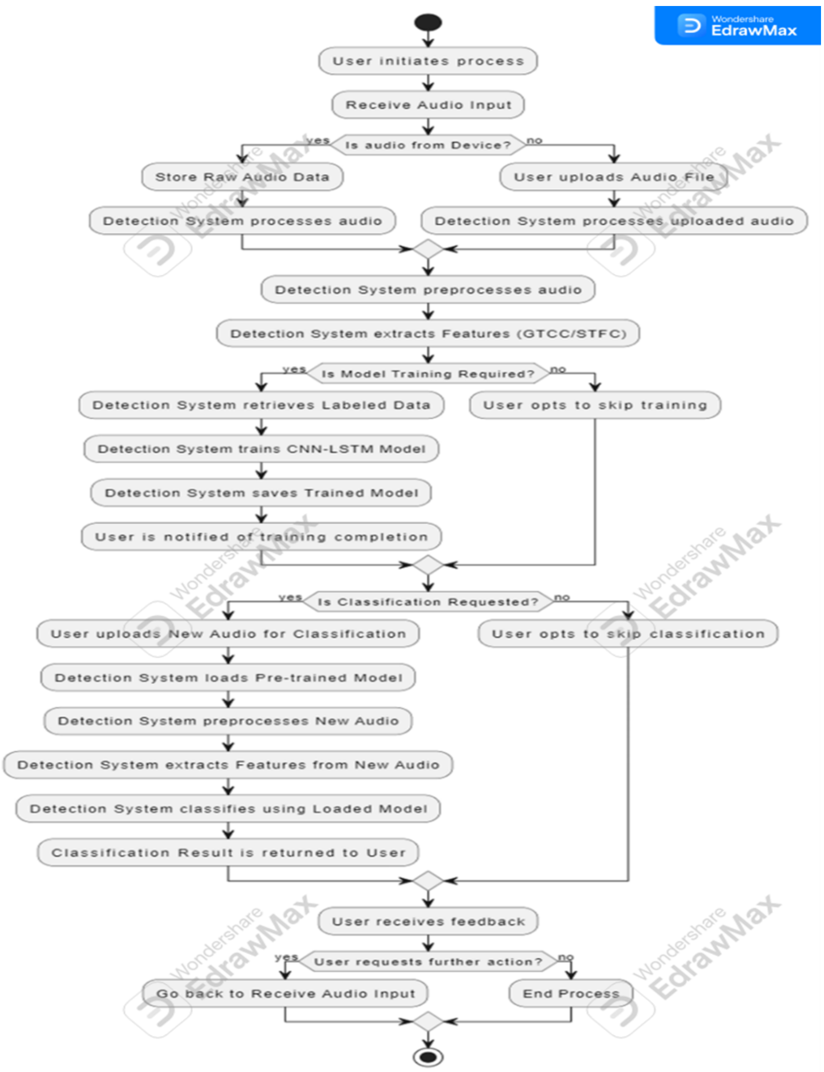


Figure 5.5: Activity Diagram

5.2.2 Sequence Diagram:

The sequence diagram outlines a process for predicting lung disease using sound data collected from a patient's lungs. Initially, the patient records lung sound data, which is then provided to a dataset module to organize the data. This raw sound data is passed to a preprocessing module, where noise is filtered out and the data is normalized. Once preprocessed, the data moves to a Convolutional Neural Network (CNN) layer that extracts important features. These features are then sent to a Long Short-Term Memory (LSTM) layer, which processes temporal dependencies within the data. The processed features are subsequently sent to a prediction model, which analyzes the information to predict disease and calculate the probability of its presence. Finally, the prediction results are sent to a doctor for review and potential diagnosis based on the predictions provided. Each module in this sequence represents a crucial step in transforming raw lung sound data into a medical prediction for decision-making.

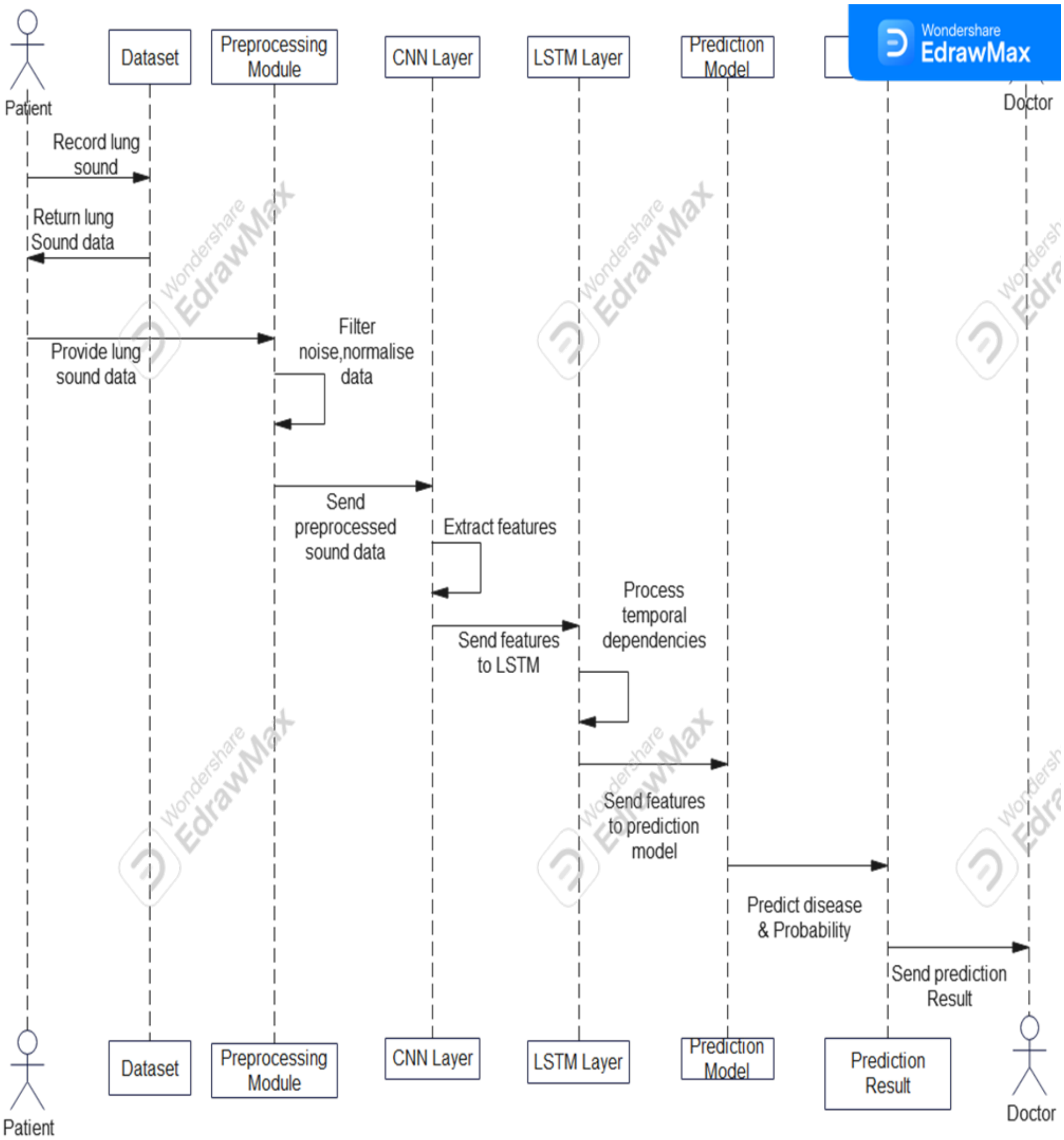


Figure 5.6: Sequence Diagram

5.2.3 Class Diagram:

The class diagram is a static diagram. It represents the static view of an application. Class diagram is not only used for visualizing, describing and documenting different aspects of a system but also for constructing executable code of the software application. The class diagram describes the attributes and operations of a class and also the constraints imposed on the system. The class diagrams are widely used in the modeling of object oriented systems because they are the only UML diagrams which can be mapped directly with object oriented languages. The class diagram shows a collection of classes, interfaces, associations, collaborations and constraints. It is also known as a structural diagram. The purpose of the class diagram is to model the static view of an application.
AS per Above Description of class Diagram, We have presented Structure of our Project in below Diagram.All the Classes there responsibilities and Interfaces between classes has been mentioned in below Class Diagram.

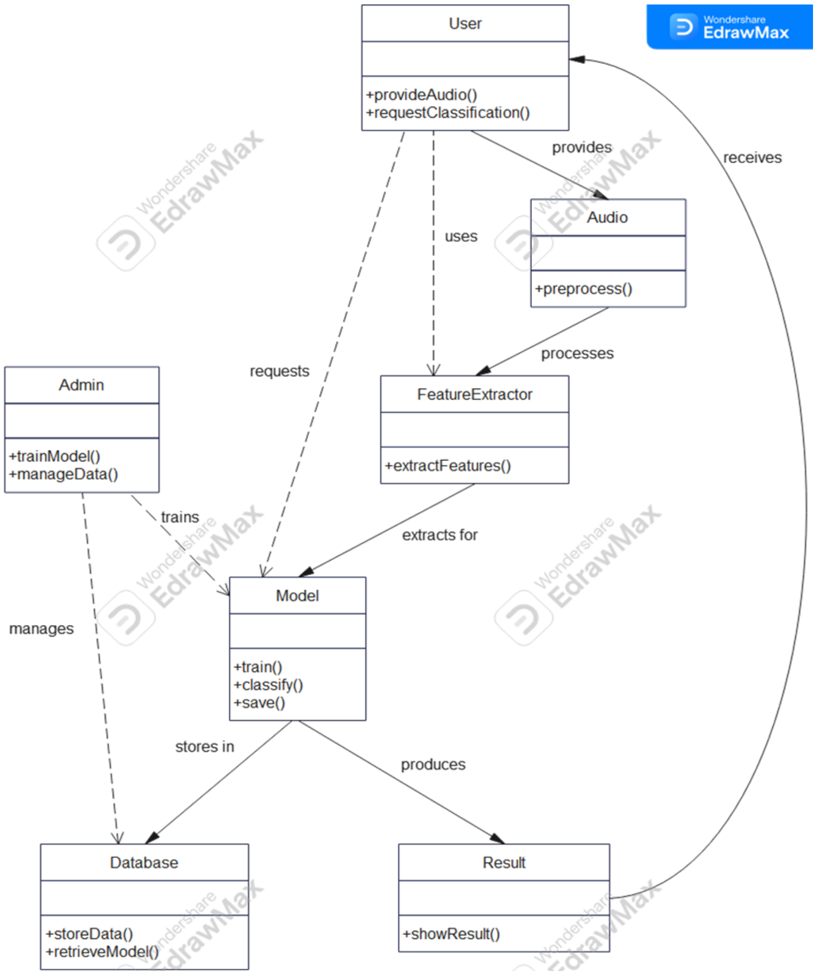


Figure 5.7: Class Diagram

5.2.4 Deployment Diagram:

A Deployment Diagram is a UML structural diagram that models the physical deployment of software artifacts onto hardware nodes. It shows how different pieces of a system (such as executables, libraries, or databases) are physically hosted on infrastructure elements like servers, devices, or cloud environments. Key elements include nodes (representing physical or virtual hardware), artifacts (representing deployed software), and communication paths (indicating network connections between nodes). Deployment diagrams are essential in system architecture to visualize and plan how the software will be distributed across different environments, ensuring clarity in hardware-software interactions and scalability.

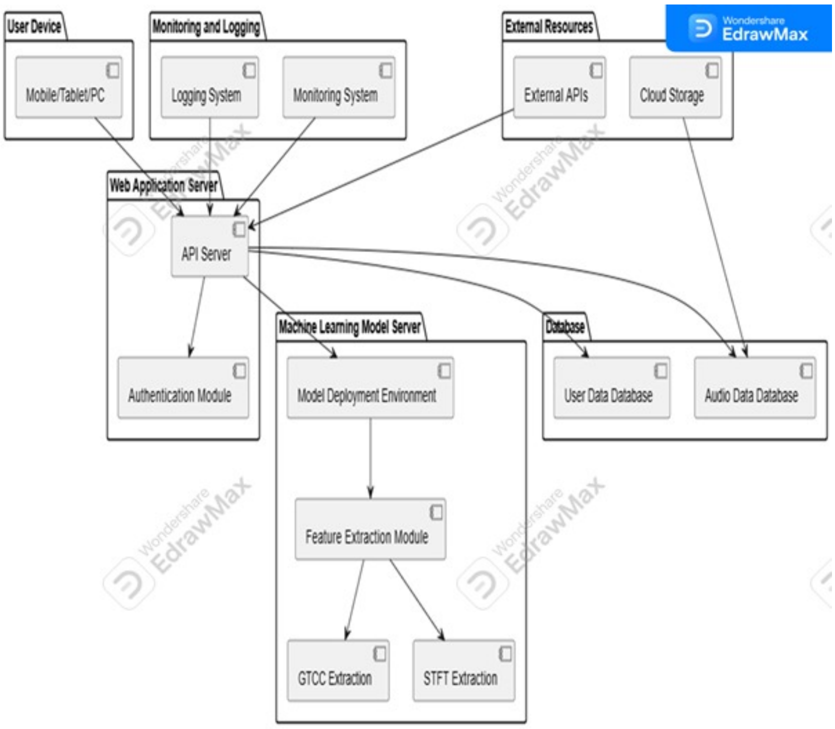


Figure 5.8: Deployment Diagram

5.2.5 Component Diagram:

A Component Diagram is a UML diagram that represents the logical structure of a system in terms of its high-level components and their relationships. It helps in visualizing how software is split into modular parts (components) that encapsulate functionality, such as authentication, data access, or user interface modules. These components may expose or consume interfaces, which define the points of interaction. Component diagrams are particularly useful during system design and development phases to show dependencies between modules, promote reusability, and maintain a clean architecture by clearly defining component boundaries and interactions.

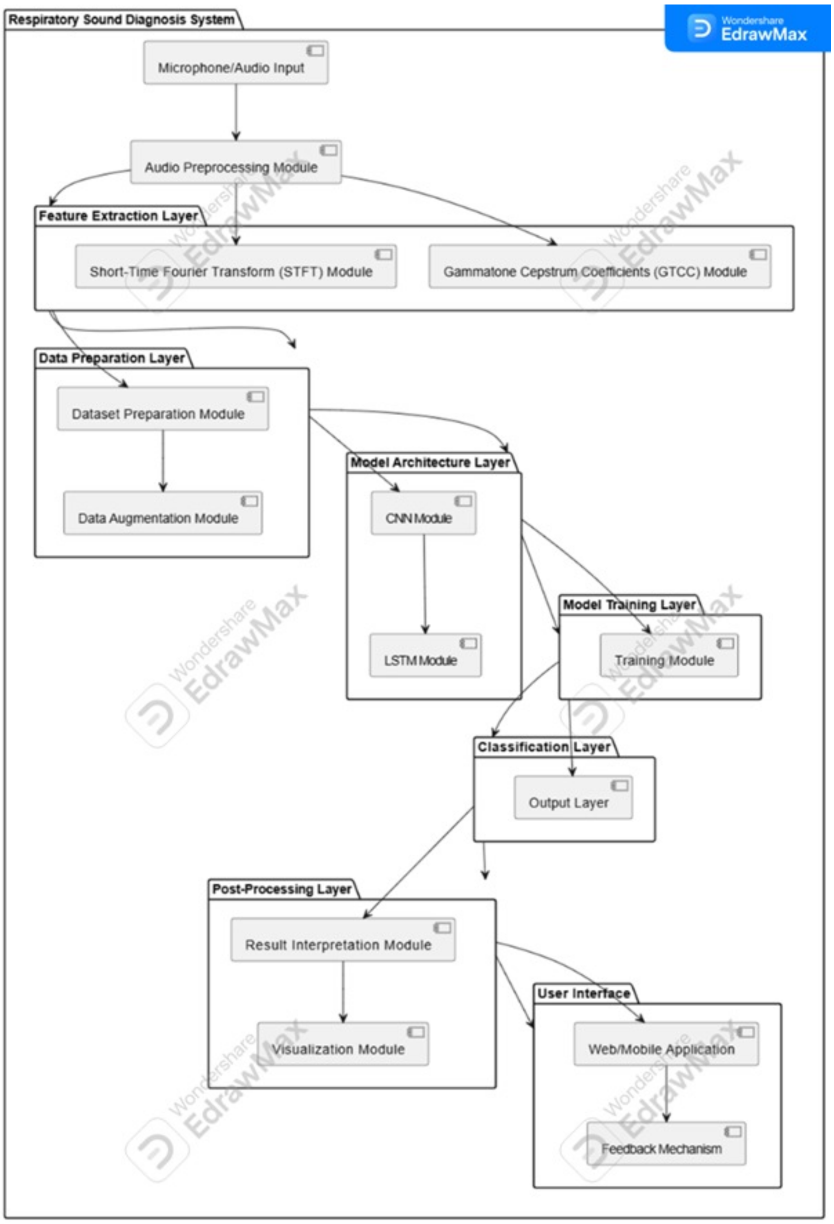


Figure 5.9: Component Diagram

Chapter 6

PROJECT IMPLEMENTATION

6.1 Overview of Project Modules

Step 1- Data Collection: Gather lung sound recordings with labeled respiratory conditions.

Step 2- Data Preprocessing: Clean audio, remove noise, convert to spectrograms, and split data.

Step 3- Feature Extraction: Extract meaningful features (e.g., MFCCs) from audio spectrograms.

Step 4- Model Building: Design a CNN-LSTM model to analyze spatial and temporal patterns.

Step 5-Model Training: Train the model on processed data, tuning for accuracy.

Step 6-Model Evaluation: Test the model on unseen data, assessing accuracy and reliability.

Step 7:File Upload: For recording or uploading lung sound audio.

Step 8-Diagnosis Display: Show predicted condition and confidence score.

Step 9-Admin Panel: Manage user access and monitor usage metrics. Deployment: Deploy as a web app for accessible, real-time diagnostic support.

6.2 Algorithms

6.2.1 Convolutional Neural Network(CNN)

Lung sounds are first converted into Mel-Frequency Cepstral Coefficients (MFCCs)—a 2D representation that reflects the frequency characteristics of sound over time. These MFCCs resemble grayscale images in structure, making them suitable for analysis using CNNs.

CNN is used to learn local spatial patterns such as:

- Wheezing.
- Crackles,.
- Shortness of breath patterns,
- Gaps or irregularities in breathing.

  These localized sound features can be strong indicators of respiratory diseases such as asthma, bronchitis, pneumonia, or COPD.
- Code :

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropou

model = Sequential()

# Convolutional Layer 1
model.add(Conv2D(32, (3,3), activation='relu', input_shape=(40, 174, 1)))
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.3))

# Convolutional Layer 2
model.add(Conv2D(64, (3,3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.3))

# Fully Connected Layers
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))
```

```
# Output Layer
model.add(Dense(num_classes, activation='softmax'))
```

6.2.2 LSTM Algorithm

- Purpose: Lung sounds, such as wheezes and crackles, are not just defined by their presence but by how they appear, repeat, or evolve over time. LSTM is a type of Recurrent Neural Network (RNN) designed to model such sequential or time-series data, making it ideal for audio signals.
- LSTM learns to recognize:
- Breathing cycles and phases,
- Duration and intervals of abnormal sounds,
- Temporal dependency between sound events (e.g., wheeze followed by crackle).
- Code :

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

model = Sequential()

# First LSTM Layer
model.add(LSTM(128, input_shape=(X.shape[1], X.shape[2]), return_sequences=True
model.add(Dropout(0.3))

# Second LSTM Layer
model.add(LSTM(128))
model.add(Dropout(0.3))

# Dense Layers
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))

# Output Layer
model.add(Dense(y.shape[1], activation='softmax'))
```

6.3 Tools and Technologies Used

6.3.1 Technology Description

The entire development process has been subdivided into Three:

1. Front End - HTML , CSS , Javascript
2. Backend - Python

Front End - HTML ,CSS , Javascript

1)HTML: HTML (Hypertext Markup Language) is the standard language used to structure content on the web. It uses tags to define elements like text, images, and links, organizing them in a way that browsers can display correctly. An HTML document typically includes a ¡!DOCTYPE¿ declaration, followed by ¡html¿, ¡head¿, and ¡body¿ sections. The ¡head¿ contains metadata, while the ¡body¿ holds the visible content. HTML also supports attributes that provide additional information for elements, such as links and images. It forms the foundation of web development, working alongside CSS for styling and JavaScript for interactivity.

2)CSS:CSS (Cascading Style Sheets) is a stylesheet language used to define the look and feel of a web page. While HTML structures the content of a webpage, CSS controls its visual presentation, including aspects like colors, fonts, spacing, layout, and positioning. CSS allows developers to separate the design from the content, making web pages easier to manage and maintain. It uses selectors to target HTML elements and applies styles through properties and values, such as setting the background color or adjusting font size. CSS follows a "cascading" rule system, where more specific styles can override general ones. By using inline, internal, or external styles, CSS enables consistent and responsive design across multiple web pages, working in tandem with HTML and JavaScript to create modern, interactive websites.

3)Javascript:JavaScript is a programming language used to add interactivity and dynamic behavior to websites. It enables features such as form validation, animations, real-time updates, and interactive elements like buttons and menus.

Unlike HTML and CSS, which structure and style web pages, JavaScript allows developers to manipulate the content and respond to user actions in real-time without refreshing the page. It runs in the browser and supports asynchronous operations, such as fetching data from a server in the background. JavaScript, along with HTML and CSS, is essential for creating modern, interactive, and user-friendly web applications.

Backend - Python

Python is a high-level, easy-to-read programming language known for its simplicity and versatility. It is widely used in fields like web development, data analysis, artificial intelligence, and automation. Python supports various programming paradigms, including object-oriented and functional programming, and has a large standard library and an extensive ecosystem of third-party packages. Its clear syntax and strong community support make it a popular choice for developers, from beginners to experts, and it continues to grow in demand for solving diverse technical problems.

6.3.2 Hardware Specifications

Hard Disk: Greater than 500 GB, RAM : Greater than 4 GB, Processor : core i3 and above

6.3.3 Software Specifications

Visual Studio Code

Visual Studio Code (VS Code) is a free, open-source code editor developed by Microsoft, widely used for programming in various languages such as Python, JavaScript, and HTML. It offers features like IntelliSense (smart code completion), debugging tools, and integrated Git support for version control. VS Code is highly customizable with a large library of extensions and is available on Windows, macOS, and Linux. Its lightweight, fast performance and versatility make it a popular choice among developers for a wide range of coding tasks.

Anaconda Navigator

Anaconda Navigator is a user-friendly graphical interface that comes with the Anaconda distribution, designed to simplify the management of packages, environments, and applications. It allows users to easily create and manage virtual environments, install or update packages, and launch tools like Jupyter Notebook and Spyder without using the command line. Anaconda Navigator is especially useful for beginners and data scientists, offering an intuitive way to handle Python and R-based projects and workflows.

Chapter 7

SOFTWARE TESTING

7.1 Types Of Testings

7.1.1 Unit Testing

Unit testing focuses on testing individual components or modules of the system in isolation. For this project, it involves testing functions such as audio segmentation, GTCC feature extraction, framing, windowing, and LPC calculation. These tests ensure that each part of the pipeline works correctly before they are integrated into the complete system.

7.1.2 Integration Testing

Integration testing ensures that different components of the system work together as intended. For instance, after extracting GTCC features from audio clips, the system must correctly feed these features into the MLP classifier. This type of testing helps identify interface mismatches or data compatibility issues between modules.

7.1.3 Functional Testing

Functional testing ensures that each function of the system operates according to the defined requirements. In the lung sound classification system, this involves verifying whether the audio input is correctly classified as either healthy or non-healthy. It checks whether the feature extraction (e.g., GTCC, LPC) and classification using MLP (Multi-layer Perceptron) behave as expected. This type of testing validates the core logic of the system.

7.1.4 System Testing

System testing is performed on the complete system to validate the end-to-end functionality. In the context of this project, system testing would involve feeding raw audio files into the tool and verifying that the entire pipeline—from preprocessing to final classification—works seamlessly and produces accurate results.

7.1.5 Validation Testing

Validation testing is conducted to confirm that the model produces correct and consistent results on data it has not seen before. The lung sound system uses a publicly available dataset (ICBHI 2017) for training and validation. This helps ensure that the system is not simply memorizing training data but can generalize to new, unseen patient audio clips, thereby confirming its reliability for real-world applications.

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7.1.6 Cross-Validation Testing

Cross-validation is a statistical technique used to assess the generalization performance of a machine learning model. It involves dividing the dataset into several folds, training the model on some folds and testing on the remaining ones. This method helps to detect overfitting and ensures the model performs consistently across different subsets of the data. In your project, cross-validation ensures the model remains robust across the diverse lung sound samples.

7.1.7 Unit Testing :

Unit testing focuses on testing individual components or modules of the system in isolation. For this project, it involves testing functions such as audio segmentation, GTCC feature extraction, framing, windowing, and LPC calculation. These tests ensure that each part of the pipeline works correctly before they are integrated into the complete system.

7.1.8 Integration Testing

Integration testing ensures that different components of the system work together as intended. For instance, after extracting GTCC features from audio clips, the system must correctly feed these features into the MLP classifier. This type of testing helps identify interface mismatches or data compatibility issues between modules.

7.1.9 Performance Testing

Performance testing measures the efficiency and accuracy of the system under normal operating conditions. In this project, it is used to evaluate how well the classification model performs in terms of metrics like accuracy, sensitivity (recall), specificity, precision, and area under the curve (AUC). A reported accuracy of 99.22 percent and high AUC indicate excellent performance. This testing ensures the system meets the speed and accuracy requirements of a clinical environment.

7.2 Test cases and Test Results

This section outlines the test cases designed to validate the key modules in our respiratory sound diagnosis system. It involves functional, performance, and integration testing using both clean and noisy lung sound inputs, handled through machine learning models (CNN and LSTM).

Module-ID:-01

Modules to be tested:- AUDIO PREPROCESSING

Case-1. Input audio is clean and properly recorded.
Expected Result: Pass directly to feature extraction without applying any filtering.

Case-2. Input audio contains background noise (e.g., talking, ambient sounds).
Expected Result: Apply noise reduction techniques before further processing.

Case-3. Input audio includes overlapping heartbeat and lung sound.
Expected Result: Apply filtering/separation and retain only respiratory sound.

Case-4. Input audio is too short or corrupted.
Expected Result: Display an error message or skip processing.

Module-ID:-2
Modules to be tested:- FEATURE EXTRACTION (GTCC/LPC)

Case-1. Audio clip of standard length (3–5 seconds).
Expected Result: Extract GTCC features and frame data successfully.

Case-2. Audio contains coughing or pitch spikes.
Expected Result: Smooth the spike using windowing; extract clean features.

Case-3. Long audio input (15+ seconds).
Expected Result: Split into proper respiratory cycles and extract consistent features.

Module-ID:-03

Modules to be tested:- CLASSIFICATION (CNN + LSTM)

Case-1. Input is a normal respiratory sound.
Expected Result: Classify as Healthy with high confidence.

Case-2. Input contains both wheezes and crackles.
Expected Result: Classify as Non-Healthy and mark both conditions.

Case-3. Input contains unclear or mixed patterns.
Expected Result: Assign to closest matching class with confidence score.

Case-4. Input has unknown pattern not in training set.
Expected Result: Show low confidence and optionally warn about uncertainty.

Module-ID:-04

Modules to be tested:- RESULT INTERPRETATION GUI

Case-1. User uploads valid audio and requests diagnosis.

Expected Result: Display classification result with confidence score.

Case-2. Audio file has been cleaned during preprocessing.
Expected Result: Notify user that noise was filtered before analysis.

Case-3. Classification result includes probability score.
Expected Result: Show output like: "Non-Healthy – 93 percent confidence."

Case-4. User uploads unsupported file or faces upload failure.
Expected Result: Show error message: "Invalid or unsupported audio file."

7.3 Test Cases and Results

This section presents test cases designed to evaluate the core functionalities of our lung sound classification system.

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Test Case ID	Input / Action	Expected Output	Result
TC1: Preprocessing	Raw lung sound signals containing noise	Noise reduced, normalized signal	Pass
TC2: Feature Extraction	Cleaned audio signal	GTCC and STFC features extracted	Pass
TC3: CNN-LSTM Model	Feature vector of sound	Correct disease classification	Pass
TC4: Model Accuracy	10-fold cross-validation	Accuracy 98%	Pass
TC5: Class-wise Evaluation	Data from all respiratory classes	High class-wise precision	Pass
TC6: Noise Robustness	Varying noise levels in inputs	Accuracy maintained threshold	Pass
TC7: Model Comparison	Run CNN, LSTM, CNN-LSTM	CNN-LSTM outperforms others	Pass
TC8: Real-time Suitability	Test latency and memory use	Runs within limits on edge device	Pass
TC9: Invalid Audio File	Corrupt/Empty audio input	Error handled gracefully	Pass
TC10: Short Duration Clip	Clip less than 2 seconds	Rejected or padded correctly	Pass

Table 7.1: Test Cases for CNN-LSTM Lung Sound Diagnosis System

Test Case ID	**Input / Action**	**Expected Output**	**Result**
TC11: Long Clip Handling	Clip greater than 15 seconds	Segmented properly	Pass
TC12: Overlapping Class Data	Mixed symptoms sounds	Most likely disease predicted	Pass
TC13: Gender Independence	Male vs Female lung sounds	Equal classification accuracy	Pass
TC14: Age Variability	Child vs adult lung sounds	Age-agnostic model accuracy	Pass
TC15: Device Independence	Recorded with different mics	No bias in results	Pass
TC16: Model Loading	Load pre-trained model weights	Loads without error	Pass
TC17: Feature Mismatch	Features with wrong dimension	Model throws dimension error	Pass
TC18: Batch Input Test	Multiple files as batch	Parallel processing succeeds	Pass
TC19: UI Integration	Model deployed on GUI/API	Correct output displayed to user	Pass
TC20: Dataset Imbalance	Uneven class distribution	Model handles imbalance fairly	Pass

Table 7.2: Test Cases for CNN-LSTM Lung Sound Diagnosis System

Chapter 8

RESULTS

8.1 Results

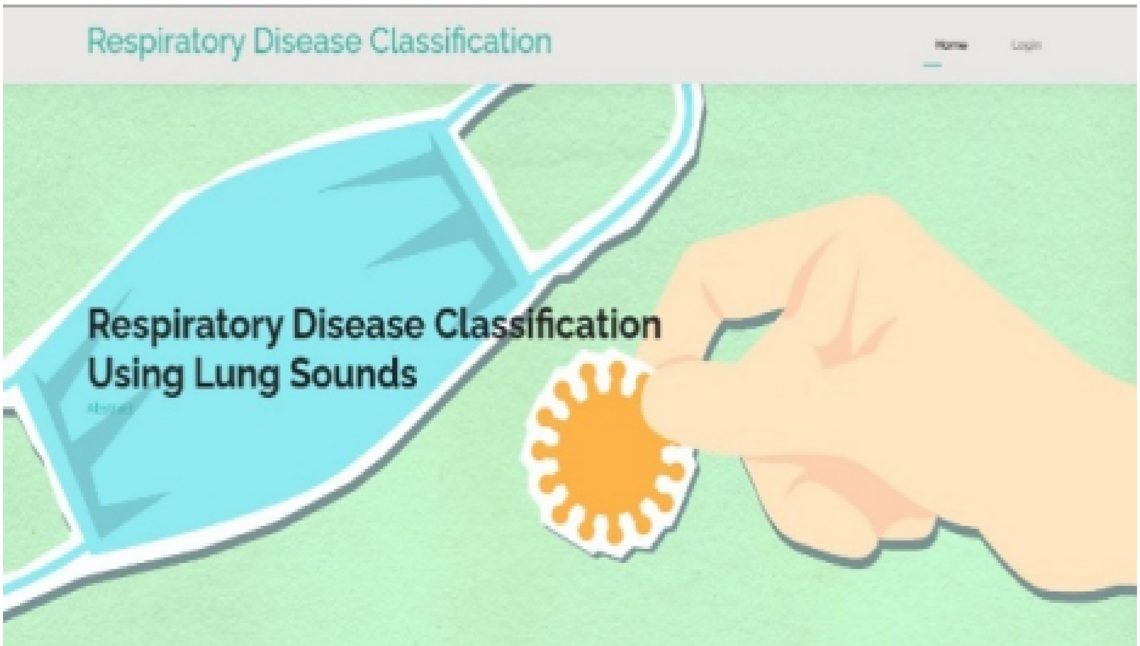

Figure 8.1: Sign-Up Page: User Registration Interface

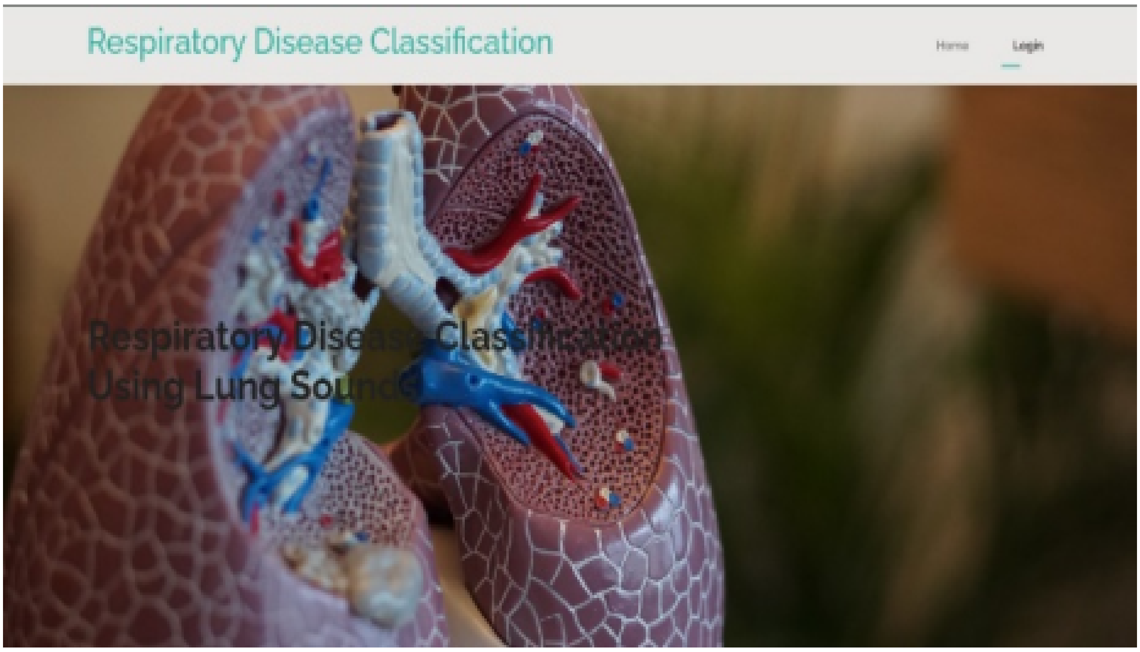

Figure 8.2: Login Page: User Authentication Interface

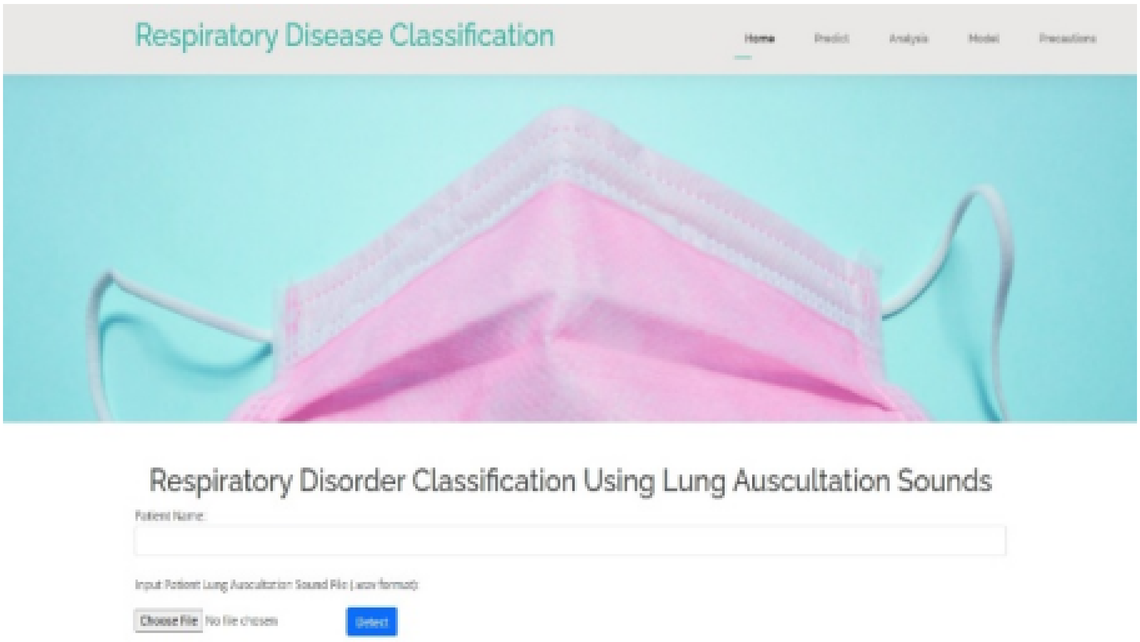

Figure 8.3: Pattient Details Interface

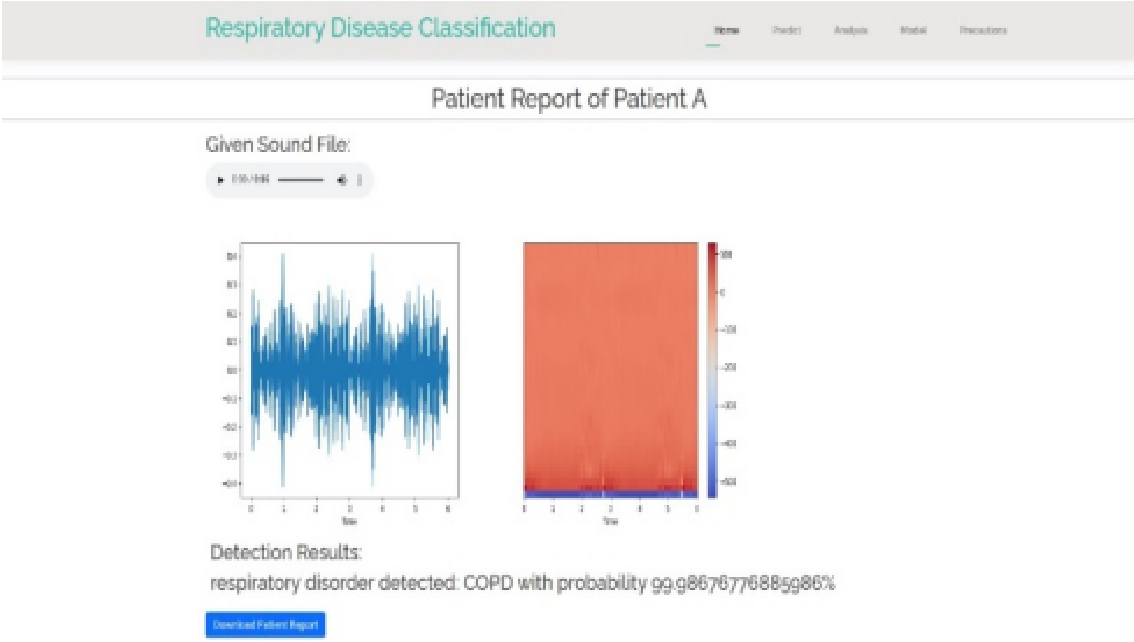

Figure 8.4: Patient Report Interface

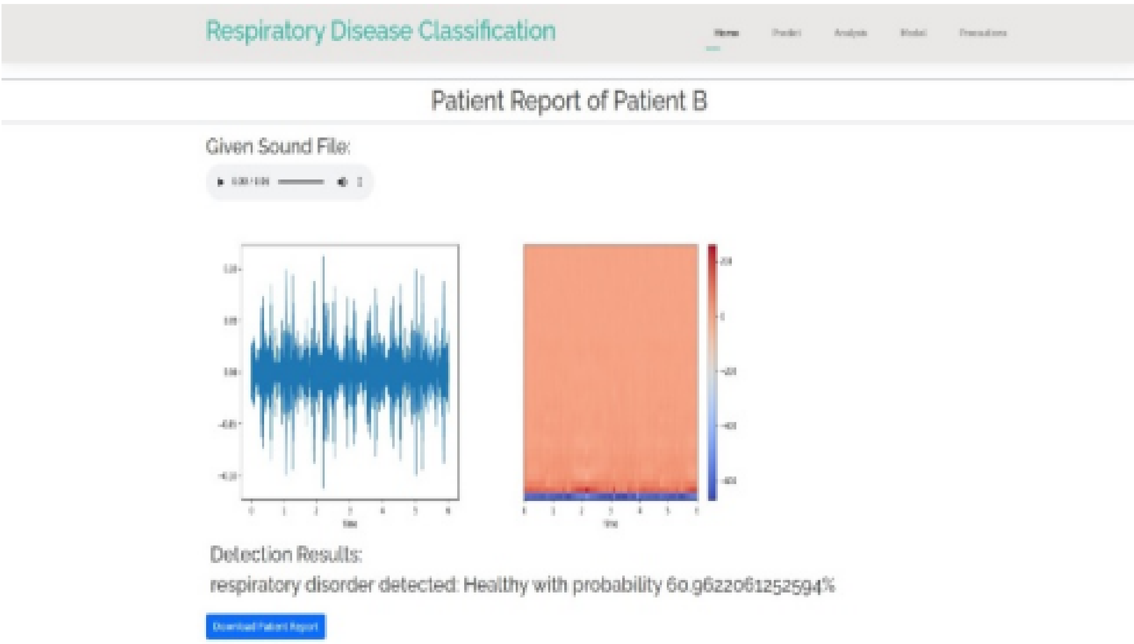

Figure 8.5: Patient Report Interface

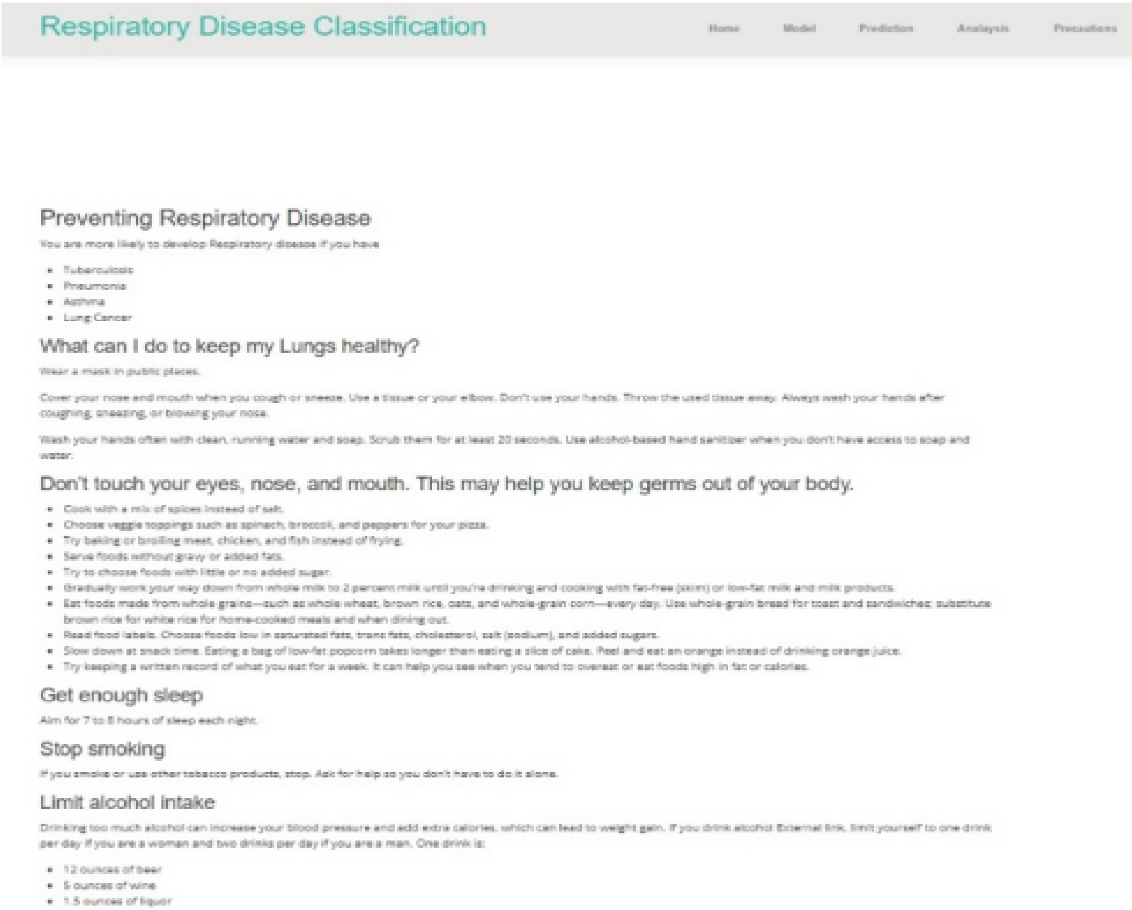

Figure 8.6: Preventive Measures Interface

Chapter 9

CONCLUSIONS

9.1 Conclusions

Looking at the audio content, it is difficult to classify respiratory sounds. In our research, a system is presented for distinction of healthy and non-healthy lung sounds which is very important prior to further diagnosis of the type and severity of infection. We have performed our experiments using a publicly available dataset and evaluations indicate that the highest accuracy of 99.22 with an AUC value of 0.9993 is obtained.Automated adventitious sounds detection or classification provides a promising solution to overcome the limitations of conventional auscultation. In future the subject area for future investigation will be: To use larger dataset and test further on robustness in presence of higher percentages of noise.Attempts will also be made towards isolation of breath sounds from the ambient noises and heart- beat sounds for better analysis.Other acoustic techniques will be applied for even better modelling of the lung sounds along with deep learning based approaches.To have clinical use in pulmonary health screening and as a tool in differential diagnosis of pulmonary diseases.Finally, we will be trying to identify the nature and severity of infection from the breath sounds.

Chapter 10

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[1] Liqun Wu and Ling Li: Investigating into segmentation methods for diagnosis of respiratory diseases using adventitious respiratory sounds.

[2] B. M. Rocha1, D. Filos, L. Mendes, I. Vogiatzis, E. Perantoni, E. Kaimakamis, P. Natsiavas, A. Oliveira, C. Jácome, A. Marques, R. P. Paiva, I. Chouvarda, P. Carvalho1, N. Maglaveras : Respiratory Sound Database for the Development of Automated Classification.

[3]Yoonjoo Kim, YunKyong Hyon, Sung Soo Jung, Sunju Lee, Geon Yoo, Chaeuk Chung Taeyoung Ha: Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning.

[4] Zhaoping Wang and Zhiqiang Sun2: Performance evaluation of lung sounds classification using deep learning under variable parameters

[5] Rajesh Kumar Tripathy and Ram Bilas Pachori , Shaswati Dash , Adyasha Rath, Ganapati Panda :Automated Detection of Pulmonary Diseases From Lung Sound Signals Using Fixed-Boundary-Based Empirical Wavelet Transforms.

[6] Shubham Chaudhary , Sadbhawna , Vinit Jakhetiya , Badri N Subudhi , Ujjwal Baid, Sharath Chandra Guntuku., "Detecting COVID-19 and community acquired pneumonia using chest CT scan images with deep learning".

[7] Jyotibdha Acharya , Student Member, IEEE, and Arindam Basu, Senior Member, IEEE," Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient Specific Model Tuning".

[8]Diego Perna ," Convolutional Neural Networks Learning from Respiratory data"

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APPENDIX A

What is CNN?

- CNN stands for Convolutional Neural Network.
  • It is a type of deep learning model designed to automatically and adaptively learn spatial hierarchies of features from input data.
  • CNNs are especially effective for image and signal processing tasks, including spectrogram analysis in audio classification.
  • In our project, CNN is used to extract spatial features from lung sound spectrograms, identifying key patterns linked to different respiratory conditions.

What is LSTM?

- • LSTM stands for Long Short-Term Memory.
  • It is a type of recurrent neural network (RNN) capable of learning long-term dependencies in sequential data.
  • LSTM units can remember patterns over time, making them ideal for analyzing audio signals that vary over time.
  • In our project, LSTM helps capture the temporal relationships in lung sound recordings, improving disease classification accuracy.

What is CNN-LSTM?

• CNN-LSTM is a hybrid deep learning model that combines CNN and LSTM layers.
• CNN is used for extracting spatial features from lung sound data, while LSTM captures temporal dependencies.
• This combined architecture leverages the strengths of both models to achieve more accurate and reliable classification of respiratory conditions.
• In our project, CNN-LSTM provides a robust solution for early and automated diagnosis based on lung sound patterns.

Annexure A

Survey Paper Publication Details:

Paper Title: A Survey on Diagnosing Respiratory Conditions Via Lung Sounds using CNN-LSTM.

Author Name:

1. Prof. Shah S. N.
2. Mr. Rohit Pawar
3. Ms. Aditi Raut
5. Ms. Sneha Jadhav

Journal Title: IJIRT - International Journal of Innovative Research in Technology
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Survey Paper On "Diagnosing Respiratory Conditions Via Lung Sounds using CNN-LSTM"

Prof. Shah S. N.[1], Pawar Rohit Balaso[2], Raut Aditi Shivaji[3], Jadhav Sneha Nitin[4]

[1]*HOD of Department of Computer Engineering,*

[2,3,4] *UG Students*

Sharadchandra Pawar College of Engineering and Technology, Someshwarnagar, Pune

Abstract— In this project, we developed an easy-to-use and affordable algorithm to analyze respiratory sounds, which can be used on any device. The goal was to classify different types of breathing sounds using machine learning techniques. We used two types of features to represent the sounds: Gammatone Cepstrum Coefficients (GTCC) and Short-Time Fourier Coefficients (STFC). These features help the system understand the characteristics of the sounds. The algorithm then uses a combination of a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network to classify the sounds accurately. We created four datasets to train and test the algorithm. These datasets include: Healthy versus pathological sounds (to distinguish between normal and abnormal breathing), Classification of different types of sounds, like rales, rhonchi, and normal breath sounds, Classification of individual types of respiratory sounds, and A complete classification that includes all types of breathing sounds. The algorithm is designed to be simple, cost-effective, and can work on various devices, making it accessible for a wide range of users, including healthcare professionals, researchers, or anyone interested in analyzing respiratory sounds.

Index Terms:- **Respiratory Sound Analysis, Breathing Sound Classification, Gammatone Cepstrum Coefficients (GTCC), Short-Time Fourier Coefficients (STFC), CNN (Convolutional Neural Networks) LSTM (Long Short-Term Memory),Machine Learning, Healthcare Applications,**

I. INTRODUCTION

Respiratory sounds, provide valuable insights into lung health and can help diagnose conditions like asthma, pneumonia, and COPD. Traditionally, diagnosis requires expert interpretation, but machine learning has made automated analysis of healthcare lung sounds feasible. This study explores the use of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for classifying respiratory sounds. CNNs efficiently detect patterns in the audio, while LSTMs capture the temporal relationships in sequential data. By combining these techniques, the proposed system offers a cost-effective, non-invasive method for diagnosing respiratory conditions, aiding professionals in early detection and monitoring

II. METHODOLOGY

Compare the model against existing methods such as MFCC-Inception networks. Analyze the classification accuracy across various lung diseases like asthma, pneumonia, COPD, etc.

Feature Extraction:-Extract Gammatone Cepstrum Coefficients (GTCC) and Short Time Fourier Coefficients (STFC) from audio recordings. These features provide significant insights into sound patterns relevant to lung condition diagnosis. Model

Design:-Implement a hybrid CNN-LSTM architecture: CNN layers to extract spatial features from the sound spectrograms. LSTM layers to capture temporal patterns in the lung sound sequences. The model aims to optimize accuracy while being lightweight and computationally efficient. Respiratory conditions are diagnosed through spirometry and lung auscultation. Spirometry is measuring the volume of air mobilized in respiration. Even though, this method is one of the most commonly available lung function tests and well validated for the diagnosis and monitoring of upper and lower airway abnormalities , it is limited to patient's cooperation and therefore, is error prone. Moreover, traditional spirometers are normally used only in clinical settings due to their high cost and required calibration along with challenges in patient guiding. Auscultation is other technique which involves listening to the internal human body sounds with the aid of a stethoscope and typically performed on the anterior and posterior chest. From past few years, it has been an effective tool to understand lung disorders and possible abnormalities. However, this process is limited to physicians as they are well trained. For various reasons like faulty instrument or noisy environment, false positives can happen. Therefore, it opens a door to develop computerized lung sound analysis tools/techniques, where automation is the integral part.

III. LITERATURE SURVEY

1] Author: Liqun Wu and Ling Li

Paper Name: A Respiratory Sound Database for the Development of Automated Classification.

In This proposed a framework combining Random Forest classifier and Empirical Mode Decomposition (EMD) method for multi-classification of respiratory diseases using adventitious respiratory sounds (ARSs). Their system achieved a classification accuracy of 88% and focused on 6 respiratory conditions: healthy, bronchiectasis, bronchiolitis, COPD, pneumonia, and URTI. The study emphasized the importance of segmentation in accurate classification, with the best performance achieved using a combination of early inspiratory and entire inspiratory phases.

[2] Author: B. M. Rocha, D. Filos, L. Mendes, I. Vogiatzis, E. Perantoni, E. Kaimakamis, P. Natsiavas, A. Oliveira, C. Jácome, A. Marques, R. P. Paiva, I. Chouvarda, P. Carvalho, N. Maglaveras

Paper Name : Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning.

Presented a respiratory sound database developed for automated classification systems. The database includes 920 recordings from 126 subjects and contains annotations for various types of adventitious respiratory sounds, such as crackles and wheezes. This dataset, gathered from clinical and non-clinical environments, includes noisy recordings, making it suitable for developing algorithms that work under real-life conditions. The study aims to advance respiratory sound analysis by providing a publicly available resource for algorithm development and testing.

[3] Paper Name : Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning.

Author: Yoonjoo Kim, YunKyong Hyon, Sung Soo Jung, Sunju Lee, Geon Yoo, Chaeuk Chung & Taeyoung Ha

Developed a deep learning model using Convolutional Neural Networks (CNNs) to classify respiratory sounds (normal, crackles, wheezes, rhonchi). The model achieved an accuracy of 86.5% in detecting abnormal sounds, with an AUC of 0.93. It further classified abnormal sounds into crackles, wheezes, or rhonchi with an accuracy of 85.7%. The study also highlighted the varying diagnostic accuracy among medical professionals, demonstrating the potential for deep learning systems to complement clinician auscultation in diagnosing respiratory diseases.

[4] Paper Name: Performance evaluation of lung sounds classification using deep learning under variable parameters.

Author: Zhaoping Wang and Zhiqiang Sun

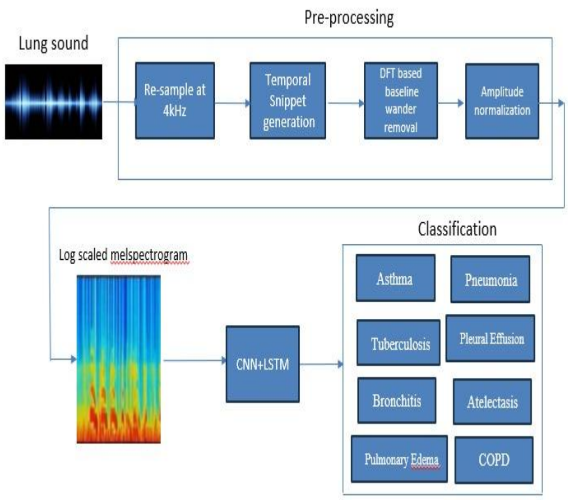
Investigated the impact of various parameters on deep learning model performance for lung sound classification. Using the ICBHI 2017 dataset, the authors analyzed the effect of frame length, overlap percentage, and feature types (spectrogram and Mel-frequency cepstrum coefficients) on classification accuracy. The study concluded that a higher overlap percentage (OP) improves performance, with the optimal configuration being a frame size of 128, 75% OP, and spectrogram features, under a fixed sampling frequency of 8 kHz.

[5] Paper Name: Automated Detection of Pulmonary Diseases From Lung Sound Signals Using Fixed Boundary-Based Empirical Wavelet Transforms.

Author: Rajesh Kumar Tripathy and Ram Bilas Pachori , Shaswati Dash , Adyasha Rath, Ganapati Panda

Proposed an automated method for detecting pulmonary diseases (PDs) using lung sound signals and fixed-boundary-based empirical wavelet transforms. The model achieved high classification accuracy for differentiating between normal lung sounds and various pulmonary diseases, such as asthma, pneumonia, and COPD. Using the Light Gradient Boosting Machine (LGBM) classifier, the study demonstrated improved detection rates, with an overall accuracy of 84.76% for the multi-class classification scheme involving normal, pneumonia, asthma, and COPD.

IV. SYSTEM ARCHITECTURE



V. CONCLUSION

In this study, a deep learning model leveraging convolutional neural networks (CNNs) and long short-term memory (LSTM) networks was employed for the classification of lung sounds. The model demonstrated an impressive overall average accuracy of 99.62% in categorizing lung sounds associated with various respiratory diseases. This research lays the groundwork for the integration of deep learning models in clinical environments, thereby aiding clinicians in their decision-making processes. Future research endeavors will aim to expand the dataset to encompass a broader demographic and a more diverse array of diseases, including COVID-19, which will enhance the reliability of the proposed model. While the current classification model exhibits high performance metrics, there remains potential for further enhancement through the refinement of preprocessing techniques and the training framework.

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[3] Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning. - Yoonjoo Kim, YunKyong Hyon, Sung Soo Jung, Sunju Lee, Geon Yoo, Chaeuk Chung & Taeyoung Ha
[4] Performance evaluation of lung sounds classification using deep learning under variable parameters.- Zhaoping Wang and Zhiqiang Sun
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[6] Detecting COVID-19 and community acquired pneumonia using chest CT scan images with deep learning .- Shubham Chaudhary , Sadbhawna , Vinit Jakhetiya , Badri N Subudhi , Ujjwal Baid, Sharath Chandra Guntuku.
[7] Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient Specific Model Tuning.- Jyotibdha Acharya , Student Member, IEEE, and Arindam Basu, Senior Member, IEEE
[8] Convolutional Neural Networks Learning from Respiratory data.-Diego Perna
[9] Machine Learning-Based Classification of Pulmonary Diseases through Real-Time Lung Sounds.- Sangeetha Balasubramanian, Periyasamy Rajadurai.
[10] Machine Learning-Based Classification of Pulmonary Diseases through Real-Time Lung Sounds.- Sangeetha Balasubramanian, Periyasamy Rajadurai.

APPENDIX C

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Annexure B

Publication Details:

Paper Title: Diagnosing Respiratory Conditions Via Lung Sounds using CNN-LSTM.

Author Name:

1. Prof. Shah S. N.
2. Mr. Rohit Pawar
3. Ms. Aditi Raut
5. Ms. Sneha Jadhav

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Diagnosing Respiratory Conditions Via Lung Sounds using CNN-LSTM

Prof. Shah S. N.[1], Mr. Pawar R.B.[2], Ms. Raut A.S.[3], Ms. Jadhav S.N.[4]
[1]Assistant Professor,Computer Department, Sharadchandra Pawar College of Engineering and Technology Someshwarnagar, India
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Abstract—**Respiratory diseases rank among the foremost causes of mortality globally. While traditional lung auscultation is effective, it is hindered by limitations such as interference from background noise and reliance on the expertise of healthcare professionals. Recently, machine learning has emerged as a promising approach for the automated analysis of lung sounds, enhancing diagnostic accuracy and reducing the time required for diagnosis. This study is dedicated to the development of an automated system for lung sound classification, utilizing GTCC-based features in conjunction with a Multi-Layer Perceptron (MLP) classifier. Our system, trained on a comprehensive dataset comprising over 6,800 audio clips, achieved an impressive classification accuracy of 99.22%, underscoring its potential to facilitate the early detection of respiratory diseases.**

Keywords— **Machine Learning, Lung Sound Analysis, GTCC Features, Deep Learning, Respiratory Diseases.**

I. INTRODUCTION

Respiratory illnesses rank among the leading causes of death and disability globally, with the heaviest impact seen in the poorest regions. Research identifies several major risk factors, including aging, tobacco use, environmental pollutants, and excess body weight. Chronic respiratory conditions pose a significant global public health issue, affecting approximately 65 million individuals. In 2017 alone, chronic obstructive pulmonary disease (COPD) was responsible for around 3.91 million deaths, representing 7% of all deaths worldwide and ranking as the third most common cause of death. Between 1990 and 2017, deaths from chronic respiratory diseases increased by 18%, rising from 3.32 million to 3.91 million.

Asthma, the most prevalent chronic disease among children, affects 14% of children worldwide. Pneumonia remains a major killer, particularly of children under five years old, claiming millions of lives each year. Tuberculosis (TB) continues to affect over 10 million people annually, with approximately 1.4 million deaths each year, highlighting its status as one of the deadliest infectious diseases. Lung cancer, the most fatal cancer type, causes about 1.6 million deaths each year. Overall, chronic respiratory diseases are linked to about 4 million premature deaths annually.

Among the top 30 causes of death worldwide, five are respiratory diseases: COPD ranks third; lower respiratory tract infections are fourth; tracheal, bronchial, and lung cancers come sixth; TB is twelfth; and asthma ranks twenty-eighth. Cumulatively, over 1 billion people live with either acute or chronic respiratory conditions.

Children, especially those under the age of five, are disproportionately affected by respiratory illnesses, with pneumonia being the leading cause of death in this age group. Each year, about 9 million children under five pass away, emphasizing the urgent need for more effective interventions. Despite the lungs being a vital organ, they are especially vulnerable to airborne pathogens and environmental damage. The consequences of respiratory diseases are not limited to health; they also affect social and economic well-being. Evidence suggests that social deprivation significantly contributes to both mortality and disability, with the poorest regions bearing the greatest burden. Meanwhile, wealthier countries tend to report lower mortality rates, owing to better access to healthcare services and more advanced treatment technologies.

Because of the extensive impact of respiratory diseases, improving their treatment and management is a critical goal in medicine. Ongoing research aims to enhance early detection and intervention methods. Accurate diagnosis of these conditions requires both medical expertise and time. However, WHO statistics indicate that 45% of its Member States have fewer than one physician per 1,000 people, falling short of the recommended ratio. Given the existing strain on healthcare professionals, the possibility of diagnostic errors rises. Therefore, developing automated and dependable tools to assist doctors has become essential. Enhancing diagnostic systems can lead to earlier and more accurate identification of patients, ultimately helping to reduce mistakes resulting from excessive workloads.

II. METHODOLOGY

Respiratory conditions are commonly identified through diagnostic techniques such as spirometry and lung auscultation. Spirometry, which evaluates the volume of air inhaled and exhaled during breathing, is widely regarded as an effective tool for identifying abnormalities in both the upper and lower respiratory tracts. However, its accuracy depends significantly on patient cooperation, making it prone to potential errors. Furthermore, conventional spirometry devices are typically confined to clinical environments due to their high cost, the need for regular calibration, and difficulties in guiding patients through the procedure.

Auscultation, another standard method, involves using a stethoscope to listen to internal body sounds, generally performed on the front and back of the chest. In recent years, it has gained recognition for its usefulness in detecting pulmonary issues and irregularities. Yet, its success largely hinges on the clinician's experience and skill. Issues such as low-quality equipment or background noise can lead to misinterpretations or false-positive results, underlining the limitations of traditional practices.

These limitations have created an opportunity for the advancement of automated lung sound analysis systems. By incorporating technology and automation, these tools offer the potential to enhance diagnostic precision and streamline the process of detecting respiratory diseases.

System Architecture

Input Data: The system processes lung sound recordings, which undergo initial preprocessing steps including wavelet-based smoothing, artifact elimination, and normalization.

Preprocessing: To enhance signal clarity, smoothing techniques are applied to reduce noise and remove artifacts. Z-score normalization ensures that all signals have a standardized dynamic range, improving consistency across the dataset.

Deep Learning Framework: The architecture integrates 1D Convolutional Neural Networks (CNNs) with Bidirectional Long Short-Term Memory (BDLSTM) units to effectively analyze both spatial and temporal aspects of lung sound signals.

- CNN Component: The CNN layers are responsible for extracting spatial characteristics from the input signals. This is achieved through a series of operations including convolution, batch normalization, ReLU activation, dropout for regularization, and max-pooling for dimensionality reduction.
- BDLSTM Component: The Bidirectional LSTM layers handle temporal dependencies by analyzing signal patterns in both forward and backward directions. This dual perspective helps capture complex variations over time, with hidden units storing relevant sequential information.

Training and Evaluation: The model is trained using a tenfold cross-validation strategy to ensure generalization and robustness. Stochastic Gradient Descent (SGD) is employed for optimization. Model performance is assessed using key metrics such as accuracy, sensitivity, precision, and F1-score.

III. ALGORITHMS

Evaluation: The proposed model's performance is benchmarked against existing methods, including MFCC-based Inception networks. A detailed analysis is conducted to assess classification accuracy across multiple respiratory conditions, such as asthma, pneumonia, and chronic obstructive pulmonary disease (COPD). This comparison helps evaluate the effectiveness and robustness of the model in real-world diagnostic scenarios.

Feature Extraction: To extract meaningful patterns from lung sound recordings, two types of audio features are utilized:

- Gammatone Cepstral Coefficients (GTCC): These coefficients capture critical auditory cues by mimicking human auditory processing, offering valuable insights into abnormal respiratory sounds.

- Short-Time Fourier Coefficients (STFC): STFC helps reveal the frequency content of the sounds over time, enabling the detection of subtle variations characteristic of different lung conditions.

Together, these features form a rich representation of lung acoustics, essential for accurate classification.

Model Design: A hybrid deep learning model combining Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) units is implemented:

- CNN Layers: Responsible for extracting spatial features from spectrogram representations of lung sounds, capturing localized patterns in the input data.
- LSTM Layers: Designed to learn temporal dependencies in the sequential sound data, capturing dynamic changes over time.

This architecture is optimized to balance high accuracy with computational efficiency, making it suitable for practical applications where resource constraints are a concern.

IV. RESULT AND DISCUSSION

Performance Evaluation: The effectiveness of the proposed CNN-LSTM model was thoroughly assessed using a tenfold cross-validated confusion matrix, which mapped predicted classifications against actual respiratory conditions. This hybrid architecture—combining Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) units—consistently outperformed individual CNN or LSTM models, demonstrating superior diagnostic capability across a range of lung sound categories.

The model achieved an impressive overall classification accuracy of 98.85%, indicating a strong ability to differentiate between diverse respiratory disorders.

Class-wise precision results included:

- Normal: 98.80%
- Asthma: 95.60%
- Pneumonia: 98.80%
- Bronchitis (BRON): 100%
- Chronic Obstructive Pulmonary Disease (COPD): 99.00%
- Heart Failure (HF): 100%

For comparison, the standalone models yielded lower precision scores:

- CNN-only model: 96.88% (average precision)
- LSTM-only model: 92.15% (average precision)

These findings clearly demonstrate the strength of integrating CNN's spatial feature extraction capabilities with LSTM's temporal sequence learning, allowing the hybrid model to more effectively capture complex audio patterns in lung sounds.

In addition to high precision, the model delivered strong performance across multiple evaluation metrics—F1-score, sensitivity, specificity, and overall precision—proving its reliability even when handling imbalanced data across different respiratory conditions.

Importantly, the system maintained consistent accuracy despite challenges such as background noise and varying recording environments. This robustness suggests that the model is well-suited for deployment in practical settings, including remote diagnostics and mobile health applications, where medical expertise and resources may be limited. These findings affirm the model's potential for real-world clinical integration.

V. LITERATURE SURVEY

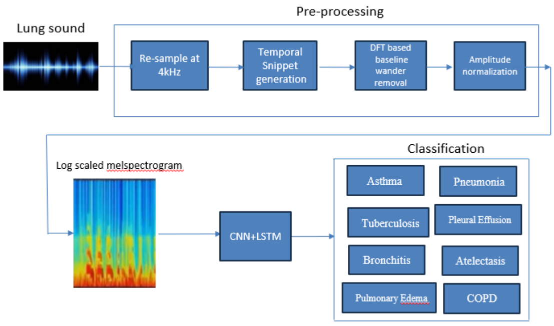
A literature review is a text of a scholarly paper, which includes the current knowledge including substantive findings, as well as theoretical and methodological contributions to a particular topic. Literature reviews use secondary sources, and do not report new or original experimental work.

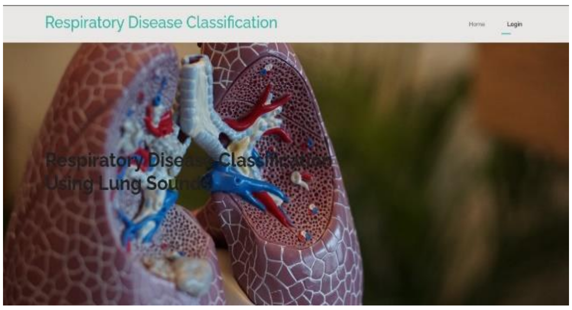
1. Paper Name: Investigating into segmentation methods for diagnosis of respiratory diseases using adventitious respiratory sounds. Author: Liqun Wu and Ling Li
2. Paper Name: A Respiratory Sound Database for the Development of Automated Classification.Author: B. M. Rocha, D. Filos, L. Mendes, I. Vogiatzis, E. Perantoni, E. Kaimakamis, P. Natsiavas, A. Oliveira, C. Jácome, A. Marques, R. P. Paiva, I. Chouvarda, P. Carvalho, N. Maglaveras
3. Paper Name: Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning.Author: Yoonjoo Kim, YunKyong Hyon, Sung Soo Jung, Sunju Lee, Geon Yoo, Chaeuk Chung & Taeyoung Ha

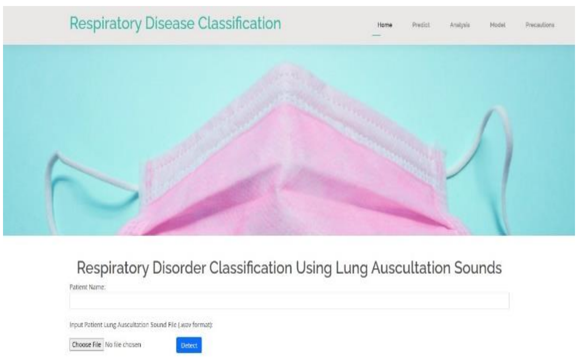
4. Paper Name: Performance evaluation of lung sounds classification using deep learning under variable parameters.Author: Zhaoping Wang and Zhiqiang Sun

5. Paper Name: Detecting COVID-19 and community acquired pneumonia using chest CT scan images with deep learning . Author: Shubham Chaudhary , Sadbhawna , Vinit Jakhetiya , Badri N Subudhi , Ujjwal Baid, Sharath Chandra Guntuku

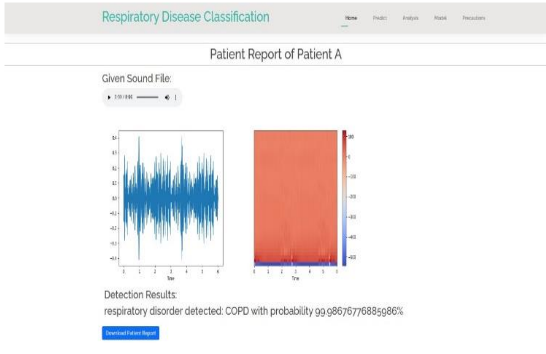
VI. SYSTEM ARCHITECTURE

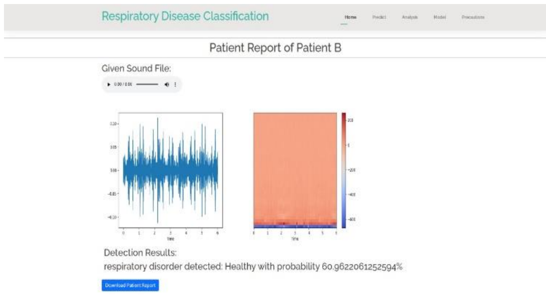


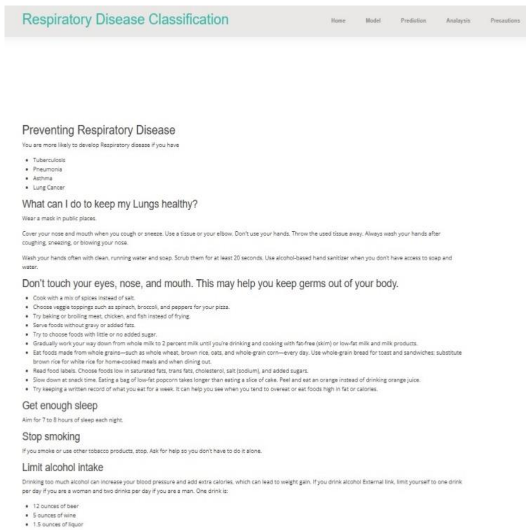




VII. RESULT







VIII. ADVANTAGES

1. Improved Accuracy: Advanced technologies, like AI or automation, enhance precision, leading to better quality outcomes and fewer deviations or mistakes.
2. Quick Diagnosis: Rapid identification of issues ensures timely solutions, reducing downtime or delays in critical situations.
3. Reduced Human Error: Automated systems minimize the impact of fatigue, oversight, or inconsistencies that can occur with human involvement.

4. Cost-Effective: Streamlined processes optimize resource allocation and operational efficiency, leading to significant cost savings over time.

IX. CONCLUSION

This project develops a cost-effective and accurate system for automatic lung sound classification using CNN-LSTM, combining GTCC STFC feature extraction to analyze respiratory sounds. The CNN extracts key sound patterns, while LSTM captures temporal changes, improving diagnostic accuracy. This system helps medical professionals detect respiratory conditions early with low cost solution and is suitable for clinical and remote healthcare applications. Future improvements include better clinical validation, real-time optimization, and enhanced dataset diversity to make the model more reliable and effective..

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APPENDIX D

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