# MACHINE LEARNING & DEEP LEARNING APPROACHES FOR RESPIRATORY SOUND-BASED DISEASE DETECTION


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## FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering.


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## APPROVAL

This Project titled "**Machine Learning & Deep Learning Approaches for Respiratory Sound-Based Disease Detection**", submitted by **Md. Toufiq Imrog** and **GM Musfiqur Rahman** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **15-07-2024.**

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# DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Md Assaduzzaman, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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# ABSTRACT

Throughout the past decennium, there occurred a lot of scrutiny in the field of spontaneous respiratory sound inspection. The efficacy about decision-making could be improved by the automated systematization about respiratory sounds that could identify anomalies beforehand stages about respiratory dysfunction. It would be advantageous to develop an automatic machine & deep learning-based respiratory sound classification system. The predominant role about the first scientific challenge were to develop algorithms which could distinguish pulmonary audio clips taken originating at both non-medical & medical domains. About 920 recordings in the database were obtained from 126 subjects & were produced by 2 empiricists groups in Portugal & Greece. Recorded were 6898 respiration cycles. Respiratory specialists annotated the cycles as involving Wheezes, Crackles & aggregating both, or absence of abnormal breathing sounds. To facilitate effectiveness of our models, the dataset split up into 3 subcategories: A split of 70% data for training, 15% data for testing, and 15% data for model validation. The importance of having a robust and generalizable model, various data pre-processing techniques were applied. These techniques included Adam Optimizer, Sequential Minimal Optimization and Gradient Descent. We implemented and evaluated several machine learning & deep learning architectures, encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) which are widely used in various fields. Among those, CNN emerged as the most effective model, achieving 99.5% accuracy during training & 98.5% accuracy during testing along with a validation accuracy of 98.5%, thus outperforming the other models. ANN & SVM also demonstrated high performance, with accuracies around 96.6% & 91.5%, while KNN & RF achieved an accuracy of 88.3% & 88.1% respectively. In a clinical setting, the suggested method is very important since it can help doctors with automated illness identification & diagnosis.

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# CHAPTER 1

# Introduction

## 1.1 Overview

According to medical research, 15% of the global population is affected by the majority of respiratory illnesses. It has been determined respiratory illnesses affect around 230 million people and result in more than 300,000 fatalities annually. According to the researcher's prediction, respiratory diseases would rank third globally in terms of cause of death in 2030, closely behind heart disorders [1]. According to the conventional method, a doctor uses the stethoscope to listen for respiratory sounds to make illness predictions. The respiratory conditions include but are not limited to pneumonia, TB, COPD, bronchitis and asthma. Over 230 million instances of respiratory disorders are documented according to the medical database worldwide [2].

Due to limited resources and outdated methods, it can be difficult for doctors to monitor and identify respiratory illness symptoms in their early stages. Since these illnesses are typically contracted at home, in public or at work. It is not feasible to access medical specialists alongside the assets everywhere. The quantity regarding labor required for impulsive breathing illness empathy which is still too high to be employed for respiratory disease detection anywhere in real time.

Generally speaking, respiratory noises are categorized as accidental or normal. The identification of adventitious sounds and changes in the chest wall's transmission properties are critical components in the diagnosis via sound examination & surveillance of breathing disorders. Physicians identify abnormal respiratory sounds by auscultation [3]. Participants in the first ICBHI which is International Conference on Biomedical and Health Informatics were tasked accompanying creating algorithms that describe sound recordings taken from non-medical (like visits carried out in residences) and clinical settings. The aim intended to categorize whether crackles, wheezes or both were present in every breathing loop regarding a brief audiotape (10-90s) that was made at a single site [4].

The majority of digital stethoscopes on the market now only have a basic recording feature without automatic analysis [5]. To receive feedback from the physicians, consumers must also input their data online. Many new technologies have been created to give customers more intellectual analysis including the utilization of digital stethoscopes through deep learning & machine learnings algorithms [6].

The literature has presented several deep learning & machine learning techniques encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) [7].

This study aims to examine respiratory sounds in hospitalized patients and detect notable differences in the evolutionary behavior of sounds. Those detections may play a role in fostering exacerbation typologies which may have clinical implications. Thus, the goal of this research is to address the idea that variations in respiratory sounds during exacerbations can be identified by a computerized system and that these variations agree with the observations made by medical professionals. Because the algorithm may be carefully tailored and fitted to match the data and attributes along with excellent results that can be achieved.

### 1.2 Background and Present State

The categorization of healthcare pulmonary conditions is important for both hospitalization and teaching responsibilities. Conversely, the efficacy of the old technique is approaching its maximum potential since typical diagnostic approaches primarily hinge on arbitrary, physician-experience-dependent testing using telemetry devices. In addition, the process of identifying and choosing classification criteria from individuals takes an extensive period of patience and dedication. Once more, it is critical nevertheless difficult to identify diseases like pneumonia, COPD, asthma promptly and accurately because of a lack of assets & a range of competence [8].

However, developments in algorithms for DL and ML provide viable ways to automate pulmonary evaluation. Regarding the purpose of categorizing pulmonary noises, spotting irregularities and offering preliminary diagnosis methods encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) have been investigated. The advantages regarding ML & DL for medical use, especially in the diagnosis of breathing-related illnesses, is being shown by current studies. By utilizing the enormous volumes of information gathered from electronic diagnostic instruments and different audio equipment, systems like convolutional neural network achieved favorable outcomes in the classification of pulmonary patterns.

Therefore, the project described in this work intends to increase illness identification precision and supports medical personnel in their medical diagnostics by investigating different deep learning & machine learning strategies which will boost precision appertaining to pulmonary evaluations. The purpose of this project is developing an adaptable, computerized approach that enables instantaneously identification of diseases of the respiratory tract, overcoming the present shortcomings in analytical effectiveness & medical availability.

### 1.3 Problem Statement

As all participants knows, breathing-related illnesses are the main trigger of thousands of premature demises globally. Therefore, one of the foremost important areas of scientific inquiry is the prompt identification of breathing-related issues. However, respiratory inspection is now the widely prevalent approach in recording the sounds made by inside of us. Nevertheless, recent advancements in ML and DL techniques provide promising avenues towards computerized, non-intrusive illness detection using respiratory audio analysis [9]. The goal of the endeavor aims to create a pulmonary audio categorization technology which employs ML and DL to help clinicians identify and diagnose illnesses automatically. This could help in resolving the technical difficulties related to Acoustic assessment utilizing deep learning & machine learning. That includes the following:

1. Medication delays as a result of insufficient earlier identification.
2. Increase the precision of illness diagnostics.
3. Examine how to integrate databases that are multifunctional.
4. Examine how well numerous approaches can distinguish breathing circumstances through audio inputs.
5. Create ML & DL strategies to raise the precision and dependability of breathing disorder identification techniques.

### 1.4 Objectives

The need to enhance the quality of healthcare and the state of worldwide medicine is what drives the unrelenting quest to advance the diagnosis of illnesses using the latest innovations. Respiratory disease is a serious disease that requires prompt and correct diagnosis to effectively treat. The phrase "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" sums up a strong dedication to using cutting-edge techniques to meet such a challenging goal.

Early diagnosis is crucial for respiratory disorders that include ailments like pneumonia, asthmatic conditions along with COPD which is chronic obstructive pulmonary disease. Potentially, DL & ML algorithms can offer a low-cost, non-invasive way to detect certain illnesses early on. By automating the screening process, doctors may focus more of their attention on treatment strategies.

To develop machine learning models for identifying abnormal conditions by assessing how well different models that diagnose respiratory illnesses based on sound data and comparing their accuracy, robustness, and processing efficiency to ascertain which approach performs best. Therefore, the produced machine learning models were verified in a clinical setting to provide medical practitioners by conducting a meticulous and in-depth inspection appertaining to the clinical breathing sound clips considering high accuracy and sensitivity in disease detections.

Therefore, it will be easier to recognize some symptoms early on by enhancing public health outcomes and lessening the negative social and economic effects of respiratory disorders and reducing the death rate.

## 1.5 Scope and Limitations

### 1.5.1 Project Scope

Pulmonary diseases pose significant illnesses globally and early detection is crucial for effective management and recovery. The study's concentration on "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" broadens the definition of the issue to include healthcare diagnosis in general and breathing disorders in particular. Numerous breathing-related illnesses such as infectious diseases Asthma, Influenza, breathing tract infections and chronic pulmonary disease are common and sometimes fatal infections that continue to be a worldwide health problem. Reliable and prompt identification is therefore necessary for successful care.

The topic of discussion includes the difficulties posed by conventional breathing disorder diagnosis techniques that might pose limits to comprehensive pinpointing, sensitiveness, and uniqueness. The problem's purview essentially includes the difficulties in diagnosing illnesses through pulmonary sounds as well as the possible improvements provided by various theoretical evaluations of various techniques. By focusing on these fields, the study hopes to improve our capacity to lessen the negative effects of pulmonary audio-based identification of illnesses on general well-being and improve the quality of currently used screening methods.

### 1.5.2 Project Limitation

The core focus appertaining to the current study is via developing DL & ML algorithms capable of diagnose illnesses via pulmonary sounds, however there are several challenges along the road. One of the primary restrictions involves the database integrity and accessibility. It might be challenging to gather an adequate and comprehensive variety of audio tapes from various illnesses related to breathing, and issues with the input data may have an impact on the efficacy of the algorithm. The investigation aims to ascertain the efficacy of such methods in precisely determining a variety of breathing disorders by assessing previous studies on respiration audio recording as well as associated ailments, compiling and preparing breathing problems audio databases putting various algorithms into practice, assessing achievement, contrasting efficiency and constraints looking into possible improvements to the user experience and lastly making recommendations for future research directions along with the implications and outcome.
Furthermore, considering to the variability in illness signs brought due to various triggers, stages of the illness, and numerous components, it may be difficult to obtain reliable precision in a variety of scenarios.

## 1.6 Report Organization

The suggested study has a thorough format that walks viewers through the methodology, conclusions and ramifications of the study. Every section has a distinct function and adds to the indenture's ultimate cohesion and depth.

1. **Chapter 1: Introduction**

The study is introduced in the first chapter, which also provides context regarding the importance of pulmonary audio-based illness diagnosis by using Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) alongside the necessity appertaining to contrasting those methods of diagnosis. It provides an overview of the project's goals, topics of inquiry and general structure.

2. **Chapter 2: Literature Review**

A thorough analysis of pertinent scholarship and earlier studies is provided in the context section. An extensive grasp of the fundamental theories, technical developments and approaches to respiratory sound-based diagnosis is provided in the following paragraphs. It lays outward the background underlying the present investigation and identifies lacking in our understanding.

3. **Chapter 3: Research Methodology**

The strategy used to carry out the analysis is described in the project's procedure section. It sheds light on the framework structure, information-gathering techniques, design concept and the reasoning underlying particular methodology selections. The legal concerns and potential constraints on the investigation are also covered in this chapter.

4. **Chapter 4: Implementation**

We used DL and ML algorithms to identify breathing disorders in audio recordings. First, we preprocessed the recordings to make sure that the sound sources were mint and balanced. Regarding the best sound evaluation, the algorithm's architecture—which includes CNN, KNN, SVM, ANN & RF—was customized. Certain computing capabilities and variables have been employed throughout the learning process. Measures like precision and F1 scores were used in inspection and emulate assessment, and cross-validating was used to confirm results. The framework performed well, according to the outcomes, and an incorrect assessment provided information on misconceptions.

5. **Chapter 5: Result and Analysis**

The outcomes from the study regarding the use of CNN, KNN, ANN, RF & SVM in respiratory sound-based diagnosis are presented in this section. Comprehensive evaluations of the effectiveness of various oversight strategies are offered including graphical depictions and empirical data to corroborate the outcomes.

6. **Chapter 6: Impacts on Society, Environments and Sustainability**

The subsection on social effect delves into the wider consequences that the study discoveries hold for healthcare and medical diagnostics. Subsequently talks about the way better ways to identify illnesses related to breathing might benefit results from therapy care for patients and healthcare in general. Future technological developments and their effects on society are taken into account.

### 7. Chapter 7: Conclusions and Future Works

The entirety research is summarized in the last section. It provides proposals for real-life uses and additional inquiry as well as summarizing the main results and restating the results of the study. A path for academics concerned with building upon existing work is provided in the discussion of its consequences for subsequent studies.

The viewer is guided along the study process from beginning to conclusion to wider consequences and suggestions by an organized arrangement that guarantees a logical flow of content. By applying various DL & ML encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) that enables in-depth overview of the method of inquiry along with possible significance in shaping both conceptual understanding and real-world applications appertaining to respiratory sound-based diagnosis.

## 1.7 Summary

The importance of respiratory sound analysis in the context of diagnosing respiratory illnesses is investigated in this research study. It highlights how deep learning & machine learning technologies imaginably employed for improved accuracy and effectiveness of respiratory audio data-based disease identification while addressing the shortcomings of traditional diagnostic methods. The introduction gives context for the work and emphasizes the significance of automated and accurate respiratory illness identification systems in enhancing patient outcomes by outlining the objectives, significance, and methodology of the study. The significance of this subject is covered in this introduction, along with how deep learning and machine learning may help with sound-based respiratory disease diagnosis.

# CHAPTER 2

# Literature Review

## 2.1 Overview

The length, pace and audio of respiration become critical elements in the diagnosis of breathing-related conditions. To ensure that the fundamental ideas and techniques utilized in this research on "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" are easily comprehended & it is essential to lay the groundwork with preliminary information and terms defined.

In DL & ML, numerous frameworks and techniques encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN)—play a crucial role in leveraging information gained from disparate activities for improved Respiratory Disease Detection. By accomplishing this, the technique nevertheless gives medical professionals a versatile tool to help them throughout therapy but furthermore produces encouraging outcomes with a balanced accuracy.

The concept of "Detection" describes how clinical audio data is used to identify respiratory disease detection. These terms are used consistently throughout the study to investigate the connections among various deep learning & machine learning frameworks moreover to compare various detection techniques. Viewers must have a shared knowledge of these preliminary steps before delving into the details of the research and grasping the subtleties of the sophisticated methods used in the diagnosis of respiratory sound-based diseases.

## 2.2 Related Works

This part provided an overview of the researcher's many analysis techniques including features and techniques for identifying respiratory disorders. The physical systems and automated techniques for respiratory disease diagnosis are explained in the linked work section. For example,

Radogna et al. [10] An elegant respire exploration gadget poised to utilized for recognizing chronic obstructive pulmonary disease is proposed by tangible gadgets such as the Breathing Controlling Unit. Artificial Neural Network and MLP method combined in creating a classification approach that anticipates pulmonary acoustic important events among people who have particular breathing conditions, notably asthmatic conditions along with COPD.

Aykanat et al. [11] A straightforward and reasonably priced computerized oscilloscope was suggested for recording breathing audio clip on the display that could utilized & function every type of apparatus. 1,630 participants provided 17,930 pulmonary sounds for the tracking device detected to capture. MFCC characteristics in the Convolutional Neural Network and Support Vector Machine are two types of machine learning approaches that were employed in the research. Although using an SVM technique with MFCC capabilities is a well-accepted method for classifying audio, the customers evaluated the CNN technique's effectiveness using their own experiments. Four data sets—safe vs unhealthy, rale, rhonchus and conventional classifying discourse are utilized. Unique classification of respiratory speech form and Assigning categories to all sound formation, covering every type of audio clip, was produced based on each CNN and SVM model in order to classify pulmonary noise.

Bai et al. [12] Forecasting flare-ups might lessen the unavoidable negative effects and cut down on the significant expenses related to sufferers of COPD. One of the main causes of a deteriorating standard of lives and the reason why individuals with chronic obstructive pulmonary disease (COPD) end up in hospitals is severe flare-ups. The most recent version has the capacity to identify severe COPD flare-ups a standard appertaining to 4.4 days prior to their onset. Using the collected information, a DT categorization was built, evaluated & representing automated symptom-based aggravation diagnoses. Real-world essential instructional technologies are paying considerable amounts of thought to deep learning-based models like CNN and LSTMS.

BA Demirci et al. [13] In this study, the Respiratory Sound Database is used to classify the data using ANN, SVM & KNN representing feature extraction, amalgamation appertaining to MFCC, WT & EMD techniques were employed. In this study, 20% appertaining to the features was used considering test case and the remaining 80% being trained when using ANN method for classification. Again, employing K-Nearest Neighbor technique resulted the peak precision evaluation about 98.8% when employing the WT feature and 82.7% when using the MFCC feature. With the ANN method best result attained with the Empirical Mode Decomposition methods that is 88.9%.

N Melek et al. [14] to diagnose diseases, a ML technique were created to the research that can automatically identify sounds from the breathing structure such as sneeze & cough. Numerical and statistical features were prepared using some feature extraction like the MFCC technique. To successfully classify respiratory sounds in the dataset with over 3800 distinct sounds, three different classification approaches were taken into consideration. The classification techniques employed were ensemble aggregation SVM & DT classification. SVM with radial basis function kernels was able to categorize cough and sneeze sounds with an 83% success rate compared to other sounds.

A Monaco et al. [15] here, we describe a framework for classifying respiratory sounds using two types of features. We cross-validated a neural network model's classification performance using the ICBHI publicly available dataset. The accuracy and precision of the suggested model were 85% ± 3% and 80% ± 8% respectively, which are in good agreement with the body of literature.

Liu et al. [16] have suggested looking at the duration, frequency and cepstral domains of the typical wheezing and crackling respiration audio. Six essential traits were chosen among the 46 variables that were successfully retrieved. It is suggested to use the Gaussian mixture to categorize each of those respiratory noises.

Fernandez-Granero et al. [17] a variety of simple layer-organized neuron-like cells made up this system. Failure dispersion wards was used throughout the system evaluation process. Radial-base artificial neural networks are often employed for training under supervision. Since those networks may be developed in a single step rather than repeatedly like Multiple Layer Perceptron's perform that may be employed to represent curves with good results. Systems built on radials pick things up rapidly. By accordance to a provide information vector, the layer that is concealed outcomes are merged proportionally to create the network answer which is compared with the result that represents the level's intended resolution. In a regulated way, the weights are conditioned using a defined proportional method. The utilization appertaining to DL & ML methods representing the prevention appertaining to complications of COPD has great promise.

Almir Badnjevic et al. [18] created a specialist diagnosis algorithm an example of using data on patient signs and ventilation measures allowing for differentiation between individuals having COPD, asthma and other forms of normal pulmonary function. Details of 3657 cases were utilized to create precise classification techniques and these results were subsequently confirmed employing features originating at 1,650 client gathered throughout 2 years span of time. The outcomes we achieve suggest that the specialized diagnosis method has a sensitivity of 96.45% and specificity of 98.71% for accurately identifying individuals with COPD and asthma.

G Altan et al. [19] The approaches of DL represent an effective machine learning approach that combines structured instruction using a feature-based distribution of classification parameters with unstructured research to minimize modification. During the present research, the empirical characteristics of spectral modifications recovered using the Hilbert-Huang transformation are employed to analyze multidimensional pulmonary audio. The suggested system's categorization step employed an algorithm developed using deep learning to distinguish between COPD clients and fit people. Employing statistical characteristics predicated upon the Hilbert-Huang modify, the suggested DL approach was able to achieve excellent classification performance rates of delivering a specificity of 96.33%, sensitivity of 91%, and achieving an accuracy rate of 93.67% correspondingly.

Y Kutlu et al. [20] A vital diagnostic tool for heart and breathing disorders is pulmonary audio. The classification of respiration based on vulnerable and intermediate levels appertaing to COPD methods is the main goal representing the research. Smoking-related lung conditions include COPD that is among the deadliest and prevalent. For the identification step DBN method being one of choice. The pulmonary echoes were distinguished among various stages of COPD with high classification performance rates for showcasing precise results: 95.84% accuracy, 93.34% sensitivity, and 93.65% specificity correspondingly when 3D-SODP quantification parameters were used in conjunction with the DBN. The outcomes indicate the machine learning approach can recognize the seriousness of COPD by utilizing 3D-SODP quantization on respiratory data.

Khatri et al. [21] the outcome of artificial neural network (ANN a regressive approach) is superior compared to that of popular categorization or regression algorithms. Analyses on this path may also be carried out additionally by fine-tuning the classifier's variables or through applying certain machine learning methods along with some deep learning approaches like Multilayer Perception and Artificial Intelligence. For the most significant occurrence stage, the precision and recall were 77.1% and 78.0% correspondingly having an accuracy of 81%. While on the other hand, the figures were 83.9% and 83.2% when comparing the non-peak instances.

Y Liu et al. [22] Additionally, an electronic technique for dynamically deciphering pulmonary patterns captured by stethoscopes is being presented. This method has numerous applications including self-screening and healthcare. In the immediate vicinity of model of deep CNN that is made up appertaining to 3 maximum-pooling class, 3 completely connected stages and six stages based on structure. Lastly, the constructed design underwent validation using an initial collection of twelve participants whose precision and recall were compared to the average outcomes of five pulmonary specialists. Thus, we compute the percentages of recall and precision just for wheezes and crackles and that come out to be 94.5% and 92.5% respectively confirming our findings and showing that the deep neural network models possess robust representations of features on these two aberrant pulmonary signals.

Similar to the research stated above, the goal of the research is to detect both typical and atypical breathing audio.

### 2.3 Comparison Between Existing Works

The attached research part explains the computerized strategies and structures used in the detection of breathing-related illnesses. A review of the study's numerous analytic methodologies, encompassing characteristics and ways to recognize illnesses related to breathing was given in this section. In conclusion, this study's contrast evaluation provides an essential perspective that allows the efficacy of different models based on DL & ML utilization along with diagnosis of breathing-related illnesses to be evaluated. It reveals a multidimensional viewpoint that combines ancient and modern methods highlighting the need for an all-encompassing strategy for healthcare diagnosis. The outcomes provide helpful perspectives for improving current diagnosing techniques in addition to advancing our knowledge of pulmonary sound-based illness identification. The present contrast study establishes a firm basis to address the socioeconomic effect debate, recommendations and implications for further study in the following sections. A thorough discussion of the experiment including the methodology and efficiency is given in Table 2.3.1.

TABLE 2.3.1: Table of Comparison Study.

| SL No. | Name of Authors | Applied Models | Optimal Algorithm Performance |
|---|---|---|---|
| **1.** | N Melek et al. [14] | RBF, DT & SVM. | SVM & RBF=83% |
| **2.** | A Monaco et al. [15] | DNN, SVM, RF. | MLP= 0.85 ± 0.03% |
| **3.** | Liu et al. [16] | GMM & MFCC | GMM=98.4 % |
| **4.** | Fernandez-Granero et al. [17] | DT & AI | Sensitivity=78.1%<br>Accuracy=87.8% |
| **5.** | A Badnjevic et al. [18] | RF, GB & LR | Sensitivity=96.45%<br>Specificity=98.71% |
| **6.** | G Altan et al. [19] | Deep Learning | Specificity=96.33%<br>Accuracy=93.67%<br>Sensitivity=91% |
| **7.** | Y Kutlu et al. [20] | DBN | Sensitivity=93.34%<br>Specificity=93.65%<br>Accuracy=95.84% |
| **8.** | Krishan L. Khatri et al. [21] | MLP & ANN | Accuracy=81%<br>Precision=77.1%<br>Recall=78.0% |
| **9.** | Y Liu et al. [22] | CNN & LMFS | Precision=94.5%<br>Recall=92.5% |

## 2.4 Open Issues

Many inquiries are yet unanswered in the study "Deep Learning & Machine Learning and Approaches for Respiratory Sound-Based Disease Detection." Such obstacles have an impact on the database as well as the deeper utilization of DL and ML models in this field.

1. **Statistical Diversification:** The tendency of the algorithm to be broadly applied to other demographics might be limited by the database's insufficient variation in demographics.
2. **Sound and Recorded Efficiency:** Diversity in the settings used for recordings contributes sound, which affects the precision of illness identification.
3. **Unbalanced Classification Statistics:** Predictive models may be skewed to be a result of unbalanced diseases category prevalence.
4. **Pattern Removal:** Retrieving pertinent characteristics using intricate audio files is still a difficult task.
5. **Practical Applications:** In real-life situations involving ambient sound, algorithms developed on constrained samples won't function effectively.
6. **Confidentiality and Ethics Issues:** Managing vital medical information necessitates giving legal concepts and confidentiality considerable thought.
7. **Medical Integrity:** To ensure such algorithms' effectiveness in medical applications more studies must be done to incorporate with medical practices in an appropriate manner.

It is imperative that such obstacles be resolved in order to progress research and enhance the usefulness of pulmonary audio analysis in illness identification.

## 2.5 Summary

The review looks closely at earlier research that utilizes ML & DL techniques in detecting respiratory diseases. It highlights the various feature extraction approaches used in these investigations. By emphasizing the positive aspects, it draws attention to the similarities and variations in the methods. It also examines the many models and classifiers that are employed, encompassing CNN, SVM NN & DT. In addition, it addresses a broad spectrum of respiratory ailments, including asthmatic, bronchi, COPD & pneumonia. Last but not least, it talks about constraints including dataset diversity and quantity, variable recording conditions, and difficulties with real-time processing in practice.

# CHAPTER 3
# Methodology

## 3.1 Overview

The inhalation & exhalation phases appertaining to breathing audio provide vital details regarding the breathing structure. The parameters for carrying out different projects or research, as well as the functional and non-functional needs, should be established and identified using the specified models or methodology. Identifying possible risks and uncertainties related to the project and putting risk mitigation methods into practice are the final steps in the technique, which also includes the project strategy, goals, and the allocation of technical and human resources.

Thus, in addition to providing insights into project management and financial considerations, researchers can systematically develop and evaluate DL & ML techniques representing pulmonary sound-based illness detection, thereby contributing to advancements in automated healthcare diagnostics and patient care. The last steps in the approach include determining potential risks and uncertainties associated with the project and implementing risk mitigation strategies. Other steps include project strategy, goals, and the distribution of technical and human resources. In addition to offering insights into project management and financial considerations.

## 3.2 Proposed Methodology

The procedure proposed within the paper outlines about a systematic framework for applying DL & ML methods. It begins with dataset collection & preprocessing which includes acquiring respiratory sound recordings and Implementing various prompt procedure techniques toward enhancing the quality appertaining to the data. Once relevant data is collected using feature extraction techniques, these models are optimized through Adam Optimizer, Sequential Minimal Optimization and Gradient Descent for performance using appropriate algorithms. The precision, specificity & sensitivity appertaining to the trained models' ability towards detecting diseases are assessed using predefined criteria.

Therefore, additional factors in such evaluations include TP, TN, FP & FN. Therefore, the suggested techniques provide a structured approach to deep learning and machine learning for respiratory sound data analysis with the goal of diagnosing respiratory diseases.

This study suggests a comprehensive, thorough different technique of diagnosing diseases via pulmonary sounds. First, the database is acquired, annotated, and labeled. Next, important pre-processing activities such as statistics cleansing, determining features, or attribute selection are carried out. A range of deep learning & Machine learning layouts encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) techniques that employed and carefully evaluated in accordance using categorization efficiency metrics. By the final phase of the research endeavor, the most effective algorithm technique for identifying breathing-related conditions had been identified, providing an invaluable resource for managing breathing-related conditions and safeguarding healthcare worldwide.

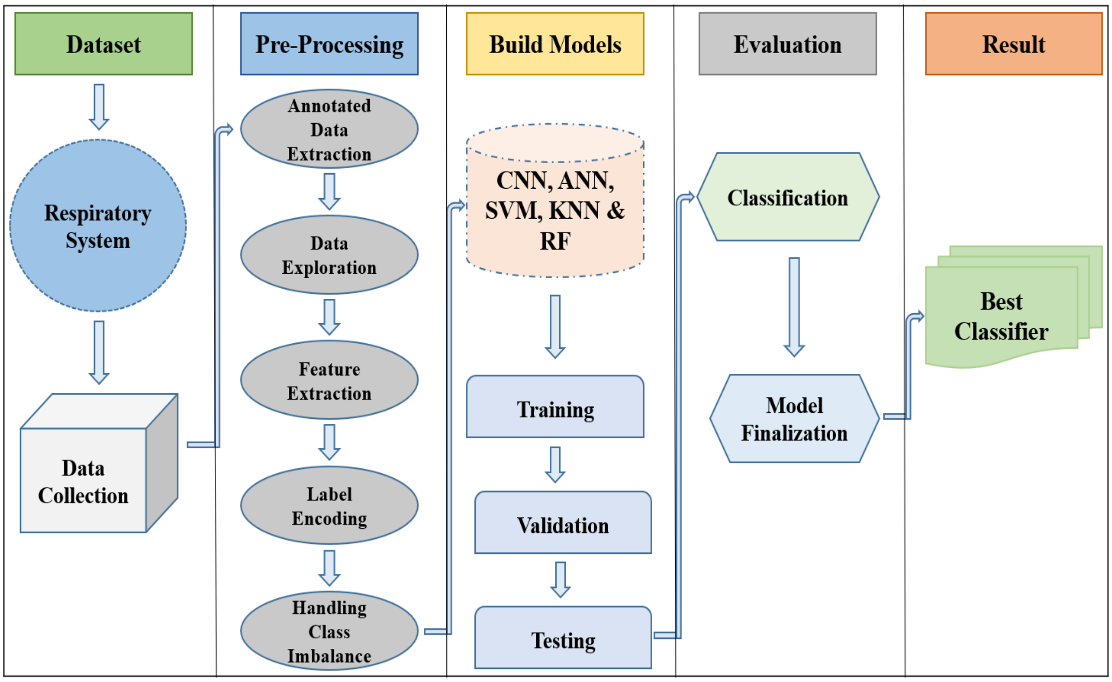


Figure 3.2.1: Proposed Methodology.

### 3.2.1 Data Collection

Nowadays diseases are the prior enemy of humanity, respiratory disease is one of them. To get rid of this problem we find out a way of respiratory disease detection where we work on a dataset [23] that contains several patients' respiratory sound. Two research teams in Greece and Portugal develop these sounds and the permission of recording of patients sound is concerned by the patient's own self. There are two categories of respiratory sounds: adventitious (abnormal) and normal. The sounds produced by the respiratory system when there is normal airflow are those that are normally heard.

TABLE 3.2.1.1: Dataset Description.

| Data Topics | Total Counts |
|---|---|
| Respiratory Cycles | 6,898 |
| Crackling | 1,864 |
| Wheezing | 886 |
| Both Crackling & Wheezing | 506 |
| No. of Patients | 126 |
| No. of Recordings | 920 |
| Recording Time | 5.5(Hours) |
| Length Per Recording | 10s – 90s |
| Age Groups | 3 (Children, Adult & Elderly) |

### 3.2.2 Data Preprocessing

For ensuring high-quality inputs for the machine learning and deep learning frameworks, analyzing information regarding this study entails a number of crucial processes. Initially the collection of data is imported and examined with the use of Python packages like the numpy program and pandas. After eliminating information to get rid both damaged or missing tracks every soundtrack are standardized in regards to duration & sample frequency. To improve the audio experience methods to minimize noise have been employed that make use of multiple sources. Once more, Adam Optimizer, Sequential Minimal Optimization and Gradient Descent Optimizer were identified as key elements compared to the recorded sound information provided. After normalizing such traits, a revised database appropriate to framework assessment and instruction is produced ensuring uniformity as well as comparison between instances.

#### 3.2.2.1 Annotated Data Extraction

Annotation extracting data for study entails the identification and analysis of identified pulmonary audio files which exhibit certain properties, such as crackling and wheezing. The process is essential while building ML and DL algorithms because it gives the techniques the information they need to recognize anomalies linked to various illnesses related to breathing. By extracting annotations, their efficacy and adaptability in actual healthcare environments are improved & the potential to reliably detect and categorize illnesses is ensured.

#### 3.2.2.2 Data Exploration

Exploring data for studies entails examining breathing audio database to comprehend its properties, including attribute patterns, category dispersion, and statistical integrity. Organizing and design are guided by the structures, disparities, and possible abnormalities found in the results, which are found in this preliminary phase. By verifying computer training algorithms are constructed on a strong basis through reliable information inquiry, its precision and dependability in diagnosing illness were eventually improved.

#### 3.2.2.3 Feature Extraction

High-dimensional vectors can be converted to lower-dimensional vectors through the attribute selection process. Attribute or feature selection methods are utilized over simultaneously analyze the rhythm, frequency & rapidity domains appertaining to the prompt created after respiratory sounds have been pre-processed. Several feature extraction techniques, including Adam Optimizer, Sequential Minimal Optimization and Gradient Descent are applied in this study. These techniques are used to find the respiratory sound coefficients.

#### 3.2.2.4 Label Encoding

During the study, the category categories of pulmonary sounds—such as wheezing, crackling, and regular breaths—are mapped to integers using labeled encode. The development of models is made easier by this method, which makes it possible for ML and DL algorithms to handle collected information efficiently. The algorithms' ability to recognize sequences linked to different illnesses related to breathing is enhanced through embedding labeling, which enhances the ability to discriminate and increases the precision of illness identification.

#### 3.2.2.5 Handle Class Imbalanced

For the purpose to achieve an equitable representation of illnesses related to breathing, methods like enhancement underutilized categories or creating computerized information are used in the studies to address the disparity between groups. Such approaches improve the capacity of the system to correctly categorize a range of illnesses & aid in avoiding distorted predicted outcomes. Enhancing the reliability and adaptability of ML and DL in a variety of clinical demographics requires tackling social disparity.

### 3.2.3 Model Build

Researchers trained the pulmonary sound-based diagnosis system using a variety of DL and ML models through the modeling and validation stage. The CNN, ANN, SVM, KNN, MLP, and LR algorithms are among them. Our extracted database was used for developing every algorithm to recognize the distinctive traits of various illnesses related to breathing. Throughout the development process, we made certain the algorithms were adequately setup & tweaked over the greatest efficiency.

### 3.2.4 Evaluation

Once the algorithms were trained using an alternative tests a database, their effectiveness was assessed. F1 score, precision, recall, accuracy, and confusion matrices comprises those assessment criteria. During this step, the audio files were identified & the effectiveness of every prototype was evaluated according to the findings. The thorough examination appertaining to the data made it possible to pinpoint the benefits and limitations of every technique regarding on its capacity to accurately recognize multiple pulmonary sound-based illnesses.

### 3.2.5 Results

According to the basis of the assessment metrics, we identified the method of classification that functioned the most effectively. Regarding the diagnosis of respiratory-based disorders, our algorithm demonstrated the best level of precision as well as reliability. The final step consisted of recording this ideal algorithm's results and effectiveness. It will eventually be used in everyday life to effectively diagnose illnesses by analyzing breathing sounds.

## 3.3 Hardware/ Software Requirements

### 3.3.1 Hardware Requirements:

Strong infrastructure is necessary toward enabling effective training of deep and machine learning frameworks including Random Forest, CNN, SVM, ANN, KNN and LR. These comprises:

1. **HPC:** Possessing sophisticated dual-core processors (Intel Xeon or AMD Ryzen) & adequate storage to have the capacity to tackle the challenging duties related to ML and DL evaluation.
2. **GPU:** During deep learning and machine learning simulations, a graphics processing unit (NVIDIA or RTX series) is an absolute must over speeding up retraining and cutting down on the quantity of effort spent on modeling and construction.
3. **Automated Instrument:** The highest-quality automated instruments must be used to record precise and unambiguous breathing audio during gathering information. Such gadgets ought to be able to capture sounds in outstanding detail and work using stored information methods.
4. **Professional-Grade Sensors:** Professional-grade sensors & acoustic adapters may guarantee the accuracy of auditory samples even settings without automated instruments.

### 3.3.2 Software Requirements:

The characteristics and parameters, which a computer program requires in order meeting the demands and desires established by its consumers and customers are commonly referred to as demands of the software. These comprises:

1. **Frameworks:** Employing well-known DL platforms enabling modeling, instructional material & assessment, which include PyTorch or TensorFlow.
2. **Programming Language:** Python offers a flexible popular framework to analyzing information & the implementation of deep and ML techniques.
3. **Libraries:** Constructing and testing algorithms for DL becomes easier using Keras, a distributed NN Interface that runs upon the apex TensorFlow. It provides a toolkit available as which is especially helpful for generating DL algorithms.
4. **Tools:** With their robust data models and methods over cleaning, transforming and assessing the results, NumPy and Pandas are essential frameworks to obtain

working with massive databases. Once more, the Jupyter Notebook provides a collaborative atmosphere wherein scientists may mix written explanations, coding & graphics.

5. **IDE:** With functionality such sophisticated programming completion, troubleshooting or application navigation—all of that are very helpful to intricate ML projects—PyCharm is a potent developer's environment or Integrated Development Environment created exclusively to obtain the programming of Python. A flexible programming writer offers a multitude of modules enabling Python programming and statistical research.

### 3.4 Project Management and Financial Analysis

The objective appertaining to the research is toward employing ML & DL techniques toward constructing and assess computerized identification methods representing breathing illness. For doing this we have to follow some project management aspects as well as financial analysis too. The financial analysis has done to estimate the project's costs such as equipment, research and potential return on investment.

#### 3.4.1 Project Management:

1. **Project Planning:** Describe the project in detail, outlining its objectives, deadlines, tasks and achieving the goal.
2. **Resource Allocation:** Assign technical and human resources to the production, review and acquisition of data.
3. **Timeline management:** It involves keeping an eye on the advancement of a project in relation to predetermined schedules and resolving any delays or bottlenecks.
4. **Risk management:** It involves identifying possible risks and uncertainties related to the project and putting risk-reduction plans into action.

#### 3.4.2 Financial Analysis:

1. **Research Expenses:** Examine costs associated with gathering data, preparing it for modeling, validating the model & finally for testing.
2. **Equipment Costs:** Determine how much it will cost to buy the project's necessary gear and software.
3. **Personnel Costs:** Compute the projected costs of the project team's wages and

benefits.

4. **Return on Investment (ROI):** Evaluate the possible ROI by considering the expected savings and advantages of automated illness detection systems.

Table 3.4: Projected Expenses Representing the Respiratory Sound Project.

| SN | Elements | Projected Expenses (BDT) |
|---|---|---|
| 01. | Hardware | 23500-25000 |
| 02. | Visiting Stakeholders | 5000-5500 |
| 03. | Software and Tools | 6000-6500 |
| 04. | Data Collection and Processing | 3500-4000 |
| 05. | Documentation and Report Writing | 3500-4000 |
| 06. | Miscellaneous (e.g. licenses, tools) | 4000-4500 |
| 07. | Contingency (10% of Cost) | 4500-5000 |
| Total Estimated Cost | | 50000-54500 |

### 3.5 Summary

The following steps provides a guideline how we can implement methods for getting the best output from the specific dataset. For this at first, we have written requirement analysis so that we can get the knowledge of implementing models. Then we select the dataset as we mention earlier. From the dataset we processed the data and apply models encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN). Using those models, we can get automated systems that detect respiratory diseases utilizing DL & ML methods. This process is considered as the methodology which provides a systematic approach for research and financial aspects for the development of effective medical disease detection systems. Here we have analysis the full data and justify our approach for in-future implementation. This process gives a complete output of " Deep Learning & Machine Learning approaches for respiratory sound-based disease detection and sharing information with practitioners, healthcare stakeholders.

# CHAPTER 4
# Implementation

## 4.1 Overview

Apparently are several conditions that must be met in order over the academic endeavor on "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" to be implemented successfully. The following subsection describes a methodical approach to developing & evaluating ML and DL models towards the categorizations appertaining to illnesses utilizing pulmonary sounds. The process begins by selecting & modifying trained algorithms & proceeds to the algorithm's testing phase. The particular procedures include the framework topologies, training techniques & variables that are used to gauge the efficacy appertaining to algorithms. For the purpose appertaining to utilize similar DL and ML methods to breathing disorder diagnosis, this established approach provides an identifiable development path & guarantees repeatability.

## 4.2 Train Model

Our database has to be divided into 3 categories: testing, validation, and training data. The algorithm undergoes training utilizing the dataset. Utilizing that training dataset algorithm generally learn about the pattern and relationship of provided data. We have taken 70% of our data randomly as training data. A technique for training files often teaches users regarding the relationships and patterns in the information that is supplied. Typically, training information is kept in an organized way enabling supervised teaching. In order to get the best results, multiple designs need to be set up when models developed using deep learning and machine learning are being trained to optimize categorization of pulmonary sound-based illness diagnosis through Adam Optimizer, Sequential Minimal Optimization and Gradient Descent. In addition to developed procedures encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) algorithms representing the present investigation. By examining these models through rigorous testing and analysis, our study provides toward proceeding the field appertaining to ML & DL with implications for improving diagnostic accuracy and efficiency in clinical settings.

### 4.2.1 Model Architecture

#### 4.2.1.1 Convolutional Neural Networks (CNNs)

The quantitative melding of two distinct variables for generating another feature is commonly known as "convolution" in a convolutional neural network [24]. The proposed study effort intends to provide a thorough and Performing an in-depth examination appertaining to clinical pulmonary sound clip representing respiratory sound-based illness identification by utilizing CNN deep learning approaches to support medical specialists. Additionally, it seeks to increase the prediction accuracy of respiratory audio analysis for prompt and early illness identification.

It has been noted that noise levels in audio inputs are often greater than those in visual inputs. Because the Adam optimization approach is statistically structured that uses reduced evocation facility & performs superior representing clamorous processed data. Thus, it is utilized to optimize the model in this way [25].

The feature maps' dimensionality is decreased by the pooling layers. Again, activation layers introduce non-linarites and facilitate the learning of complicated patterns. Other layers carry out specific tasks in related procedures. Again, overfitting is avoided by randomly removing a certain percentage of neurons during training that is handled by the dropout layer. Therefore, the output layers forecast the output or outcome. A thorough discussion appertaining to the experiments efficiency is given in Figure 4.2.1.1.1.

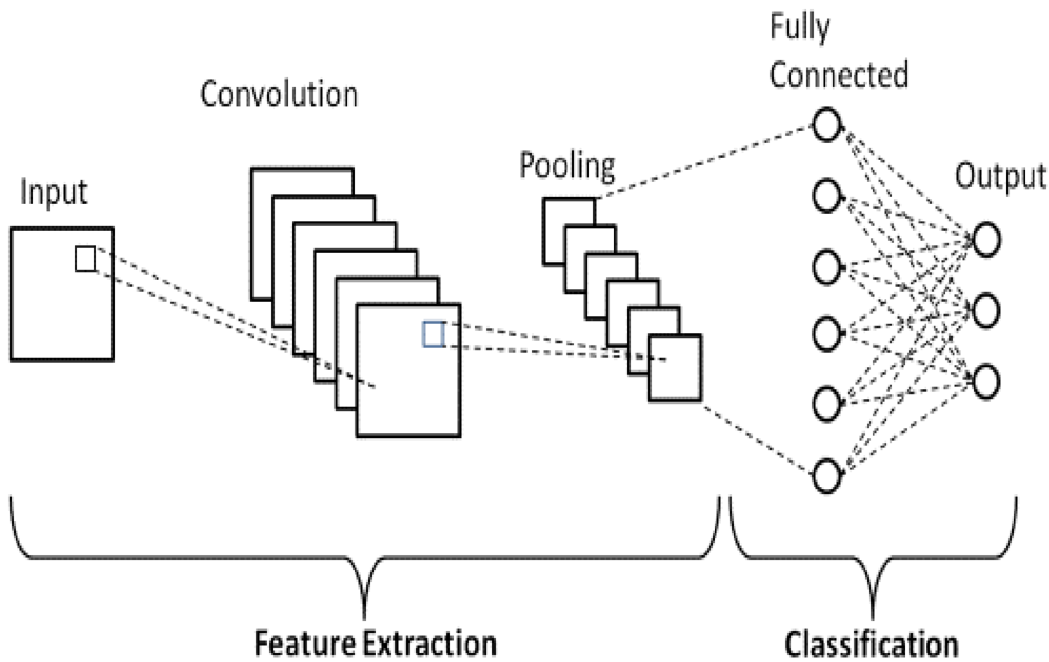


Figure 4.2.1.1.1: Diagrammatic illustration of CNN [26].

Developing a sophisticated DL framework intended towards progressive gathering of features is the Convolutional Neural Network (CNN) architecture illustration. The convolutional, pooling data, and explicitly linked levels are among the various levels that are displayed. Although the pooled layers reduce the representations of features to lessen their complexity and cognitive burden, the convolutional components employ algorithms to identify regional trends like perimeters, appearances, & forms. The ultimate categorization is made by integrating the attributes obtained into the entirely linked levels towards the completion with the structure. Because of its multilayered framework, CNN's algorithm is very good for jobs involving recognizing the contents of multimedia content. It can also understand complicated structures in information.

#### 4.2.1.2 K-nearest neighbor (KNN)

KNN is a well-liked oversea and nonparametric classification method that uses The dataset's training typifying are grouped closely together (K denotes the number of neighbors) to determine a sample's distance from the closest sample. Using a distance equation, the categorization techniques determines KNN appertaining to undisclosed features within the database. After that, it estimates the data label using the majority vote method. Manhattan, Chebyshev, and Euclidean distance measures are a few that are frequently used. Depending on the distance metric and K value, various KNN types are employed in this study [27].

The following are the fundamental procedures followed while using K-Nearest Neighbor methods for classification:

- The value of k is ascertained.
- Distance functions are used to calculate the distances among the original feature and every additional piece of features in the training database.
- KNN features or information which matches the new features, the closest are choose.
- The updated or fresh database is assigned to the group towards the majority appertaining to the chosen features affiliated to.

A thorough discussion appertaining to the experiments efficiency is given in Figure 4.2.1.2.1.

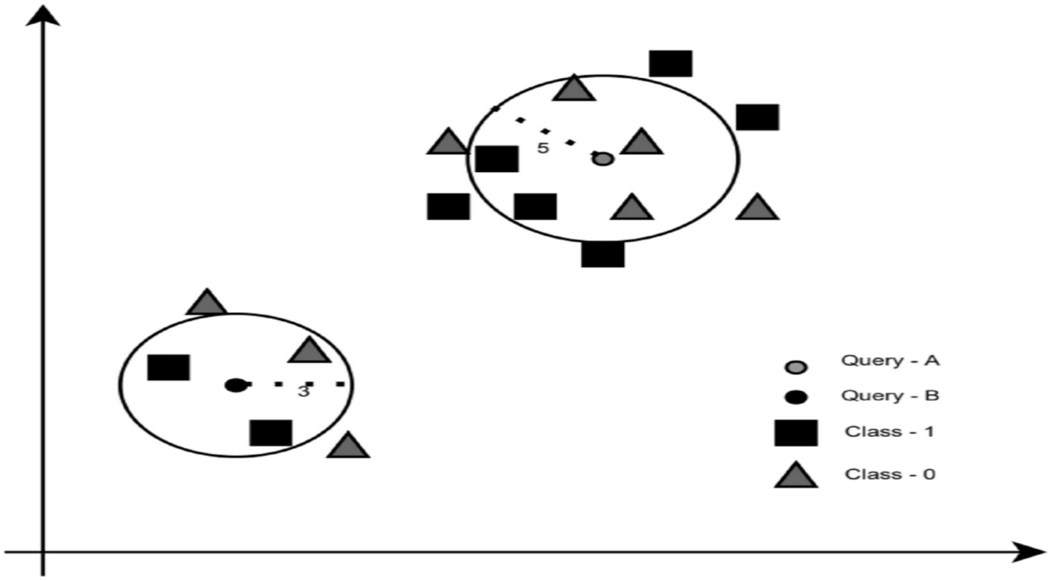


Figure 4.2.1.2.1: Diagrammatic illustration of KNN [28].

A simple, instance-based method for training is shown within the k-nearest-neighbors architecture illustration. Contemporary variables have categories within the space of characteristics according to the overwhelming classification that they share with KNN. The proposed technique's flexibility is shown by the illustration, which demonstrates the way every statistic is assessed when compared with its neighbors and lacks a comprehensive learning procedure above preserving an initial database. The dimension metrics & KNN selection affect the bias-variance equilibrium and determine how successful the KNN algorithm, is. The following algorithm is especially simple for utilizing and instinctive, resulting in approach appropriate for compact through moderate-sized databases whenever accessibility and interpretation remain crucial.

### 4.2.1.3 Random Forest

With the convenience of application to classification and regression issues, RF remains a widely used method in statistical applications. Despite strongly coupled parameters alongside elevated multidimensional problems—a common occurrence in bioinformatics—it demonstrates good predictability & effectiveness. Subsequently, it has been utilized by academics to filter parameters to decrease complexity, which enables a cost-effective characteristic selection to be produced by including the characteristic expense within the underlying decision tree design [29].

As previously stated, this represents a collection about categories constructed using the training data set booting. A particular group of attributes is determined by chance throughout a continuous procedure resulting in the tree structure, suggesting there is barely any association between their trees. They are often highly resistant towards amplification, simple to tweak and typically useful whenever the variety of attributes in the prediction surpasses compared to the quantity available data. In most cases, the average result in analysis and the category median in categorization represents the ultimate result [30]. With a result, the approach allows for evaluating the extent to which an attribute reduces these impurities. A thorough discussion appertaining to the experiments efficiency is given in Figure 4.2.1.3.1.

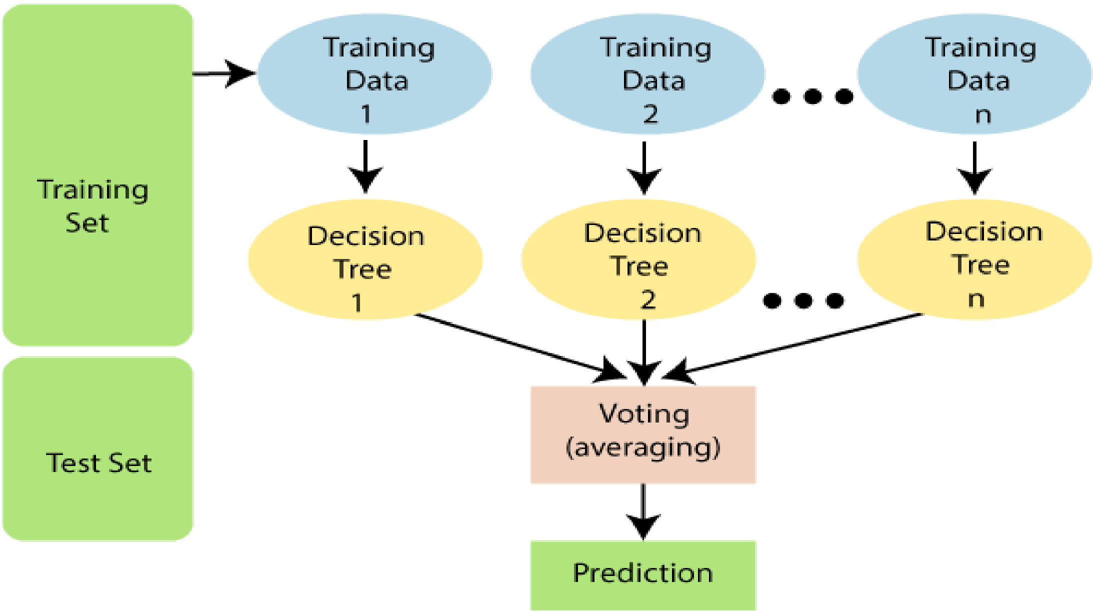


Figure 4.2.1.3.1: Diagrammatic illustration of RF [31].

A single instance from an approach to learning made consisting of several DT is shown in the random-forest (RF) structure illustration. For the purpose of arriving during the most accurate forecast, both the distinct branches in the canopy are programmed using an arbitrary allocation about the information and variables (e.g., through the overwhelming vote with categorization or combining with extrapolation). The technique improves its capacity to generalize while reducing over-fitting. The variety that comprises the forests is depicted throughout the graphic, that is important in assessing the Random Forest algorithm's resilience. It is an effective and adaptable technique throughout a variety of statistical models since its aggregate structure.

#### 4.2.1.4 Support Vector Machine

The supervising ML method is a Support Vector Machine that is employed to both classification and regression. However, this method is most appropriate towards issues with categorization and is utilized with extrapolation situations. Finding a circular region within a space with three dimensions that accurately classifies the information's elements is the purpose underlying SVM models. The amount appertaining to characteristics affects those hyperplane's dimensions. The coordinate system is essentially a segment assuming there are only 2 inputs characteristics. The coordinate system transforms into a two-dimensional surface if there are 3 inputs qualities [32]. According to structures that involve ML and categorization phases such an approach is crucial. Because of this, researchers continually attempt to enhance the methods they employ [33]. Information is utilized to display the outcomes regarding the mathematical procedure, yet it is critical to take amount, acquiring methods, and appropriate identification of information into account. In some industries, particularly a healthcare one, collection of information might be costly as well as difficult [34]. A thorough discussion appertaining to the experiments efficiency is given in Figure 4.2.1.4.1.

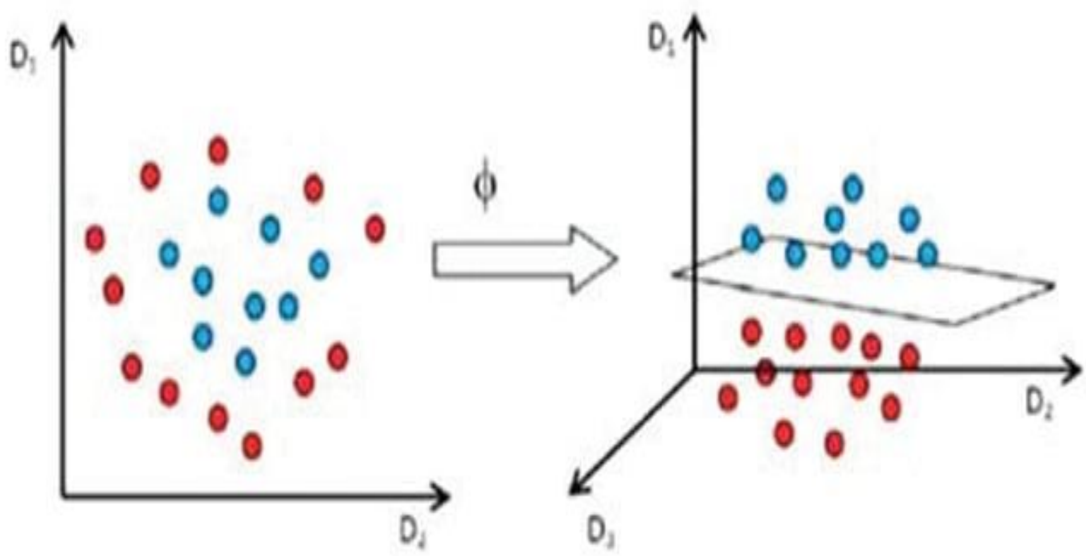


Figure 4.2.1.4.1: Diagrammatic illustration of SVM [35].

The Support Vector Machine (SVM) architecture graphic illustrates a margin-based classification which looks for a suitable hypervisor within the array of features for dividing multiple categories. The conceptual framework regarding SVM—the variables positioned nearest from the dividing hypervisor and margin—the separation among the hypervisor & those support vectors—is depicted in the illustration. The Support Vector Machine seeks to improve the variance with the objective to provide improved applicability towards unobserved evidence. The above strategy works especially well on situations with a distinct edge about differentiation such as highly dimensional environments. The graphic shows how the Support Vector Machine performs elegantly yet accurately in categorization jobs.

#### 4.2.1.5 Artificial Neural Network

Based through humanity's nerves, artificial neural networks (ANNs) comprise computer systems capable of generalization to different situations based on information regarding previously encountered ones. It is a computational framework inspired by NN seen in biology. The system employs the aforementioned strategy used processing to analyze data and comprises from a linked ensemble of neural cells. Typically, within the development stage, it is a dynamic apparatus, which modifies its framework to response to both internal and external data, which travels via the interconnected system.

Additionally, the concept of "synaptic load" refers to the relationship among multiple nodes and is represented through a number. The stimulation operation, associated load standards & component connectivity all affect a NN algorithm's result. The primary attributes of an artificial neural network comprise its potential to gather data through instances as well as generalization outcomes through dynamic functionality. Throughout development, the information is stored in the synaptic weighting within the nodes [36]. A thorough discussion appertaining to the experiments efficiency is given in Figure 4.2.1.5.1

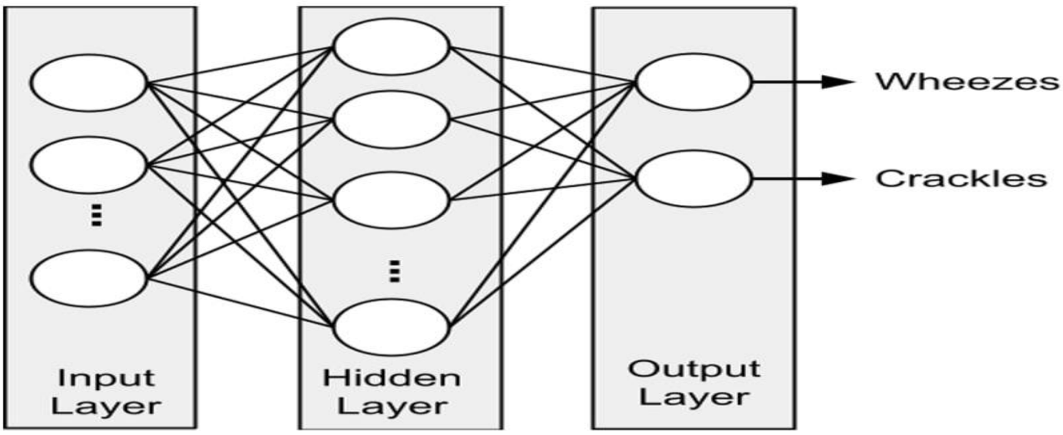


Figure 4.2.1.5.1: Diagrammatic illustration of ANN [37].

A framework with multiple tightly linked nerve cells, comprising an entry layer, a number of layers that are concealed, along with an output section, is shown in an Artificial Neural Network (ANN) illustration. After receiving data supplied by the level above, every nerve implements an activity function that is nonlinear as well as an estimated sum before sending the outcome to the level above. Artificial neural networks (ANN can simulate intricate variations in input owing to its framework. The system is completely linked, as seen within the picture, with each nerve in a particular layer being affiliated with one another in the level below it. Artificial neural networks (ANNs) exhibit great versatility & could be applied across a broad spectrum of obligations, including picture and translation to additional complicated duties including prediction and categorization.

### 4.2.2 Model Compilation

Since the Adam Optimizer, Sequential Minimal Optimizing and Gradient Descent are efficient and provide an adjustable rate of acquisition that accelerates integration, they are used in the construction of each of the algorithms. Efficiency is the primary evaluation criterion over multi-class categories using the categorization functions.

## 4.3 Model Evaluation

### 4.3.1 Precision:

In a survey of all the positive forecasts the algorithm makes, precision quantifies its percentage about accurate positive forecasts. It may be important in healthcare diagnosis to reduce errors in diagnosis and indicates how accurate the positive forecasts were. Whenever the algorithm anticipates, an individual having a breathing problem it is probably accurate if its precision is substantial [38]. The mathematical formula of precision is given below:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} --- \text{(i)}$$

### 4.3.2 Accuracy:

The aggregate number of right assumptions (true positives and true negatives) out of every assumption generated is the algorithm's projected quantity or efficiency. Accuracy might be deceptive in unbalanced data when the proportion of typical instances far outweighs that of aberrant instances even though it gives a rough notion of its efficacy [39]. The following formula:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)} --- \text{(ii)}$$

### 4.3.3 Recall:

The percentage regarding accurate positive forecasts among real positives is measured by recall or sensitivity. Subsequently shows how well the algorithm can diagnose clients who have breathing problems. With the aim to minimize the chance for false negative results and assure a majority of illnesses being accurately diagnosed accurate recall is required within healthcare diagnosis [40]. Utilize the subsequent formula to calculate it:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} --- \text{(iii)}$$

### 4.3.4 F-1 Score:

The only statistic that combines accuracy & recall calculated via the proportional average combining the two is the F1-Score. While utilizing unbalanced information it is especially helpful since that provides an additional relevant metric then reliability by itself [41]. The formula:

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} --- \text{(iv)}$$

Subsequently, as the algorithm can only imitate its initial collection of information sufficiently until losing its abilities to extrapolate, the analyzed publications repeatedly highlight the significance of such parameters in assessing its efficacy with breathing problems accurate evaluation. A special structure for tables termed the matrix of confusion, which is intended to show important prognostic metrics including recall, specificity, precision and accuracy that may be utilized to evaluate the effectiveness of a system. Since it provides an immediate evaluation of variables such TP, FP, TN and FN. Researchers emphasize how although precision is provided by accuracy more comprehensive perspectives regarding the algorithm's realistic efficacy are provided by recall, F1-score and specificity & particularly in healthcare diagnosis wherein mistakes might have a substantial financial impact. Experts may create algorithms as being secure, trustworthy & precise sufficient to be utilized in actual medical environments through concentrating on those features.

### 4.4 Summary

Regarding pulmonary sound-based illness categorization, execution comprised the development and evaluation of seven ML and DL approaches: Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN). To satisfy these unique needs representing our database, these algorithms were adjusted & improved. In order to optimize the framework's resilience and adaptability through Adam Optimizer, Sequential Minimal Optimization and Gradient Descent Optimizer for usage in practical scenarios, a comprehensive assessment procedure was carried out, utilizing criteria for evaluation encompass precision, recall, accuracy, and the F1-score. These comprehensive approach emphasizes the importance of DL as well as ML in pulmonary diagnosis in the healthcare sector whilst laying the groundwork for future research and application.

# CHAPTER 5

# Result and Analysis

## 5.1 Overview

To enable researchers in carrying out thorough studies, the equipment used to regard the analysis on "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" comprises a well-planned arrangement comprising IT infrastructure, software and information assets. The analytical infrastructure of the system is made up of efficient equipment including a strong CPU and a potent rendering unit. The system also includes labeled pulmonary audio clips and documentation that includes medical information and illness designations. Following the preliminary processing phase, important aspects associated with pulmonary waves have been captured by extracting feature using techniques like Adam Optimizer, Sequential Minimal Optimization and Gradient Descent. The information is separated among testing, valid and trained groups. These retrieved attributes were utilized in training ML & DL techniques encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN).

Once more, because it offers a uniform and relevant input over algorithm development & assessment, such algorithms have been built throughout a Python-based programmable system using DL & ML structures like PyTorch or TensorFlow. A crucial component using the simulation design involves the utilization of pre-trained algorithm structures enabling pulmonary illness diagnosis. Precisely a result, matrix structures of confusion are produced enabling in-depth study or measures utilizing criteria for evaluation encompass precision, recall, accuracy, and the F1-score are utilized towards analyzing those effectiveness appertaining to the framework. To assure these resilience or applicability of the approach, cross-validations & parametric adjustment have been carried out. To preserve moral values, legal concerns like as explicit permission & information about patients' protection have been included within the framework.

In order to advertise openness, repeatability as well as potential partnership in the field of sophisticated pulmonary diseases diagnoses, comprehensive records including program details, system design, variables including outcomes is kept up to date via the experimental phase. Consequently, it determines the best technique to perform precise and trustworthy pulmonary illness diagnosis.

### 5.2 Experimental Result

Regarding our research involving the application of ML and DL methods to the identification of pulmonary diseases, we created and assessed an enormous amount of algorithms. All of the models were painstakingly constructed with the goal of being as accurate and useful as conceivable. Throughout our examination, we discovered that the precision of every simulation varied. Therefore, it simpler enabling researchers to compare the efficacy of different structures using breathing problems sound-based diagnosis in terms of identifying the least significant signs of ailment. The confusion matrix along with ROC curve and the resultant table is given below.

#### 5.2.1 Confusion Matrix

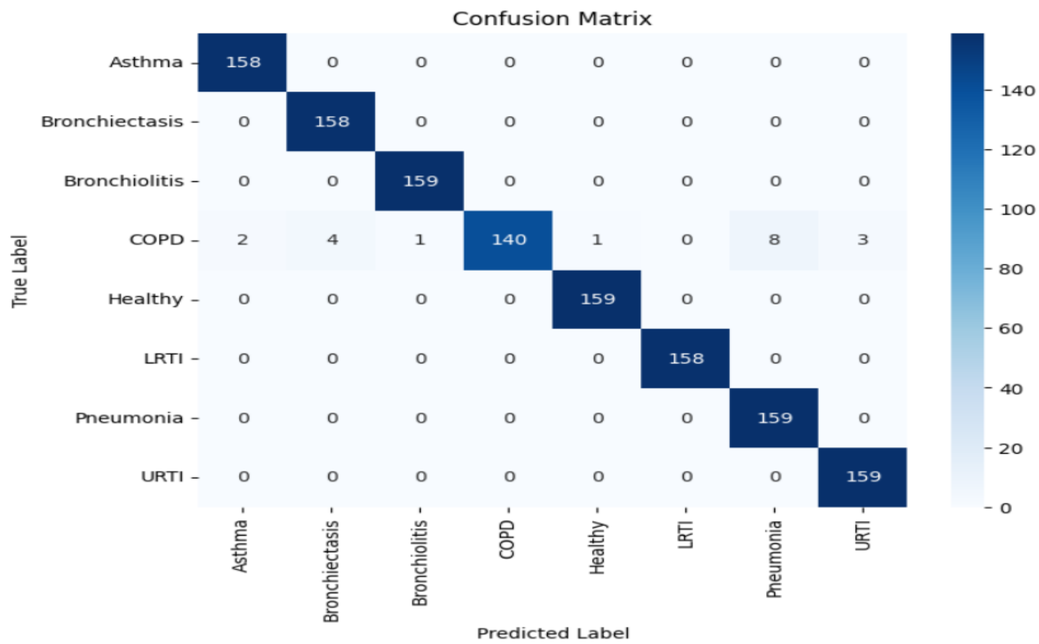


Figure 5.2.1.1: Confusion Matrix (CNN).

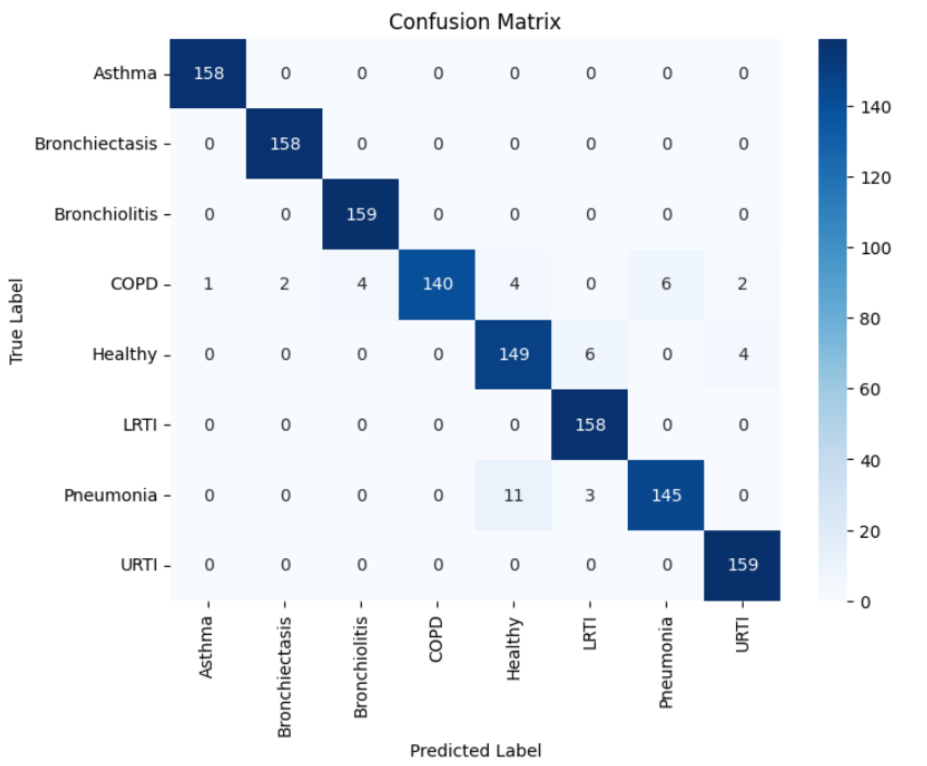


Figure 5.2.1.2: Confusion Matrix (ANN).

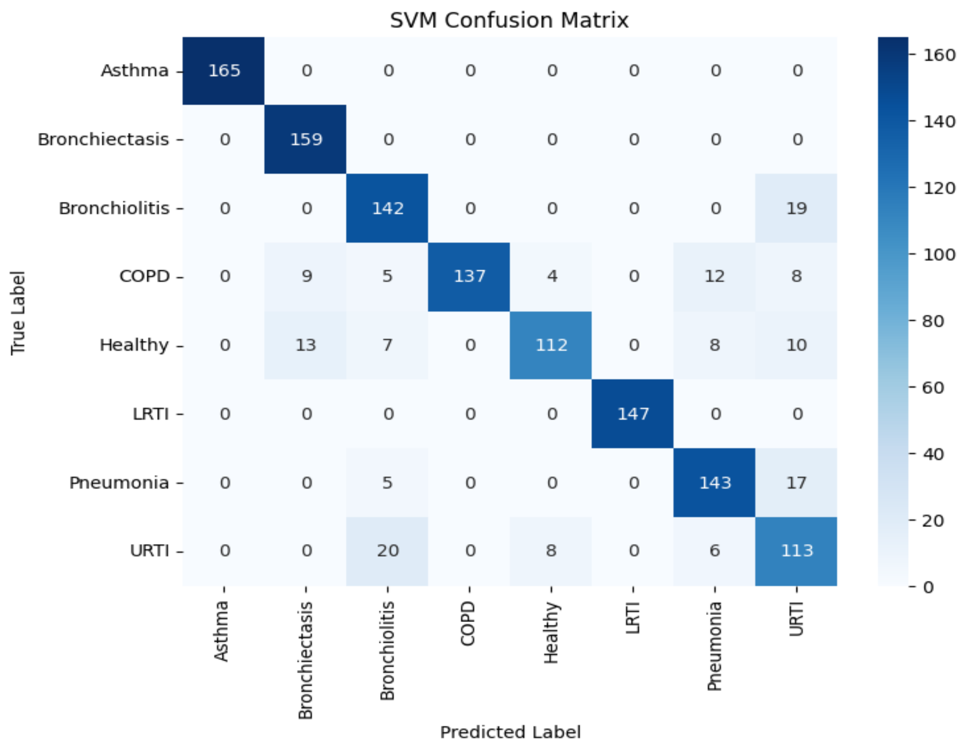


Figure 5.2.1.3: Confusion Matrix (SVM).

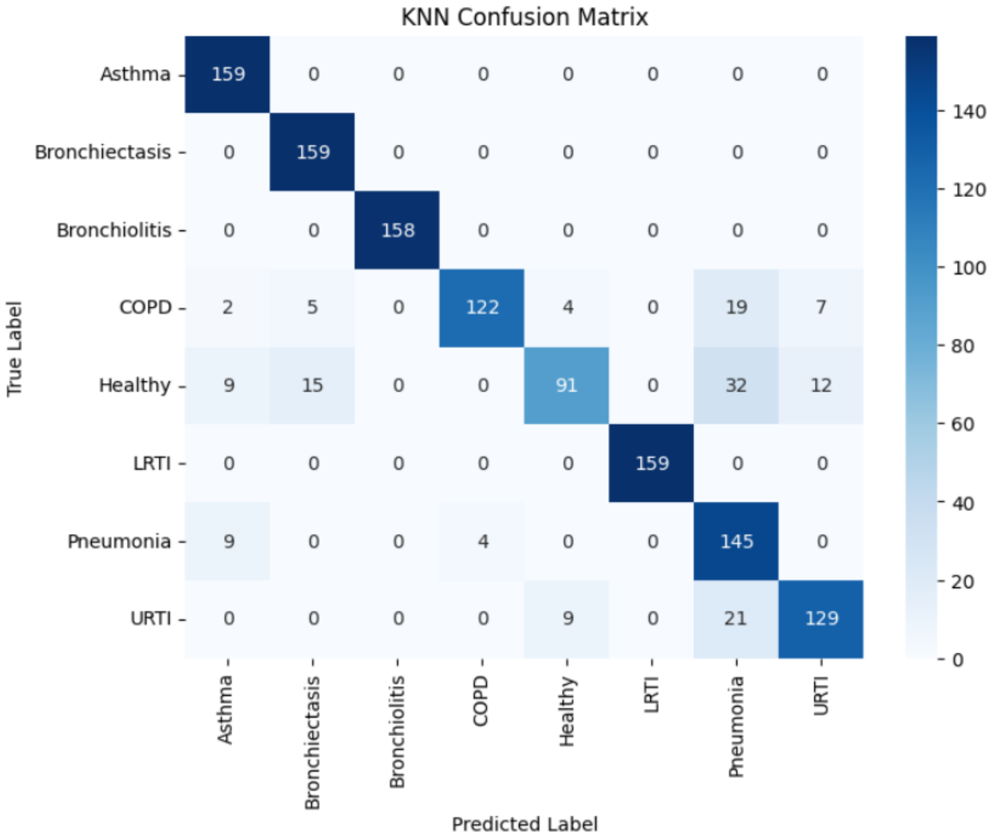


Figure 5.2.1.4: Confusion Matrix (KNN).

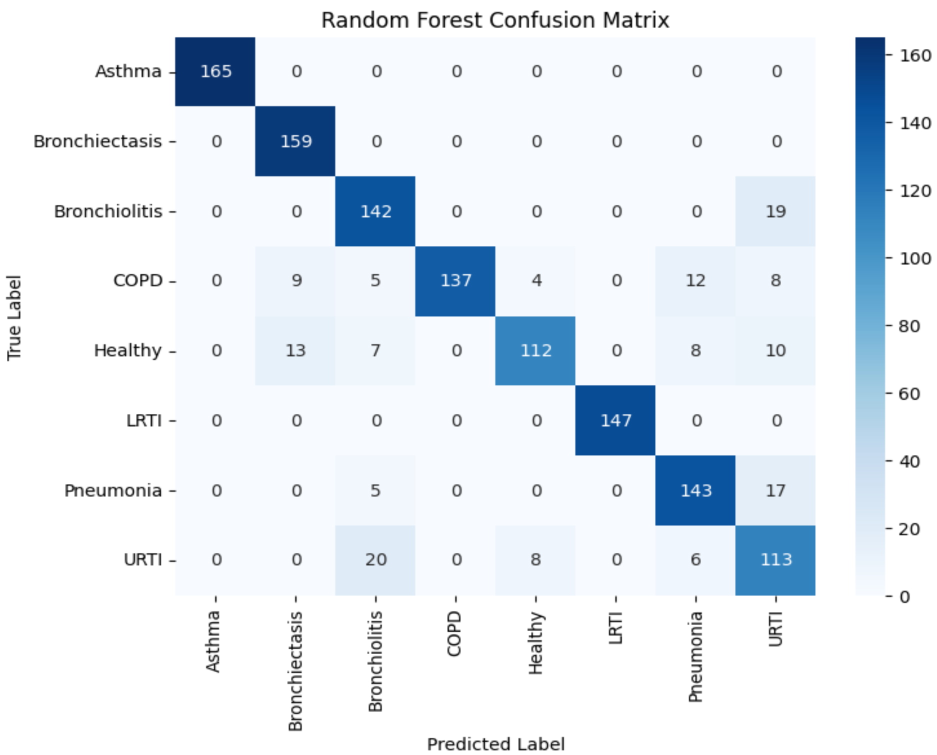


Figure 5.2.1.5: Confusion Matrix (RF).

It is demonstrated by the aforementioned pictures (figures 5.2.1.1 to Figures 5.2.5.1) offering a confusion matrix that adequately describes the effectiveness generated by 5 distinct deep learning & machine learning approaches: CNN, RF, SVM, KNN & ANN. The statistics of TP, FP, TN and FN are all included in every matrix by giving a comprehensive view on every algorithm's prediction precision or oversight dispersion. In order to demonstrate the ways that DL techniques methods manage inaccurate categorization in comparison to more conventional ML techniques such as RF & KNN as well, consider ANN & CNN matrix. The effectiveness achieved by a margin-based classifier is shown in the Support Vector Machine confusion matrix, highlighting both its advantages and disadvantages in terms of classification. The paper provides a distinctive comparison study that examines the failure sequences and categorization skills about every approach through displaying the aforementioned against one another alongside. This makes the paper a vital resource over making comparisons the models' efficacy in different settings.

### 5.2.2 ROC Curve

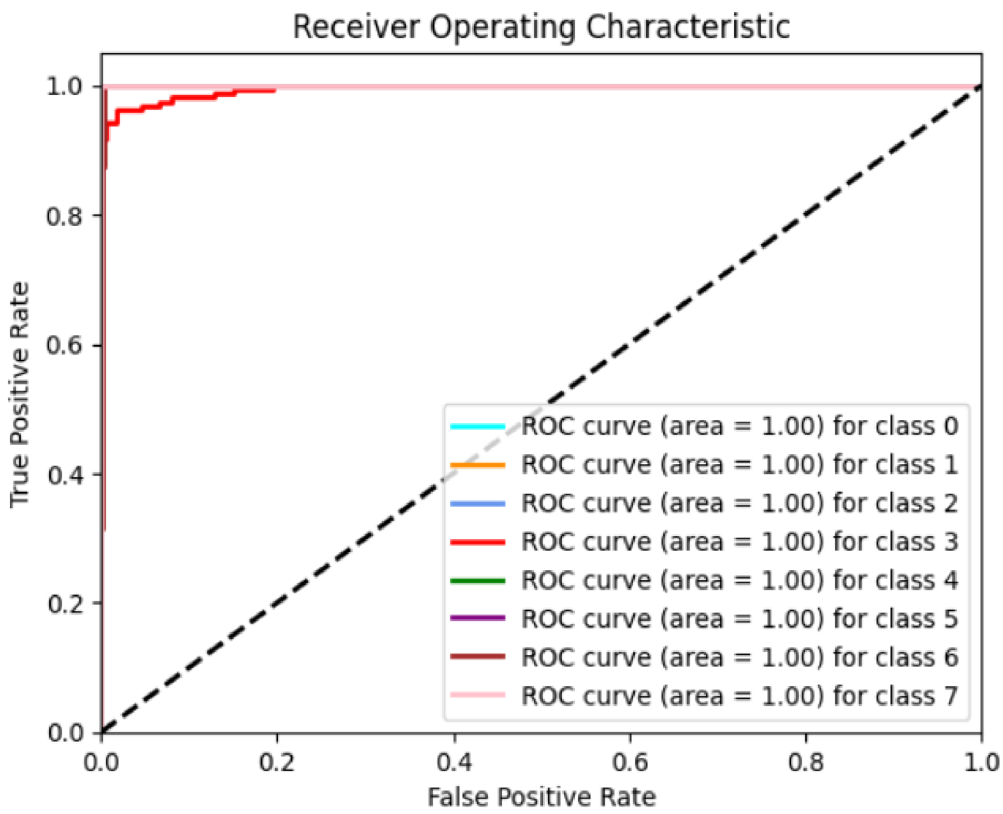


Figure 5.2.2.1: ROC (CNN).

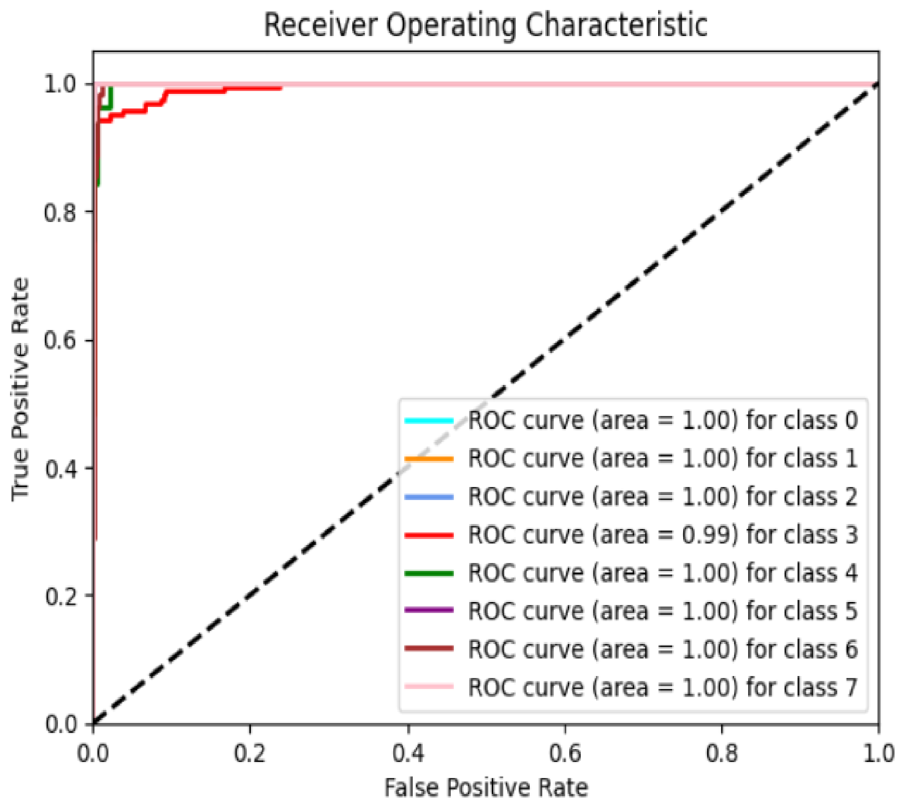


Figure 5.2.2.2: ROC (ANN).

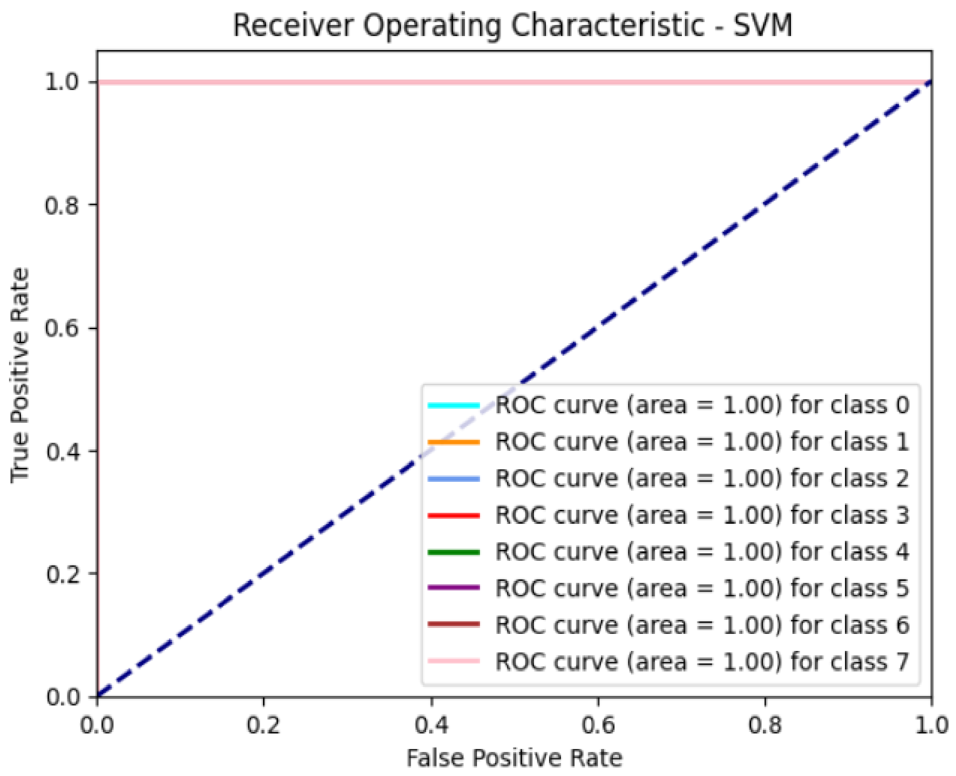


Figure 5.2.2.3: ROC (SVM).

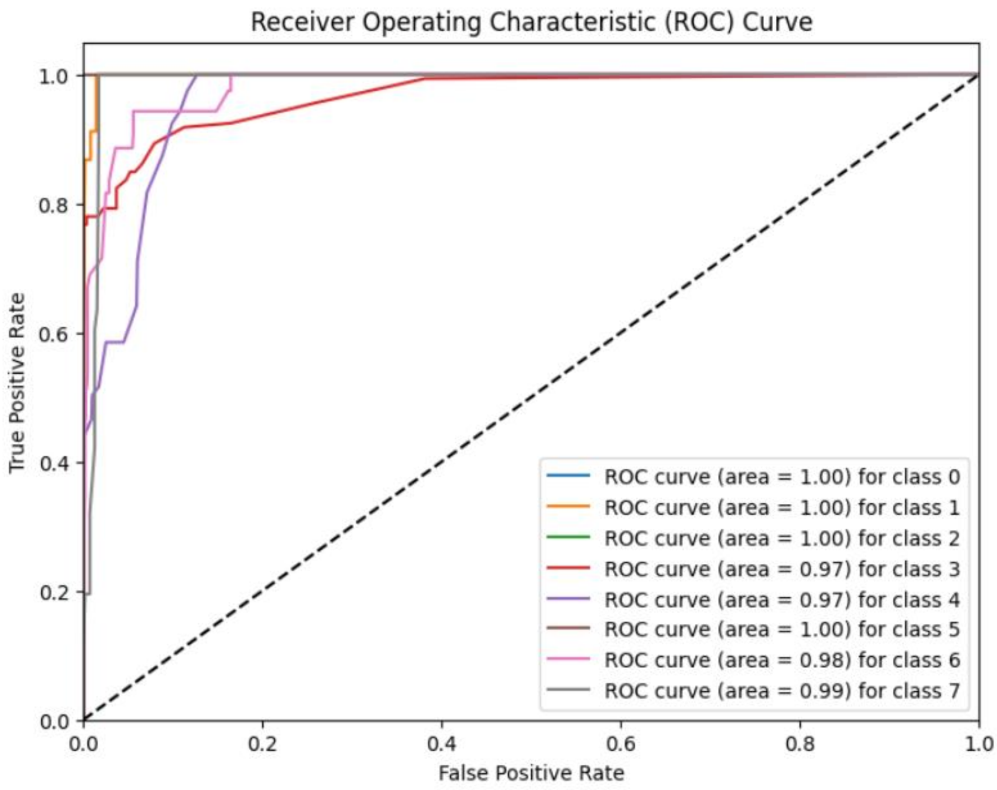


Figure 5.2.2.4: ROC (KNN).

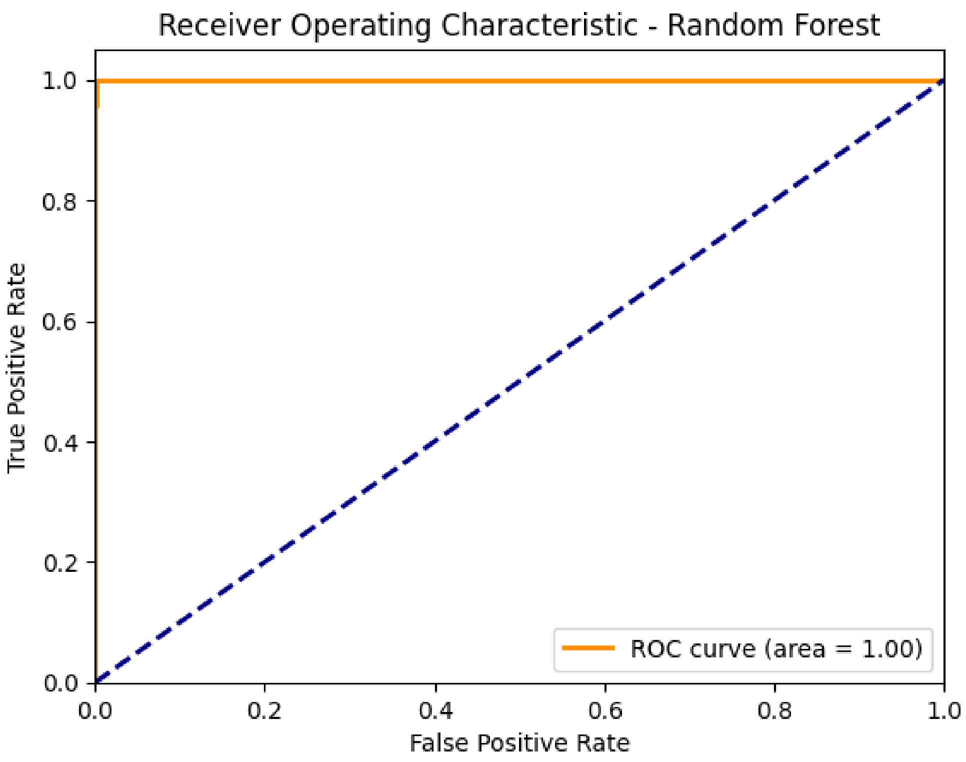


Figure 5.2.2.5: ROC (RF).

Employing each algorithm's unique receiver operating characteristic as shown in figure 5.2.1.5 corresponding to Figure 5.2.5.3, the receiver operating characteristic curve offers a thorough comparison examination generated by 5 distinct deep learning & machine learning approaches: CNN, RF, SVM, KNN & ANN. Every arc provides an illustration for every algorithm's capacity for distinguishing among categories by plotting the proportion of true positives alongside the false positive rate across various value ranges. The CNN & ANN ROC curves demonstrate the machine & deep learning algorithms' resilience. Typically, frequently display significant areas beneath the graph or AUC principles that are suggestive to higher accuracy in predicting. The effectiveness of the framework in preserving an equilibrium among sensitiveness as well as specificity is shown by the Support Vector Machine ROC curves. Regarding the other hand, the KNN & RF graphs shed illumination on the performance of combined approaches or instance-based developing at different levels. A detailed grasp for every algorithm's capacity for prediction in various contexts is made possible through the document's distinctive illustration regarding the compromises among TP and FP rates, which is achieved through contrasting various ROC curve.

### 5.2.3 Model Training & Validation

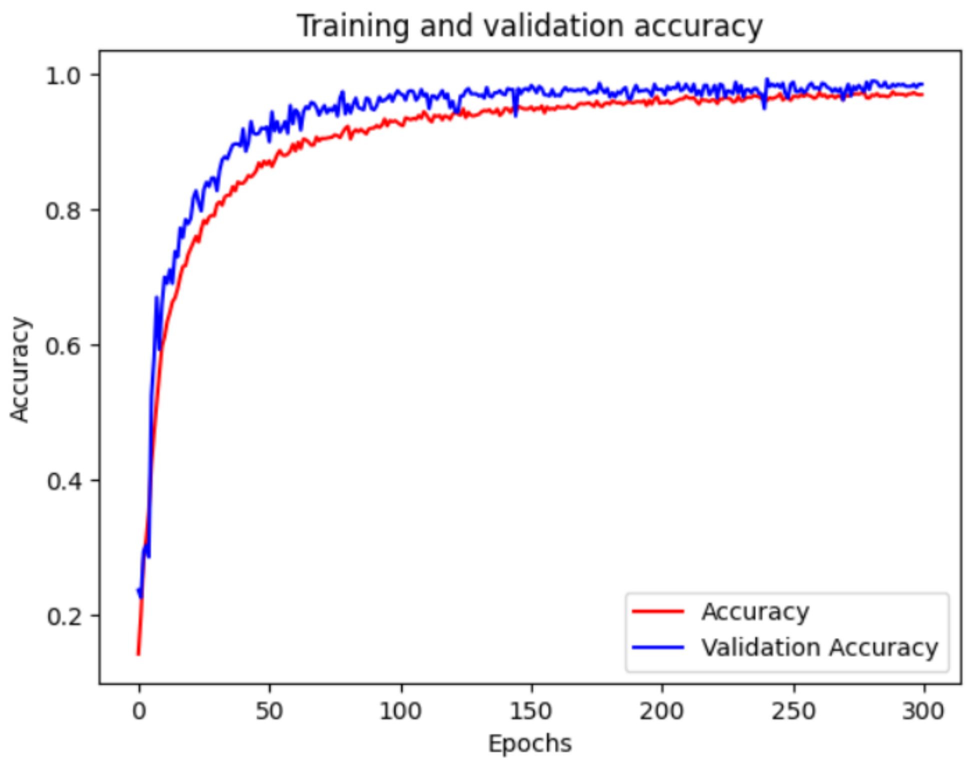


Figure 5.2.3.1 Training & Validation Accuracy (CNN).

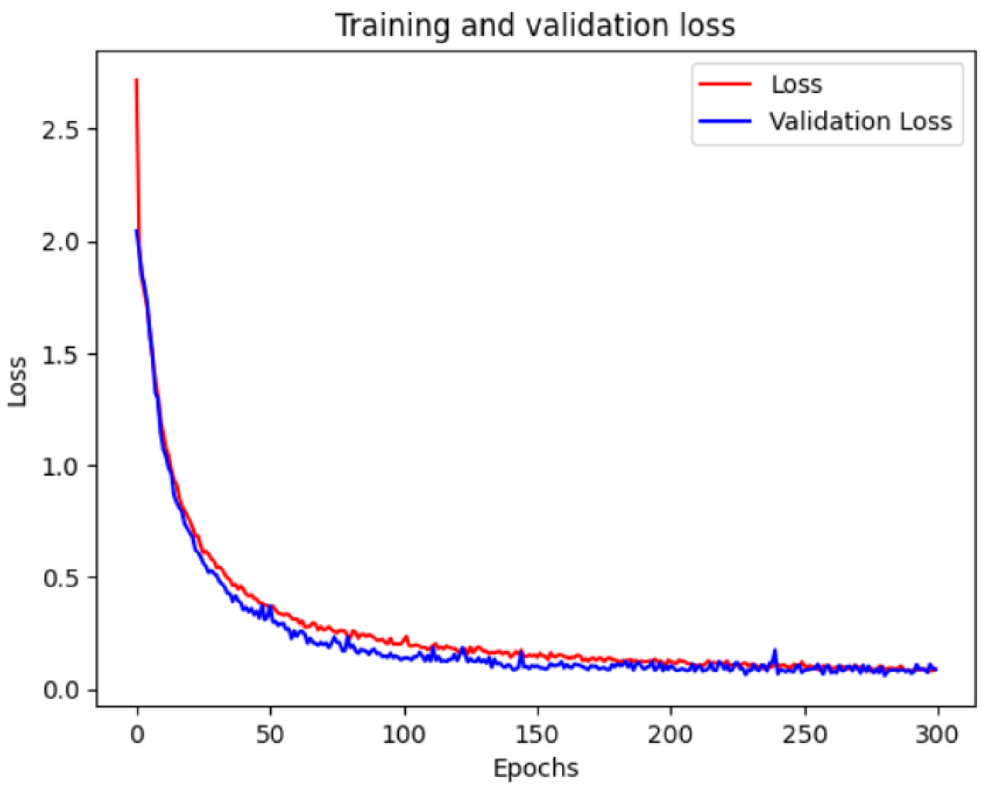


Figure 5.2.3.2 Training & Validation Loss (CNN).

In the above figures, we can see the training accuracy & validation accuracy of the proposed model CNN along with the training loss & validation loss through a graph.

### 5.2.4 Table of Result

TABLE 5.2.4.1: Result of the models (CNN, ANN, SVM, KNN & RF).

| | Classes | Precision | Recall | F-1 Score | Support |
|---|---|---|---|---|---|
| CNN | 0 | .99 | 1 | .99 | 158 |
| | 1 | .98 | 1 | .99 | 158 |
| | 2 | .99 | 1 | 1 | 159 |
| | 3 | 1 | .88 | .94 | 159 |
| | 4 | .99 | 1 | 1 | 159 |
| | 5 | 1 | 1 | 1 | 158 |
| | 6 | .95 | 1 | .98 | 159 |
| | 7 | .98 | 1 | .99 | 159 |
| | Accuracy | | | .99 | 1269 |
| | Macro average | .99 | .99 | .98 | 1269 |
| | Weighted average | .99 | .99 | .98 | 1269 |

| | Classes | Precision | Recall | F-1 Score | Support |
|---|---|---|---|---|---|
| **ANN** | **Classes** | **Precision** | **Recall** | **F-1 Score** | **Support** |
| | 0 | .99 | 1 | 1 | 158 |
| | 1 | .99 | 1 | .99 | 158 |
| | 2 | .98 | 1 | .99 | 159 |
| | 3 | 1 | .88 | .94 | 159 |
| | 4 | .91 | .94 | .92 | 159 |
| | 5 | .95 | 1 | .97 | 158 |
| | 6 | .96 | .91 | .94 | 159 |
| | 7 | .96 | 1 | .98 | 159 |
| | Accuracy | | | .97 | 1269 |
| | Macro average | .97 | .97 | .97 | 1269 |
| | Weighted average | .97 | .97 | .97 | 1269 |
| **SVM** | **Classes** | **Precision** | **Recall** | **F-1 Score** | **Support** |
| | 0 | 1 | 1 | 1 | 165 |
| | 1 | .88 | 1 | .94 | 159 |
| | 2 | .79 | .88 | .84 | 161 |
| | 3 | 1 | .78 | .88 | 175 |
| | 4 | .90 | .75 | .82 | 150 |
| | 5 | 1 | 1 | 1 | 147 |
| | 6 | .85 | .87 | .86 | 165 |
| | 7 | .68 | .77 | .72 | 147 |
| | Accuracy | | | .88 | 1269 |
| | Macro average | .89 | .88 | .88 | 1269 |
| | Weighted average | .89 | .88 | .88 | 1269 |
| **KNN** | **Classes** | **Precision** | **Recall** | **F-1 Score** | **Support** |
| | 0 | .88 | 1 | .94 | 159 |
| | 1 | .88 | 1 | .94 | 159 |
| | 2 | 1 | 1 | 1 | 158 |
| | 3 | .96 | .76 | .85 | 159 |
| | 4 | .87 | .57 | .69 | 159 |
| | 5 | 1 | 1 | 1 | 159 |
| | 6 | .66 | .91 | .77 | 158 |
| | 7 | .87 | .81 | .84 | 159 |
| | Accuracy | | | .88 | 1270 |
| | Macro average | .89 | .88 | .88 | 1270 |
| | Weighted average | .89 | .88 | .88 | 1270 |

| | Classes | Precision | Recall | F-1 Score | Support |
|---|---|---|---|---|---|
| RF | 0 | 1 | 1 | 1 | 165 |
| | 1 | .88 | 1 | .94 | 159 |
| | 2 | .79 | .88 | .84 | 161 |
| | 3 | 1 | .78 | .88 | 175 |
| | 4 | .90 | .75 | .82 | 150 |
| | 5 | 1 | 1 | 1 | 147 |
| | 6 | .85 | .87 | .86 | 165 |
| | 7 | .68 | .77 | .72 | 147 |
| | Accuracy | | | .88 | 1269 |
| | Macro average | 0.89 | 0.88 | 0.88 | 1269 |
| | Weighted average | 0.89 | 0.88 | 0.88 | 1269 |

The following table provides precision, recall, f1 score, support and accuracy for each model. If we go through the table we can see that the machine learning algorithm gives us the accuracy of KNN 88% and also shows the precision, recall, fi score which is near about same with the accuracy. But we get better accuracy on Rf 88.1%, SVM 91.5%, ANN 96.6% and got the highest accuracy on CNN which is 98.5%. If we go through the precision, recall, f-1 score, and support then we can see that from each model CNN gives us the better output then others.

### 5.2.5 Model Result

TABLE 5.2.5.1: Model Result (KNN, RF, SVM, ANN & CNN).

| Model Name | Training Accuracy | Validation Accuracy | Test Accuracy |
|---|---|---|---|
| KNN | 88.96 % | 89.1 % | 88 % |
| RF | 89.1 % | 88.1 % | 88.1 % |
| SVM | 93.5 % | 91.5 % | 91.5 % |
| ANN | 97.3 % | 95.7 % | 96.6 % |
| CNN | 99.5 % | 98.5 % | 98.5 % |

## 5.3 Comparative Analysis

Table 5.3.1: Comparison of Model Performance.

| SL No | Name of Authors | Applied Models | Optimal Algorithm Performance |
|---|---|---|---|
| **1.** | N Melek et al. [14] | RBF, DT & SVM. | SVM & RBF=83% |
| **2.** | A Badnjevic et al. [18] | RF, GB & LR | Sensitivity=96.45%<br>Specificity=98.71% |
| **3.** | G Altan et al. [19] | Deep Learning | Specificity=96.33%<br>Accuracy=93.67%<br>Sensitivity=91% |
| **4.** | Y Kutlu et al. [20] | DBN | Sensitivity=93.34%<br>Specificity=93.65%<br>Accuracy=95.84% |
| **5.** | Krishan L. Khatri et al. [21] | MLP & ANN | Accuracy=81%<br>Precision=77.1%<br>Recall=78.0% |
| **7.** | Y Liu et al. [22] | CNN & LMFS | Precision=94.5%<br>Recall=92.5% |
| **8.** | Proposed Paper | CNN | **Accuracy=98.5%** |

### 5.3.1 Deployment

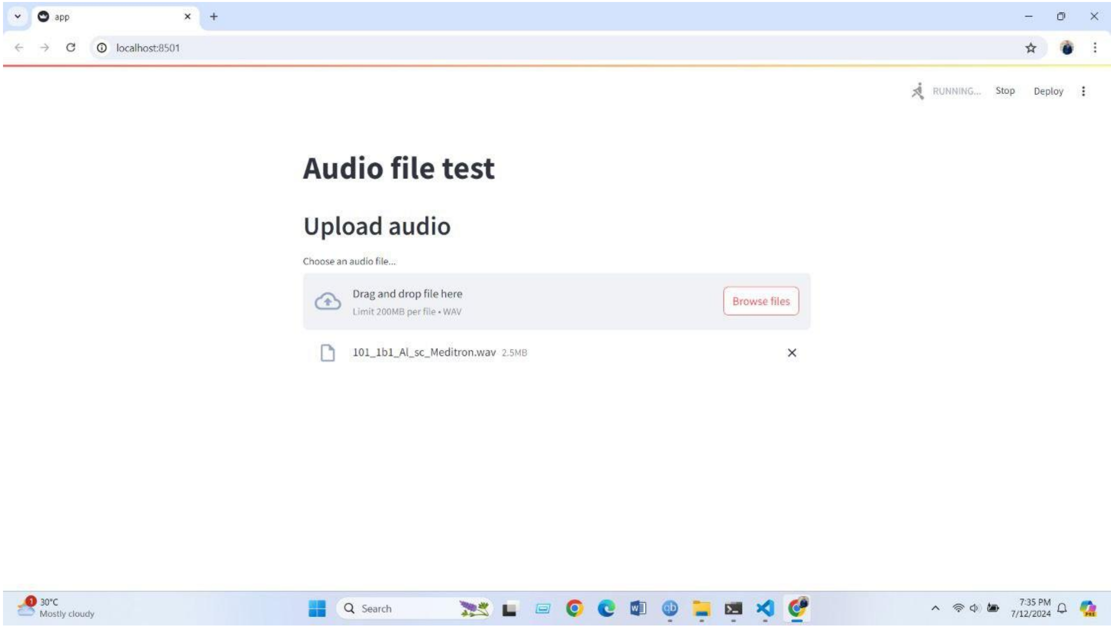


Figure 5.3.1.1 User Interface.

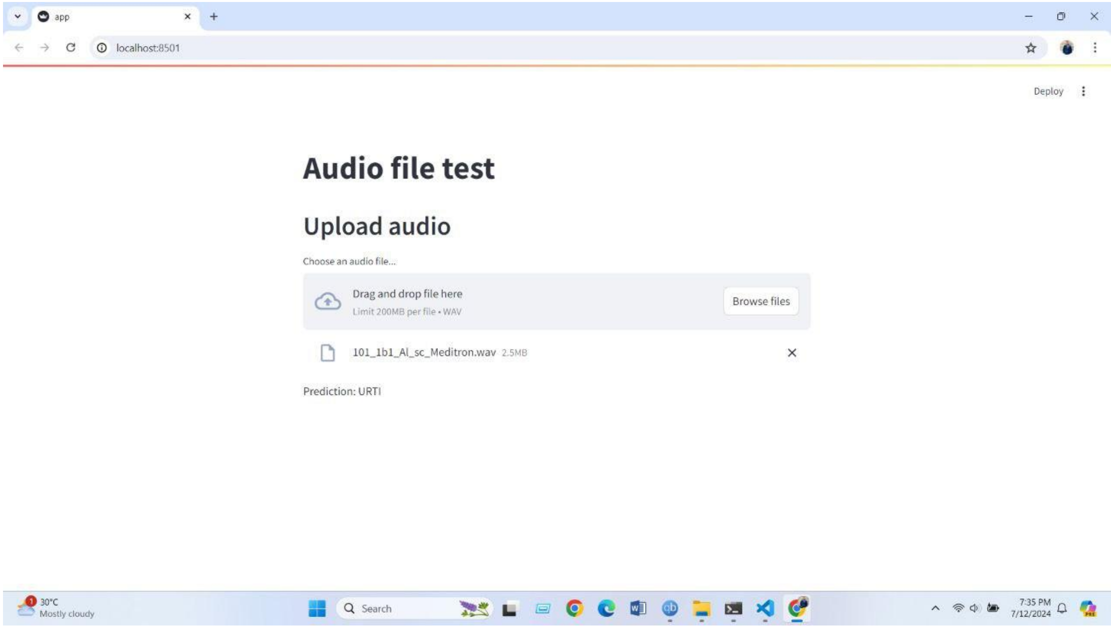


Figure 5.3.1.2 Classification Result.

Here we have used streamlit platform to deploy our proposed model (CNN). We can see the prediction of our models result like if we give input of respiratory sound of any patient it will show us the result which diseases has affected that patient. From the following image we can see that, when we give input of a patient from our dataset, then the specific result is shown as URTI which is a respiratory disease.

## 5.4 Summary

For the purpose of medical sustainability, DL & ML Models that improve the precision and efficacy appertaining to respiratory disease detection offer substantial advantages. These advanced models enable prompt treatments that can prevent significant life losses, guaranteeing health security and stabilizing the medical economy, by enabling early and accurate diagnosis of diseases. By giving doctors dependable tools to successfully manage patients health, this technology helps them improve their standard of living and lessen the financial burden that comes with disease outbreaks.

# CHAPTER 6

## Impact On Society, Environment and Sustainability

### 6.1 Impact On Life

The advantages appertaining to deep learning as well as machine learning in pulmonary sound-based illness detection for society, the economy, and the surroundings outweigh death rates in clinical studies. Through earlier illness identification and targeted treatment, this equipment merely promotes enhanced wellness yet also lessens the economic strain on individuals. It promotes environmentally friendly ways to detect by lessening the various ecological effects. Additionally, through arming medical professional’s information cutting-edge deciding resources, it strengthens the immune system towards ailments including bronchitis and breathing problems and fosters more robust and long-lasting illness identification networks around the globe.

Furthermore, the potential to accomplish underprivileged groups & areas with limited healthcare resources is presented by the low cost and easy availability using enhanced breathing disorder diagnosis technologies. Physical obstacles cannot be a limitation for the innovation created by the aforementioned study, considering that it might provide advanced techniques for diagnosis to regions in which conventional healthcare facilities could become scarce. The general objective of decreasing medical inequality and enhancing comprehensive medical assistance fairness is furthered by such globalization for sophisticated medical equipment, which is in line alongside worldwide medical care goals.

Therefore important to remember that developments in virtualization techniques, feasible processing methods and technology reliability are constantly changing. Techniques and equipment are being optimized for power consumption because scientists and innovators become more aware of ecological problems related to deep learning & ML-based approaches. Sustainable algorithms as well as the utilization of alternative energies may be integrated into servers in order to reduce the damage they cause while bringing technology advancements into the context of ecological concerns.

## 6.2 Impact on Society & Environment

1. **Impact on Society**

Despite the confines of study, the research on "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Illness Diagnosis" holds great promise regarding societal & medical advancements. The field of healthcare diagnosis could undergo an overhaul with the effective as well as diagnosis of breathing-related conditions with modern AI, ML and deep learning approaches. This could result in increased satisfaction with patients along with wider socioeconomic impacts. We implemented and evaluated several Machine learning & deep learning architectures, encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) which are widely used in various fields utilizing towards achieving implicit determination appertaining to breathing-related illnesses. This contributed to the reliability and efficacy of breathing problems sound-based diagnostic procedures empowering clinicians to generate sensible choices.

Prior to the context of general wellness, the study has a very significant social influence. Once more, a virus that circulates in the places a significant strain on the world's medical institutions. Additional properties trustworthy and precise tests could be utilized to accelerate up medical treatments minimize incorrectly diagnosed to enhance the health of patients. This may reduce the possibility of being hospitalized for respiratory-related issues and subsequent medical expenses. A further aspect of realism is added by these study’s significance on set methods & these contrasting evaluation appertaining to various techniques that open the door through the creation of optimal diagnosis procedures that have simple to implement within actual medical facilities.

Prior to conclusion, the study has an opportunity to change the course of personalized healthcare while having significant effects upon society especially in the areas of pulmonary sound-based diagnoses and assessment. Through utilizing state-of-the-art innovations, the study contributes to the theoretical comprehension of breathing disorder diagnosis along with retains an essential for genuine advancements regarding medical convenience, societal wellness effects along with the general state of many different groups worldwide.

2. **Impact on Environment**

The research on "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" mainly deals with technology along with the medical sector but it also has a subtle but substantial environmental influence. Advances in healthcare diagnoses are facilitated by the combination of numerous frameworks such as Adam Optimizer, Sequential Minimal Optimization and Gradient Descent. Again, we implemented and evaluated several DL & ML frameworks encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) which are widely used in various fields that necessitates extensive computer operations. Such steps need a lot of cognitive dominance especially when it comes to developing & optimizing advanced machine learning and deep learning strategies. They frequently depend on highly efficient technology such as graphics processing units (GPUs).

The amount of resources utilized for developing while executing such sophisticated approaches is what has a bearing upon our surroundings. Higher use of electricity is a result of the substantial processing demands particularly in situations featuring massive amounts of data & intricate structure designs. Since a result, the inquiry raises questions about how using cutting-edge medical technology may affect our natural surroundings.

In conclusion, the study's environmental effect will be crucial to take into account even if their main efforts are towards the improvement on healthcare diagnosis. Medical advances continue to be simultaneously ethical and ecologically sustainable while as endeavors strive to strike an appropriate equilibrium between scientific discovery & ecological responsibility.

### 6.3 Ethical Aspects

Concerns regarding ethics are important to the research on "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" from these initial stages of its strategy. When using healthcare sound records, it is important to follow rules of ethics and law in order to protect consumer security and anonymity. Whenever required, explicit consent—a fundamental factor in moral study procedures—is duly acquired.

The study's possible social implications for medicine underline the vitality concerning moral implementation, which guarantees innovations in diagnosis result in better outcomes for patients despite violating the liberties of individuals. Adequate record of the empirical investigation procedure facilitates accountable disclosure of data, examination & reproducibility—an additional way in which the moral aspect is expressed. Overall, its dedication to improving the community & the proper use of the latest innovations in the medical sector depends heavily on issues of ethics.

## 6.4 Sustainability Plan

The investigation entitled "Deep Learning & Machine Learning Approaches for Respiratory Sound-Based Disease Detection" has an environmentally consciousness that aims toward minimizing its negative effects on our surroundings as well as its beneficial effects upon society. In order to lower the total amount of electricity consumed related to simulation development and implementation, emphasis are being aimed at improving the efficacy of implementing resource-efficient techniques while investigating virtualization options. The analysis department is also dedicated to utilizing sustainable methods for handling information and retention.

In order to balance technical breakthroughs via ecological responsibility, the strategy places a high priority on constant understanding as well as adoption of environmentally friendly technology concepts. The analysis method includes ongoing assessment along with modification of alternative approaches demonstrating a dedication to ethical and compassionate advancements in science.

## 6.5 Summary

Thus, DL & ML algorithms that increase the precisions & effectiveness appertaining to breathing-related illnesses diagnosis have significant benefits to healthcare stability. By allowing promptly and precise detection of illnesses, these latest technologies ensure longevity and stabilize the healthcare system by permitting fast therapies which can avert fatalities. This equipment assists individuals lower their costs resulting from illnesses and enhance the quality of life by providing their with trustworthy instruments for managing illnesses. Furthermore, such designs promote environmentally friendly and healthy living through ethical building practices.

# CHAPTER 7

# Conclusion and Future Work

## 7.1 Conclusions

Competent medical management depends critically upon the quickly and precise identification & categorization of illnesses associated with breathing. This demonstrates that the constraints associated with conventional tests in order maybe addressed simultaneously enhancing the precision and efficacy using pulmonary acoustic data-based illness diagnosis through utilization appertaining to DL & ML technology. Thus, these comparisons we performed provides great importance and holds great potential that makes significant strides within current methods regarding handling breathing-related illnesses.

The present research closely examines the efficacy of several frameworks encompassing Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) & Convolutional Neural Networks (CNN) which are widely used in various fields towards the categorization appertaining to breathing-related conditions. These algorithms have been developed & assessed using the pulmonary audio database. Findings show a noteworthy improvement within the accuracy of pulmonary audio classification among distinct illness groups. Such outcomes highlight the opportunity underlying techniques for enhancing precision in diagnosis by offering a trustworthy way distinguish amongst healthy and unhealthy pulmonary acoustics. It emphasizes how crucial sophisticated extracting features & structure tuning methods are to obtaining exceptionally well categorization.

In summary, its findings offers compelling proof that indicates deep learning & machine learning algorithms might be useful instruments towards the timely and precise identification of breathing-related illnesses possibly revolutionizing medical diagnosis.

## 7.2 Further Suggested Works

The outcomes about the investigation into pulmonary sound-based diagnosis of illnesses offer insightful information and create exciting new directions for inquiry.

Prospective investigations should take note of the significant implications these findings have potentially revolutionizing diagnosis processes ensuring that they are easier to obtain & precise as well as quick. Such computerized solutions can potentially be used within a variety of wellness environments such as medical facilities & medical office as well as isolated especially underprivileged facilities in which getting specialized medical supplies as well as information might reflect a restricted. By enabling early identification & assistance such diversification about analytical skills might enhance results for patients or lessen the strain upon the medical system. It indicates a requirement towards superior and adaptable collaborative methods in order to improve or preserve reliability despite sacrificing computing effectiveness.

Furthermore, these technologies have an opportunity for better handling patients by facilitating prompt modifications to medications & ongoing tracking and oversight for persistent airway disorders. Moreover, the incorporation of such innovations within ubiquitous & portable electronics may provide contemporaneously evaluation & surveillance enabling consumers to take charge of how they are doing. Results additionally prepare the way for more investigation exploring various aspects of scientific thorough evaluation that might broaden the scope of illnesses for which computerized diagnosis could prove beneficial.

To put it briefly, the investigation's effects on breathing disorder recognition are outlined as follows: improving various tactics & investigating effective combination methods as well as broadening the focus of studies will enhance the field of medical imaging along with promote improvements in evaluation effectiveness and precision. Being considered, it establishes the foundation toward noteworthy developments in effortless diagnosis, indicating an existence in which medical technologies will come together to provide superior & higher-quality care for patients.

### 7.3 Limitations

A number of limitations should be noted even though the utilization appertaining to DL & ML algorithms towards the identifications of respiratory disease shows excellent outcomes. Firstly, the effectiveness of disease detection The efficacy is greatly influenced by the richness and variability appertaining to the training dataset. It is necessary to have robust datasets that accurately reflect the various environmental elements, disease kinds, and infection stages that can impact model performance. Furthermore, huge datasets or intricate neural network topologies may necessitate the use of extensive computational resources towards training appertaining to both DL & ML techniques. In environments with limited resources, researchers may find it difficult to access high-performance computing infrastructure. Thirdly, it is important to carefully assess if DL & ML models created in clinical system or geographic area may be applied to others. Model accuracy and performance may be impacted by regional differences in respiratory sound types and techniques, and environmental factors. Both the learning models' interpretability is still a source of concern, too. Although these models may detect diseases with high accuracy, it is frequently difficult to understand how they make their conclusions, or interpret them.

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# APPENDIX A

## Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

**Title:**
**MACHINE LEARNING AND DEEP LEARNING APPROACHES FOR RESPIRATORY SOUND-BASED DISEASE DETECTION.**

**Student ID: 201-15-14154; 201-15-13815.**

### CO Description for FYDP

| CO | CO Descriptions | PO |
|---|---|---|
| **Phase –I** | | |
| **CO1** | Integrate recently gained and previously acquired knowledge to identify a **respiratory sound-based disease detection** problem for the Final Year Design Project (FYDP) | **PO1** |
| **CO2** | Analyze different aspects of the goals in designing a solution for this FYDP | **PO2** |
| **CO3** | Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP | **PO4** |
| **CO4** | Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP | **PO11** |
| **Phase –II** | | |
| **CO5** | Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP | **PO3** |
| **CO6** | Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing detection and modeling, while adhering to relevant constraints in this FYDP | **PO5** |
| **CO7** | Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding. | **PO6** |
| **CO8** | Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks. | **PO7** |
| **CO9** | Implement ethical principles and adhere to professional standards and norms in this FYDP | **PO8** |
| **CO10** | Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP. | **PO9** |

| | | |
|---|---|---|
| **CO11** | Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP. | **PO10** |
| **CO12** | Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors. | **PO12** |

# Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

## Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

| SN | EP Definition | Attainment | CO | Justification (with Knowledge Profile) | References |
|---|---|---|---|---|---|
| 1. | **EP1: Depth of Knowledge required** | Yes | CO1, CO2, CO3, CO5, CO6, CO7 and CO8 | This project uses machine learning and deep learning models. For doing this we collect data, preprocess it to show **fundamental engineering (K3)** principles. It demonstrates **specialist knowledge (K4)** by Machine learning & deep learning models such as SVM, KNN, RF, CNN, ANN for respiratory sound disease detection. | **Page no:** [19-21] **Section:** [3.2.1, 3.2.2] **Page no:** [28-32] **Section:** [4.2.1] |
| | | | | The research-based project applies **engineering practice & design (K5)** by the figure of process of experiments. Which denotes as methodology in our paper. The project addresses **engineering practice & technology (K6)** by implementing SVM, KNN, RF, ANN and | **Page no:** [17-18] **Section:** [3.2] **Page no:** [33-35] |

| | | | | | |
|---|---|---|---|---|---|
| | | | | CNN model. | **Section:** [4.3] |
| | | | | This research-based project ensures to **K8 (Research Literature)** by studding recent journals and research papers, to advance respiratory sound-based disease detection using machine learning and deep learning, showcasing a comprehensive understanding of current methodologies. | **Page no:** [9-15] **Section:** [2.2, 2.3] |
| **2.** | **EP2: Range of Conflicting Requirements** | Yes | CO2, and CO7 | In this research-based project addresses **EP-2** by facing challenges in collecting data of respiratory sound-based disease detection, including limitations of traditional methods and the complexities of machine learning and deep learning models. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies. | **Page no:** [13-19] **Section:** [2.3, 3.2.1] |
| **3.** | **EP3: Depth of analysis required** | Yes | CO2, and CO6 | This research-based project addresses **EP-3** by comparing experimental outcomes, highlighting Deep Learning model (CNN) as the chosen significant solution for respiratory sound-based disease detection amidst multiple potential approaches. | **Page no:** [37] **Section:** [5.2] |

| | | | | | |
|---|---|---|---|---|---|
| **4.** | **EP4: Familiarity of Issues** | Yes | CO8 | This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in respiratory diseases like copd, asthma, pneumonia, urti, contributing to advancements in public health and healthcare practices which indicates **EP-4**. | **Page no:** [5-6, 9-13] **Section:** [1.5, 2.2] |
| **5.** | **EP5: Extends of application codes** | No | CO5 | N/A | N/A |
| **6.** | **EP6: Extends of stakeholders involved and conflicting** | No | CO8 | N/A | N/A |
| **7.** | **EP7: Interdependence** | Yes | CO5 | This research-based project's comprehensive approach shows high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a broader solution to complex challenges in medical diagnostics which ensures **EP-7**. | **Page no:** [17-22] **Section:** [3.2, 3.2.1] |

**Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:**

| SN | EA Definition | Attainment | CO | Justification | References |
|---|---|---|---|---|---|
| **1.** | **EA1: Range of resources** | Yes | CO11 | In our research-based project we utilize diverse resources such as high-performance computing infrastructure, GPUs, machine learning and deep learning frameworks, annotated datasets and ethical considerations to ensure systematic research and contribute to advancements in respiratory sound-based disease detection using machine learning and deep learning models. | **Page no:** [17-22, 27-33, 52-53] **Section:** [3.2.1, 4.2, 6.3] |
| **2.** | **EA2: Level of interaction** | No | | N/A | N/A |
| **3.** | **EA3: Innovation** | No | | N/A | N/A |
| **4.** | **EA4: Consequences for society and the environment** | Yes | | This project contributes to society by improving healthcare through advanced respiratory sound-based disease detection methods, while also promoting environmental sustainability by employing efficient computational resources with better accuracy for disease detection. | **Page no:** [50-53] **Section:** [6.1, 6.2, 6.3, 6.4] |

| | | | | | |
|---|---|---|---|---|---|
| **5.** | **EA-5: Familiarity** | Yes | | This research-based project expands upon existing research by examining a novel approach in respiratory sound-based disease detection through machine learning and deep learning, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field. | **Page no:** [9-15] **Section:** [2.2, 2.3] |

**Addressing CO (4, 9, 10, and 12):**

| SN | COs | Attainment | Justification | References |
|---|---|---|---|---|
| **1** | CO4 | Yes | In order to match with **CO4** this research-based project integrating effective project management and financial analysis, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle. | **Page no:** [33-35] **Section:** [4.3] |
| **2** | CO9 | Yes | This research-based project follows the ethical principles by prioritizing patient privacy, obtaining informed consent and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**. | **Page no:** [51-53] **Section:** [6.2-6.3] |
| **3** | CO10 | No | N/A | N/A |
| **4** | CO12 | Yes | This research-based project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in it's comprehensive data collection, statistical analysis, diligent methodology development and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges. | **Page no:** [17-22, 27-35] **Section:** [3.2, 4.2, 4.3] |

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