**Reducing Readmissions for Cardiorespiratory Diseases through Early Detection using Patient Respiratory Sounds**

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Declaration and Approval

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the research proposal contains no material previously published or written by another person except where due reference is made in the research proposal itself.

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Abstract

Recently, cardiorespiratory diseases have become an escalating health issue worldwide. The increase in these diseases has been brought about by exposure to pollutants such as airborne particulate matter. Patients with cardiorespiratory diseases tend to exhibit ARS such as crackles and wheezes, which are used as a basis for diagnosis of such diseases. Misdiagnoses by inexperienced clinicians almost always result in patient readmissions and in some cases pose a threat to patients’ lives.

One of the leading causes of readmissions worldwide is the misdiagnosis of diseases, especially for diseases related to respiration. They result in a significant burden on medical facilities in terms of increased cost and mortality rates. To overcome such limitations, this proposed solution aims at classifying cardiorespiratory diseases based on the severity of ARS heard from respiratory sound recordings. The methodology to be used is design thinking methodology.

The solution will use Mel-spectrograms to visualize the respiratory sounds, which will further be used in disease classification using a CNN model. The level severity of the disease will also be given together with the diagnosis. The solution is focused on complementing the inaccuracies of clinicians’ auscultation, and it may aid in the early diagnosis and reducing hospital readmissions due to symptom exacerbations.

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List of Abbreviations

ANN – Artificial Neural Network

ARS – Adventitious Respiratory Sounds

CNN – Convolutional Neural Network

DFD – Data Flow Diagram

ERD – Entity Relationship Diagram

GOLD – Global Initiative for Chronic Obstructive Lung Disease

KNN – K-Nearest Neighbor

MFCC – Mel Frequency Cepstral Coefficient

SSAD – Structured System Analysis and Design

STFT – Short-Time Fourier Transform

TB – Tuberculosis

WHO – World Health Organization

WPT – Wavelet Packet Transform

# Introduction

## Background Information

Cardiorespiratory diseases are a wide range of serious disorders that affect the heart and lungs. According to WHO, cardiorespiratory diseases are the third leading cause of death worldwide. These diseases cause a significant health and socioeconomic burden on health systems (Gibson et al., 2013). Therefore, in the last decade, significant research efforts have been dedicated to improving early diagnosis and routine monitoring of patients with cardiorespiratory diseases to allow timely interventions(Marques et al., 2014).

The occurrence of readmissions is often an indicator of deficient quality of health services(Ramírez & Herrera, 2019). Readmissions cause a burden on medical facilities in terms of increased cost and mortality rates, therefore efforts by medical experts are made to reduce them(Brunner et al., 2020). One of the leading causes of readmissions is misdiagnosis of diseases(Barzegari et al., 2017), which is preventable when artificial intelligence is introduced to complement medical decisions made during diagnosis.

Patients suffering from cardiorespiratory diseases exhibit ARS as one of the main symptoms. Respiratory sounds play an important role in indicating the respiratory health of an individual. These sounds have been validated as an objective, simple, and noninvasive marker to check the respiratory system(Jácome & Marques, 2015). Adventitious sounds are respiratory sounds superimposed on normal respiratory sounds, which can be discontinuous such as crackles or continuous such as wheezes.

Lung auscultation is an essential part of the respiratory examination and is helpful in diagnosing various disorders. It is heavily reliant on the presence of adventitious sounds produced when breathing(Perna & Tagarelli, 2019). The stethoscope has always been considered an indispensable diagnostic tool especially when it comes to auscultations, but it suffers from limitations that need to be avoided to reduce the number of readmissions due to cardiorespiratory diseases.

There is therefore a need to use a standardized and automated method to detect and classify breathing anomalies. Introducing artificial intelligence to the auscultation process can help with early detection of cardiorespiratory diseases and identify patients in need of emergency treatment(Kim et al., 2021). The proposed solution is focused on detecting the level of severity of the disease so that patients can receive the right treatment, therefore leading to reduced readmissions. At the end, the proposed solution should be able to complement the inaccuracies of clinicians’ auscultations by providing early diagnosis.

## Problem Statement

The conventional auscultation suffers from three main disadvantages. Firstly, it can become a bottleneck when there is a disproportionate number of practitioners compared to the overall population because for each patient, a medical professional is required to give a diagnosis based on adventitious lung sounds. Secondly, there is dissimilarity in the interpretation of the adventitious sounds by different medical professionals(Acharya & Basu, 2020). Lastly, accurate interpretation of respiratory sounds requires a clinician’s considerable expertise, so trainees such as interns and residents sometimes misidentify respiratory sounds(Kim et al., 2021). When patients suffering from cardiorespiratory diseases are misdiagnosed, they are likely to be readmitted due to symptom exacerbations(Brunner et al., 2020).

The proposed solution aims at classifying the respiratory sounds based on the severity of the ARS heard. The output of the model is expected to be a diagnosis and the level of severity the disease is in, using the GOLD standard. The respiratory sound data will be visualized to Mel-Spectrograms, where appropriate features will be selected, then CNN will be used in the classification of cardiorespiratory diseases. Through the output of the model, the number of readmissions is expected to reduce because necessary treatment will be assigned to the patients depending on the severity level of the disease.

## Objectives

### General Objective

To develop a neural network model to be used in the classification of cardiorespiratory diseases based on the severity of ARS.

### Specific Objectives

1. To review the current state of respiratory sound analysis
2. To investigate algorithms used in the detection and classification of adventitious respiratory sounds
3. To review the existing models used in classification of ARS and cardiorespiratory diseases
4. To develop a neural network model to be used in the classification of cardiorespiratory diseases based on the severity of ARS
5. To test and validate the developed neural network model

## Research Questions

1. What is the current state of respiratory sound analysis?
2. What are the some of the algorithms used in the detection and classification of adventitious respiratory sounds?
3. What are the existing models used in the classification of ARS and cardiorespiratory diseases?
4. How will the proposed solution be designed and developed?
5. How will the solution be tested and validated?

## Justification

The detection and classification of ARS and cardiorespiratory diseases is a growing field, with many solutions focused on using deep learning algorithms. (Basu & Rana, 2020) is focused on using a five-layer neural network in classifying the diseases and giving the correct diagnosis while (Acharya & Basu, 2020) introduced patient-specific model tuning to improve the model’s performance. From the existing solutions, patients are still prone to readmissions because the models focus on detection of ARS and disease diagnosis without giving the level of severity of the disease.

The proposed solution is necessary as it will provide both diagnosis and the patient’s level of severity as outputs. The correct treatment will be given to patients depending on their disease’s level of severity, therefore guaranteeing a reduction in hospital readmissions due to misdiagnosis and symptom exacerbations.

## Scope and Delimitations

### Scope

The proposed study is to focus on identifying adventitious sounds from the respiratory sound dataset and classifying the sounds to the corresponding disease. The classification will be done based on the severity of the ARS. This will help during treatment because appropriate treatment will be given depending on the level of severity of the disease.

### Delimitations

The study does not cover solving readmissions due to regular checkup and due to other diseases other than previous diagnosis during index hospitalizations. Effects of medications on the diagnosis of diseases will also not be covered in this study.

## Limitations

A patient’s diagnosis if often affected by diseases occurring together, this will affect the accuracy of the model in cases where there is an occurrence of two diseases. The dataset is only limited to 126 patients, with 920 recording thus will not give an accurate overview of the different levels of exacerbations during training of the model. The study is also limited to the number of cardiorespiratory disease data available in the dataset.

# Literature Review

## Introduction

This chapter aims at reviewing the current state of respiratory sound analysis together with the challenges that are currently being faced. Algorithms used in the detection of ARS will be discussed, and the advantages and disadvantages of using those algorithms will also be mentioned. The existing models used in the detection and classification of ARS will also be reviewed. Finally, a brief overview of the conceptual framework will be discussed, with an accompanying diagram.

## A Review on The Current State of Respiratory Sound Analysis

Chest auscultations are an inexpensive method used in detection of breathing anomalies. Auscultation provides direct information on lung function because pathological abnormalities in the lungs produce distinct sounds(Kandaswamy et al., 2004). The conventional auscultation method of using a stethoscope has many limitations, subjectivity of the physician during diagnosis being the main limitation(Acharya & Basu, 2020).

Previous studies(Pramono et al., 2017) have inclusively discussed other limitations of the conventional lung auscultation. These limitations include the need for the presence of an expert during auscultations, which can be limiting when an emergency auscultation needs to be performed. Auscultations also need to be performed in a quiet environment, with the patient being in a still position. Finally, the human auditory system is also a limitation when using the stethoscope for auscultations. These limitations therefore led to the development of computerized lung sound analysis.

Computerized lung sound analysis entails using an electronic equipment to record the patient's lung sounds, followed by computer analysis and classification of the sounds based on certain signal characteristics(Gurung et al., 2011). Computerized systems for recording and analyzing lung sounds have overcome many of the limitations of simple auscultation over the last 30 years(Kandaswamy et al., 2004). This can be seen clearly by the advantages offered by this system.

Automated respiratory sound classification has the ability to detect anomalies in the early stages of respiratory dysfunction, therefore improving effectiveness of decision-making(Rocha et al., 2018). Another advantage is that the use of computers to research lung sounds has numerous advantages in terms of sound storage, processing, and visualization of respiratory sounds in computers(Rocha et al., 2020). The use of electronic stethoscope in analyzing lung sounds also offers the advantages of volume adjustment, reduction of heart sounds, recording and transmitting wirelessly to a computer.

### Challenges Experienced in The Detection of ARS Using Computerized Lung Sound Analysis

Even though the computerized lung sound analysis offers many advantages, it still suffers from challenges affecting its performance. One of the limitations of using lung recordings is the presence of ambient noise in the recordings(Emmanouilidou et al., 2018). Without filtering the noise, it will be hard to detect the adventitious sounds.

Another important issue discussed by Khan (2012), is the lack of vastness in the data used in the computerized lung sound analysis systems. Only a few researchers used data from hospitals, while the majority used data from lung sound CDs that were used to train doctors and nurses. This can be limiting because machine learning models require larger datasets for training the model.

## Algorithms That Support the Automatic Adventitious Respiratory Sound Analysis

There are many algorithms used in the classification of cardiorespiratory diseases, but only 2 are the most used. The most used algorithms are ANN and KNN algorithms because of their performance(Palaniappan et al., 2013). Other uncommonly used algorithms include Support Vector Machine, Gaussian Mixture, Random Forest, Hidden Markov, Logistic Regression, Edge Detection on Spectrogram Image and finally Discriminant Analysis(Pramono et al., 2017).

### Artificial Neural Network

The goal of Artificial Neural Networks is to imitate the behavior of biological neural networks. The study on (Tocchetto et al., 2014) used wavelet packet transform in signal processing for feature extraction. The features were then fed into the ANN for classification into three categories, one normal and two pathological. An accuracy of 98.89% for Symlet-10 wavelet base on the test set was achieved. An advantage of ANN is it can adapt well to complex non-linear data and classifying it accurately and effectively.

### K-Nearest Neighbor

The work on (Abdullah et al., 2017) first filtered the audio files using a band pass filter, then used entropy as the suitable feature. These features were fed into a KNN classifier with a k-value of 9 and this reported an accuracy of 89.33% for non-smokers and 78.67% for smokers. The advantages of KNN include its simplicity and robustness. It can also distinguish between normal and abnormal respiratory sounds.

Despite the advantages provided by using ANN and KNN classifiers, they still suffer from the disadvantage of a computational burden caused by training the model. The requirement for a very large dataset to train the model to accurately recognize lung sounds is also another disadvantage(Palaniappan et al., 2013).

## Existing Models Used in The Identification and Classification of Cardiorespiratory Diseases

This study will focus on models that used ANN and KNN in the classification process of adventitious respiratory sounds. The study on (Pramono et al., 2017) gives a summary of existing models used in the automatic adventitious respiratory sound analysis. These models include:

### An Embedded Classifier of Lung Sounds Based on The Wavelet Packet Transform And ANN

In this study(Tocchetto et al., 2014), a total of 92 lung sounds were recorded, including 27 normal, 31 crackles, and 34 wheezes. As part of the training process, 60 sounds were used to train the ANN, 7 for testing and 7 for validation. The remaining 18 sounds in the database were used to evaluate the trained ANN's performance. A WPT was used to decompose lung sound signals into frequency sub-bands, and a set of statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients. The features were fed into an ANN which classified respiratory sounds into three categories: normal, wheezes and crackles. The classifier achieved a best average accuracy of 98.89% for Symlet-10 wavelet base on the test set.

The gap in this model is that only the events of an ARS was recorded, and the diagnosis of a potential cardiorespiratory disease was not given. Due to this, patients are likely to go back to hospitals due to symptom exacerbations of a particular disease for example asthma.

### Analysis of Adventitious Lung Sounds Originating from Pulmonary Tuberculosis

The study in (Becker et al., 2013) tried to demonstrate the value of computer-aided auscultation in the diagnosis and treatment of tuberculosis. Respiratory sounds were recorded from 14 different locations on the posterior and anterior chest walls of 60 healthy volunteers and pulmonary tuberculosis patients. The statistical overlap factor was used to identify the most significant signal features associated with the presence of TB in both the time and frequency domains. These features were then used to train a neural network to automatically categorize the auscultation recordings as healthy or TB-origin. The neural network had a diagnostic accuracy of 73%.

Despite the advantage of giving the diagnosis of TB patients, the model’s accuracy could be improved by filtering out the noise from the clinics and using more training samples.

### Classification of Lung Sounds Using Convolutional Neural Networks

The study in (Aykanat et al., 2017), a total of 17,930 lung sounds from 1630 subjects were recorded. MFCC features in a support vector machine was used to benchmark using spectrogram images in the CNN. To classify respiratory audio, CNN and SVM algorithms were used in the following ways: healthy versus pathological classification achieved an accuracy of CNN 86%, SVM 86%. Rale, rhonchus, and normal sound classification achieved an accuracy of CNN 76%, SVM 75%, singular respiratory sound type classification achieved CNN 80 %, SVM 80% accuracies and audio type classification with all sound types achieved CNN 62%, SVM 62% accuracies. From the results, they found out that the CNN algorithm for spectrogram image classification works just as well as the SVM algorithm.

Despite the good accuracies achieved, the model was only focused on classifying respiratory sounds to either be normal or adventitious. Disease diagnosis was not given, together with the level of exacerbation the patient might be in. This model is still susceptible to readmissions due to symptom exacerbations.

## Conceptual Framework

The solution aims at working in the following way: Physicians will record respiratory sounds using electronic stethoscopes. These recordings are stored in a database which will be accessed using the model. The dataset will be split into training and testing dataset using cross validation method. The audio files will be filtered to remove any ambient noise using a band pass filter, then be converted to Mel Spectrograms, which will be used for feature extraction. Finally, from the features extracted, CNN algorithm will be used in classification of the respiratory sounds. This framework can be seen in Figure 2.1

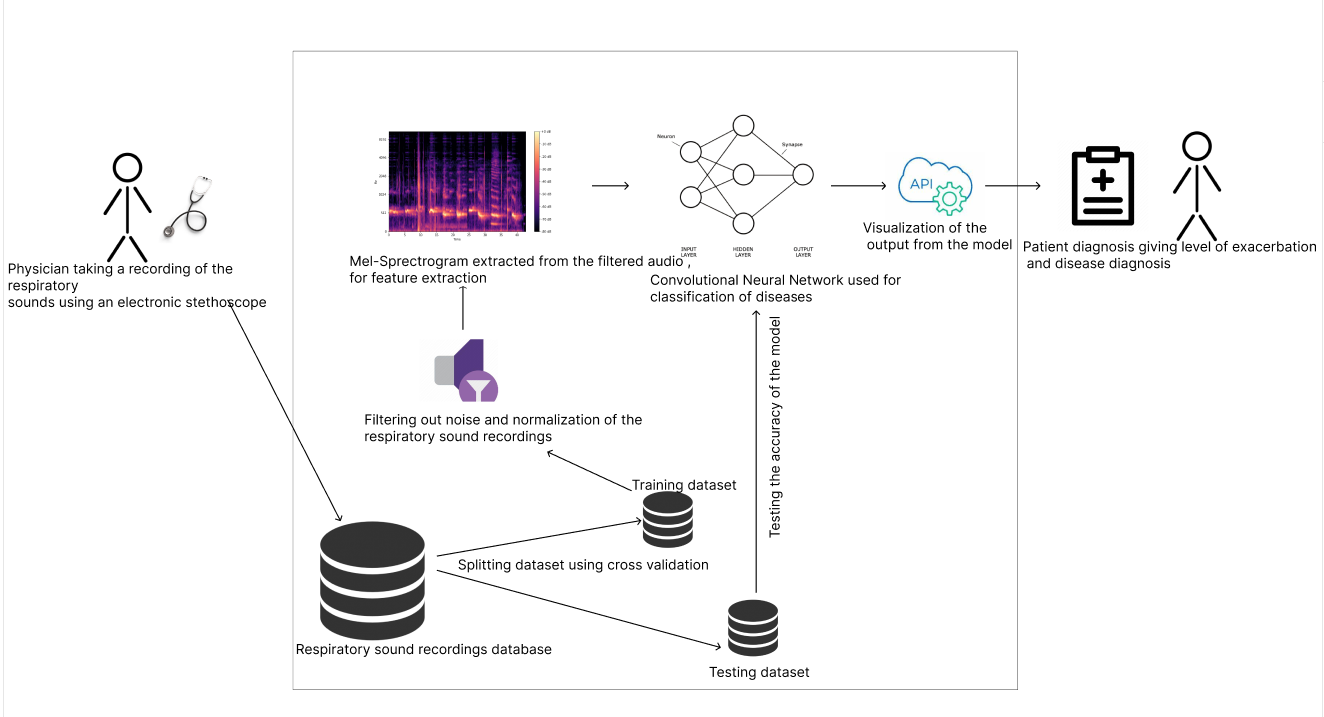


Figure . Conceptual Framework

# Methodology

## Introduction

This chapter talks about the methodology that has been selected for the proposed solution. The chapter also explains the steps followed in the methodology and how they will be applied in the solution together with the approach to be used for design and development. The methodology selected for the solution is design thinking methodology.

## Applied Methodology

The methodology selected is Design Thinking methodology. Design thinking methodology is an innovative problem-solving process that helps companies to come up with a desired outcome on a specific problem (Steinke et al., 2017). The reason for selecting this methodology is because it is an iterative process hence allowing one to go back to a previous step in case of any needed changes and because it will help in coming up with innovative solutions to get the desired outcome. The diagram for the methodology is shown in Figure 3.1

Diagram

Description automatically generated

Figure . Design thinking methodology (Adopted from(Steinke et al., 2017))

### Empathize

This is the process of getting a better understanding of the problem that is to be solved. The goal of this phase is to collect requirements by better understanding the users' experiences.

#### Researching User Needs

This phase will be focused on gaining insight into users and their needs. Medical documents and research papers will be analyzed to discover opportunities to meet new user needs that are lacking in existing cardiorespiratory diagnosis systems. This will help get a better understanding of the problem that is to be solved.

### Define

In this stage, all the information gained through the empathize stage are put together to bring focus to the parameters of the issue. The goal of this phase is to conclude with a requirement statement that clearly defines the scope and parameters of the problems. The data collected from secondary documents will be analyzed and organized to better concrete the problems defined. This will help gather great ideas and in understanding how to use them effectively.

### Ideate

This phase consists of generating different possibilities that could be potential solutions to previously defined problems, or at least a portion of a solution to the proposed challenge. Different solutions to the problem will be generated through brainstorming and this will allow for more innovative solutions to normalized problems. A system analysis of the proposed solution will also be done in this stage as seen in section 3.3.

### Prototype

This is an experimental phase. It enables teams to identify flaws in their design thinking process while also allowing them to iterate on their product. An inexpensive product with specific features will be created in this phase. The aim is to identify the best possible solution for the problem found.

### Test

The prototype created in the previous phase is tested in this step to see how well it solved the problems that were initially analyzed in stages one and two. Alterations and refinements will be made to make the product more polished for user needs. With this process, it will allow going back to previous stages and revise the information to get the best outcomes from the model. The testing paradigms that will be used are unit and integration testing.

1. **Unit Testing**

The different modules of the model will be tested independently, using glass-box mechanism. This is important as it will check if the modules are meeting the requirements set in the initial stages of development.

1. **Integration Testing**

Keras will be used to evaluate the performance of the model. This will be done by creating a plot of expected results against the results produced by the model.

## System Analysis

### Approach to Design and Development

The approach to be used in the proposed solution is SSAD which is process-oriented and based on the structured top-down decomposition of a system(Karaca, 2012). The focus of this approach is on the process and procedures of the system for example filtering out noise from the audio recordings. The reason for selecting this approach is because it consists of methods that represent how data and the related processes moves through an information system(Karaca, 2012)

The purpose of the systems analysis phase is to build a logical model of the new system. The analysis tool that will be used to draw the diagrams is Visual Paradigm.

### Use-Case Diagram

A use case describes the steps in a specific business function or process. It shows the interaction of things outside the system with the system itself. The various processes within the solution will be modelled for example filtering put noise form the audio data. This model will help in identifying actors in a specific use-case and the functions they will perform on the system.

### Sequence Diagram

A sequence diagram shows the interaction among objects during a specified time. The elements participating in a sequence diagram are objects. The messages exchanged by these elements are method invocations. The sequence diagram will be modelled to show various methods of a given class within the system. This diagram will help visualize the interactions between different objects of the system.

### System Sequence Diagram

A system sequence diagram is a dynamic model of a use case, showing the interaction among processes during a specified time. A system sequence diagram graphically documents the use case by showing the processes, the messages, and the timing of the messages. This diagram will be drawn to visualize how the actors of the system interact among each other and the system itself.

### Entity Relationship Diagram

An ERD is a model that shows the logical relationships and interaction among system entities. This will be drawn to provide an overall view of the system, the entities, their attributes, and relationships between the system entities and the system itself.

### Context Diagram

A context diagram is a top-level view of an information system that shows the system’s boundaries and scope. The context diagram contains process 0, which represents the entire information system, but does not show the internal workings. This will be drawn to show the interaction between the system and its entities, and how data flows between them.

### Data Flow Diagram

#### DFD Level 0

A level 0 DFD zooms in on the system and shows major internal processes, data flows, and data stores. This will be drawn to visualize how the data will flow between different processes and the storage of the data for example how filtered audio will be stored in the system before feature extraction.

#### DFD Level 1

A level 1 DFD zooms in on the system even more to show the most primitive processes, data flows and data stores. This will be drawn to visualize how data will flow in the most primitive processes such as splitting the dataset into two.

## System Design

### System Architecture

System architecture translates the logical design of an information system into a physical structure that includes hardware, software, network support, processing methods, and security. This will give a brief overview of the proposed system, therefore will be used to envision all components and their interaction with the system.

## Tools and Techniques Used

### Python

The programming language that will be used to develop the proposed solution is python, which is high-level and best suited for machine learning projects. Libraries within python that will be used include:

1. **Librosa**

This is a python package for audio and music analysis. It will be used for feature extraction from the audio data.

1. **Matplotlib**

This is a library used to create static, animated and interactive visualizations in python. It will be used for data visualization of the Mel spectrograms.

1. **Keras**

This python library provides an interface for artificial neural networks This library will be used to construct the CNN model, with TensorFlow in the backend.

### Kaggle

The dataset to be used to train and test the model will be retrieved from Kaggle. The dataset will be split using k-fold cross validation for training and testing, in order to increase the size of the dataset.

### GitHub

This online collaboration tool will be used to store the code and act as a backup in case of any system failures in the future.

## System Deliverables and Milestones

### Concept Defense

The concept note is a summary of the general idea of the product to be developed. The presentation will be prepared, and the idea presented before a panel for approval.

### Proposal Document

A System Proposal is a document which is presented to get project approved. This document will be needed because it defines the objectives of the solution as well as the steps to be followed during development.

### Analysis and Design Diagrams Document

This is the document that contains all diagrams of the system design and architecture of the approach chosen. The diagrams will be drawn to visualize the whole system and its processes.

### Working Prototype

1. **Split Dataset**

In this module, the dataset will be split into two; one for testing and one for training the model. This splitting will be done by performing k-fold cross validation of the dataset.

1. **Filtered Audio Recordings**

A band pass filter will be used to filter out any noise outside of certain frequencies, this will ensure more accurate results for diagnosis.

1. **Extracted Features**

Mel Spectrograms will be used to extract features from the filtered respiratory sound recordings. These features will be used to train the CNN model to be built.

1. **CNN Model**

A CNN model to be used for classification will be built. Classification will also be based off severity of the ARS from the features extracted.

1. **Patient Diagnosis Module**

In this module, the patient diagnosis will be produced as a product of the trained CNN model. The disease classification together with the severity of the disease is expected, so that the correct treatment will be given to the patient depending on their level of exacerbations.

1. **Model Test Cases**

The system will be tested to verify that all the system objectives are met. The testing paradigms that will be used are unit and integration testing.

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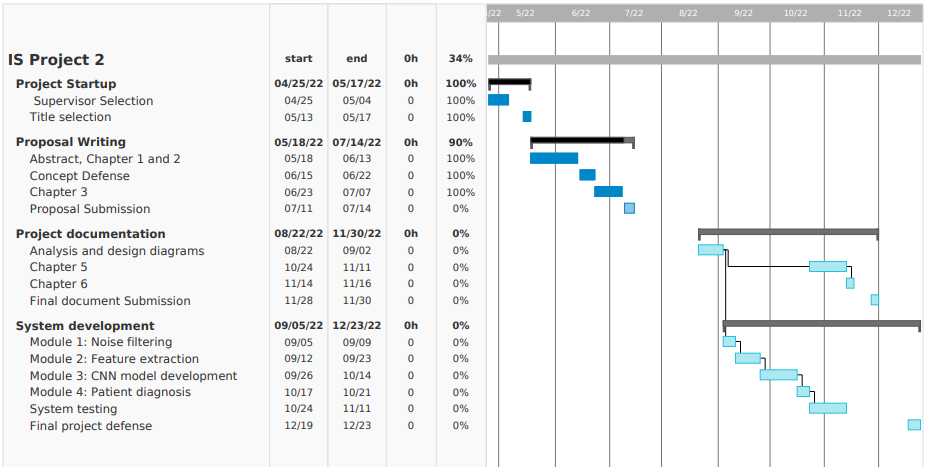
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Appendix

1. Gantt Chart



Appendix Gantt Chart