

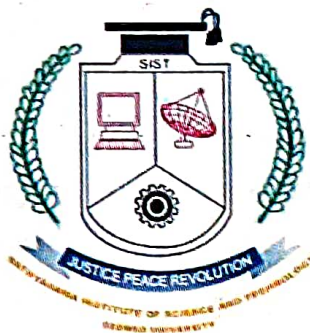
Digital Stethoscope with AI Diagnosis App for Respiratory Ailments

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Technology degree in Biomedical Engineering

By

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**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A++" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Mohammed Thoufeeque. A (40240020), Jeffrey Delaperle. S (40240012)** who have done the project work as a team and carried out the project entitled "**Digital Stethoscope with AI Diagnosis App for Respiratory Ailments**" under our supervision from June 2023 to April 2024.

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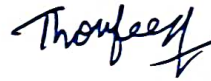
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DECLARATION

We Mohammed Thoufeeq. A (40240020), Jeffrey Delaperle. S (40240012) hereby declare that the Project Report entitled Digital Stethoscope with AI Diagnosis App for Respiratory Ailments done by us under the guidance of Ms. Sindu Divakaran is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.



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ABSTRACT

Auscultation, a non-invasive and real-time method integral to physical examinations, plays a vital role in diagnosing respiratory diseases and providing first aid by detecting abnormal respiratory sounds through a digital stethoscope. However, accurate interpretation of these sounds relies heavily on the clinician's expertise, making it prone to misidentification by trainees like interns and residents. Given the global impact of chronic obstructive pulmonary disease (COPD), responsible for nearly a million deaths annually, especially in low- and middle-income countries where access to healthcare and medical devices is limited, the significance of accurate auscultation becomes even more apparent. Our project will provide two essential components: a compact, mobile case-based stethoscope and an AI diagnosis app integrated with a highly accurate deep learning algorithm. This combination aims to classify and detect respiratory health status and ailments effectively. By merging portable hardware with advanced software, we offer a comprehensive solution for early diagnosis, treatment assessment, and ongoing monitoring of respiratory conditions.

Keywords - Auscultation, AI Diagnosis, COPD, Deep Learning, Digital Stethoscope, Respiratory Sound Classification

CONTENTS

CHAPTER	TITLE	PAGE NUMBER
	ABSTRACT	i
	LIST OF ABBREVIATIONS	iv
	LIST OF FIGURES	v
	LIST OF TABLES	vi
1	INTRODUCTION	1
2	LITERATURE SURVEY	4
3	AIM AND SCOPE	10
	3.1 SCOPE	11
4	MATERIALS AND METHODS	12
	4.1 HARDWARE REQUIREMENTS	12
	4.1.1 Traditional Stethoscope	12
	4.1.2 Electret Microphone	13
	4.1.3 Android-Based Smartphone with Case	13
	4.1.4 Components Assembly	14
	4.2 SOFTWARE REQUIREMENTS	14
	4.2.1 Visual Studio Code	14
	4.2.2 Python	15
	4.2.3 Android Studio	15
	4.2.4 Stream-lit	15
	4.2.5 Libraries	16
	4.3 ALGORITHMS USED	16

CHAPTER	TITLE	PAGE NUMBER
	4.3.1 Artificial Neural Network	16
	4.3.2 Convolutional Neural Network	17
	4.3.3 Mel-Frequency Cepstral Coefficients	17
	4.4 WORK FLOW	18
	4.5 SOFTWARE DEVELOPMENT	19
	4.5.1 Audio Acquisition	20
	4.5.2 Pre-Processing	20
	4.5.3 Creating Environment	20
	4.5.4 Feature Extraction	21
	4.5.5 Training Model	21
	4.5.6 Testing Model	22
	4.5.7 Developing Web Application	22
5	RESULTS AND DISCUSSIONS, PERFORMANCE ANALYSIS	23
	5.1 HARDWARE OUTCOME	23
	5.2 COMPARATIVE ANALYSIS OF MODELS	25
	5.3 ANN MODEL FEATURES	26
	5.4 APPLICATION INTERFACE	27
6	SUMMARY AND CONCLUSIONS	29
	REFERENCES	30

LIST OF ABBREVIATIONS

ABBREVIATIONS	DEFINITIONS
ANN	Artificial Neural Network
BiLSTM	Bidirectional Long Short-Term Memory
CNN	Convolutud Neural Network
COPD	Chronic Obstructive Pulmonary Disorder
FPGA	Field Programmable Gate Array
GUI	Graphical User Interface
IDE	Integrated Development Environment
LSTM	Long Short-Term Memory
MFC	Mel Frequency Cepstrum
MFCC	Mel-Frequency Cepstral Coefficients
PASCAL	Programming Language for Algorithms and Structure
PCA	Principal Component Analysis
ROC	Receiver Operating Characteristics
SK LEARN	Scikit-Learn
VS	Visual Studio
XSG	Xilinx System Generator

LIST OF FIGURES

FIGURE NUMBER	TITLE	PAGE NUMBER
4.1	Traditional Stethoscope	12
4.2	Electret Microphone	13
4.3	Phone Case	13
4.4	MFCC Flowchart	18
4.5	Work Flow	18
5.1	Orthogonal Views of The Hardware	23
5.2	ANN Model Overview	26
5.3	Application GUI	27

LIST OF TABLES

TABLE NUMBER	TITLE	PAGE NUMBER
5.1	Classification Report for Different Models	25

CHAPTER – 1

INTRODUCTION

In the realm of healthcare, the art of chest auscultation, the practice of listening to internal sounds within the chest, stands as a venerable diagnostic tradition. Since its inception in 1816 by Dr. Laënnec, the stethoscope has been an indispensable tool for medical professionals, allowing them to delve into the intricate symphony of sounds emanating from the heart, lungs, and intestines. Its enduring popularity is rooted in its non-invasive nature, real-time information delivery, affordability, and user-friendly design (Yoonjoo Kim et.al., 2022). Over centuries, the traditional stethoscope has served as a linchpin in the clinical arsenal, guiding healthcare practitioners in their diagnostic decisions and treatment strategies. However, this longstanding tradition is not without its challenges.

Central to the complexities of chest auscultation is the inherently subjective nature of sound identification and interpretation. Different healthcare professionals often classify lung sounds in varying ways, leading to disparities in diagnoses and variable reliability in patient assessments. This subjectivity poses a significant hurdle, giving rise to disagreements and potential misdiagnoses. Furthermore, the lack of a standardized method to easily share auscultatory sounds exacerbates the problem. Traditional stethoscopes, designed primarily for individual listening, fail to support collective hearing, a limitation that can lead to repetitive examinations for patients with unusual sounds. the sound clarity often suffers from excessive noise or insufficient amplification, partly due to the intricate patterns and characteristics of the sounds. Consequently, physicians must invest considerable time and effort in manually detecting conditions using a stethoscope accurately (Zeenat Tariq et.al., 2022). Lung auscultation's limited sensitivity across various clinical settings and patient groups diminishes its clinical effectiveness. When more reliable diagnostic methods are accessible, they should supplant lung auscultation (Luca Arts et.al., 2020). Additionally, teaching and training new healthcare professionals in auscultation become arduous tasks due to these limitations, hindering the seamless transfer of skills and knowledge.

Despite these challenges, the landscape of chest auscultation is undergoing a profound transformation, propelled by the relentless march of technological innovation. The advent of digital stethoscopes has ushered in a new era, promising solutions to the longstanding predicaments of traditional auscultation methods. Due to recent advancements in electronic technology, the digital stethoscope is gaining popularity day by day (Chowdhury et.al., 2019). These digital marvels can do more than merely listen; they can capture, store, and analyze sounds with remarkable precision. Respiratory sound analysis has emerged as a rapidly growing research area of interest. It holds the promise of automatically detecting abnormalities in the early stages of lung dysfunction (Luca Brunese et.al., 2022). One of the groundbreaking features of these digital stethoscopes is their ability to generate spectrograms, intricate visual representations of sound frequencies over time. Spectrograms, particularly, have emerged as beacons of hope in the quest to identify adventitious lung sounds, such as wheezes and crackles, with unparalleled accuracy. Analyzing lung sounds spectrograms offers a more precise prognosis for identifying respiratory abnormalities, as they directly correlate with structural defects of the lungs. Pathological respiratory sounds such as wheezing and crackles result from bronchial degeneration and loss of lung elasticity (Altan et.al., 2020). Chronic obstructive pulmonary disease (COPD) is a lung condition characterized by irreversible airflow limitation, ranking among the primary contributors to global morbidity and mortality (Ahmed et.al., 2020). The digital stethoscope achieves high accuracy detection of COPD using deep learning models and spectrograms (MFCCs) (Arpan Srivastava et.al., 2021).

The advent of digital stethoscopes enables the capture and digital storage of lung sounds, offering numerous opportunities for analysis and sharing. Spectrograms generated from these recordings visually represent the frequency spectrum over time, aiding in the identification of adventitious lung sounds like wheezes and crackles, which exhibit distinct patterns (Aviles-Solis et.al., 2020).

The integration of visual support, especially spectrograms, marks a significant leap forward in the field of chest auscultation. By providing an additional sensory input, these visual representations enhance the classification of lung sounds, minimizing the ambiguities associated with subjective interpretations. In the realm of education, this visual aid serves as a powerful tool, offering aspiring

healthcare professionals a tangible and standardized reference point, thereby elevating the quality of training.

Moreover, digital stethoscopes equipped with digital recording capabilities have paved the way for remote monitoring and telemedicine, transcending the constraints of geographical distances (Jun jie Seah et.al., 2023). Mobile applications, seamlessly integrated with these digital wonders, now empower patients to record their own heart and lung sounds in the comfort of their homes. This revolutionary development not only promotes patient engagement but also democratizes healthcare, enabling individuals to actively participate in their diagnostic journey. By bridging the gap between medical professionals and patients, these applications foster a collaborative approach to healthcare, encouraging dialogue and shared decision-making.

However, amid these transformative advancements, challenges persist, demanding the collective ingenuity of healthcare professionals, researchers, and technology developers. Standardizing sound classification remains a paramount concern. Additionally, ensuring the quality of recordings is essential to maintain the integrity of diagnostic data, requiring rigorous quality control measures and continuous advancements in recording technology.

In the ever-evolving landscape of healthcare, the stethoscope, now digitized and enhanced, stands as a testament to the enduring spirit of innovation. Its transformation from a simple listening device to a sophisticated tool integrating auditory and visual cues mirrors the progress of modern medicine (Valerie Rennoll et.al., 2021). Developing a low-cost digital stethoscope is imperative for ensuring better healthcare access, particularly in the developing world, where the current average price of \$500 renders them unaffordable for many health workers (Elhilali et.al., 2019). As chest auscultation embraces these digital advancements, it not only preserves its historical significance but also propels itself into a future where accuracy, accessibility, and patient-centric care converge. Through collaborative endeavors, the challenges that once hindered the full potential of chest auscultation are gradually giving way to a new era, where technology empowers healthcare professionals, engages patients, and ensures that the heartbeat of healthcare resonates with precision and compassion.

CHAPTER – 2

LITERATURE SURVEY

Muhammad E.H. Chowdhury et.al. (2019) introduced a groundbreaking system designed for real-time monitoring of heart diseases. The research team developed a smart stethoscope capable of continuously capturing heart sounds and integrating digital technology for analysis. The system likely incorporates algorithms and sensors to provide early detection and diagnosis of heart-related conditions. This innovative approach aims to improve patient care by allowing healthcare professionals to monitor patients remotely and make timely interventions.

Jun Jie Seah et.al. (2023), published an extensive review of the latest advancements in stethoscope technology is conducted. The paper delves into various types of stethoscopes used in chest auscultation, highlighting their applications and innovations. It likely covers topics such as electronic stethoscopes, acoustic enhancements, and emerging technologies, offering valuable insights for healthcare practitioners seeking to stay updated with the evolving landscape of diagnostic tools.

Sung Hoon Lee et.al. (2022) presented a significant development in healthcare technology with their paper. They described the creation of a fully portable and soft wearable stethoscope capable of continuous real-time auscultation. This innovation is designed for automated disease diagnosis, combining engineering expertise, sensor technology, and advanced algorithms. Such a device holds the potential to revolutionize patient monitoring and diagnosis, making healthcare more accessible and efficient.

Ali Mohammad Alqudah et.al. (2022) explored the application of deep learning models to detect respiratory pathologies from raw lung auscultation sounds. Their research likely details the development and training of neural networks and machine learning techniques for automating the diagnosis of various lung-related conditions. This approach has the potential to significantly enhance the accuracy and speed of diagnosing respiratory ailments, improving patient outcomes.

Luca Brunese et.al. (2022) introduced a neural network-based method for analyzing respiratory sounds and detecting lung diseases in their paper. The study

is likely to provide insights into the architecture of the neural network, data preprocessing techniques, and the accuracy achieved in lung disease detection. This approach offers a promising avenue for non-invasive and efficient diagnosis of lung conditions, contributing to early intervention and improved patient-care.

Ahmed J et.al. (2020) reviewed a CNN-based deep learning model utilizing Librosa features was proposed to assist in COPD detection through respiratory sounds. "MFCC" demonstrated superior accuracy. Future enhancements could include detecting heart conditions and asthma, assessing disease severity, employing data augmentation techniques, and integrating with a Breath Monitoring System for improved COPD detection. Ensuring system security and privacy preservation are vital considerations.

Luca Arts et.al. (2020) conducted a comprehensive meta-analysis to evaluate the diagnostic accuracy of lung auscultation in adult patients with acute pulmonary pathologies. This research paper likely compiles and critically analyzes existing studies to determine the reliability and effectiveness of auscultation as a diagnostic tool. The findings of this meta-analysis can guide healthcare professionals in the clinical assessment of patients with acute lung conditions.

Yoonjoo Kim et.al. (2021) presented a study that applies deep learning techniques to classify respiratory sounds, including crackles, wheezes, and rhonchi, in clinical settings. Their research likely delves into the architecture and training of deep learning models, addressing the challenges of identifying specific respiratory pathologies. This approach has the potential to streamline the diagnostic process and enhance the accuracy of respiratory condition identification in a clinical environment.

J. C. Aviles-Solis et.al. (2020) explored the use of spectrograms in an educational context in their paper. Spectrograms, visual representations of sound frequencies over time, are investigated to enhance the classification of wheezes and crackles. This research likely discusses how this visual approach can improve the teaching and learning of auscultation skills, benefiting healthcare professionals and medical students in their education and training.

Mohammed Bahoura et.al. (2020) focused on a technique called MFCC, which stands for Mel-frequency cepstral coefficient. MFCC is a method widely used

in various fields, including speech and speaker recognition, music genre classification, and now, in this study, for analyzing respiratory sounds. Specifically, the researchers aimed to implement MFCC on FPGA (Field Programmable Gate Array) hardware for real-time analysis of respiratory sounds. The novelty of this study lies in its hardware implementation using Xilinx System Generator (XSG), which is a tool used with FPGAs. The researchers compared the performance of the FPGA-based implementation with a traditional software-based one in MATLAB and found that they produced similar results.

Arpan Srivastava et.al. (2021) aimed to develop a deep learning-based model for the detection of Chronic Obstructive Pulmonary Disease (COPD) using respiratory sound recordings. They assembled a diverse dataset containing recordings from healthy individuals and those with various respiratory conditions. The data underwent preprocessing to ensure consistency, and essential audio features like Mel-Frequency Cepstral Coefficients (MFCCs), Mel-Spectrograms, and Chromagrams were extracted to capture sound characteristics. The model's evaluation demonstrated that MFCCs excelled in COPD detection, showing improvements in sensitivity post-augmentation. Future work could extend this approach to detect other diseases and enhance security and privacy measures while integrating it with health monitoring systems.

Devang Sharma et.al. (2020) presented a mobile system for preliminary cardiovascular disease screening, particularly the detection of heart murmurs, aimed at rural areas. The study employs a cost-effective digital stethoscope and a Convolutional Neural Network (CNN) model trained on open-source heart sound datasets. Experiments were conducted using various datasets, including the University of Michigan, PASCAL, and PhysioNet. The combined PASCAL datasets achieved a high validation accuracy of 97.14%. While the PhysioNet dataset yielded a validation accuracy of 79.83%, the real-life heart sounds collected by their stethoscope demonstrated the system's practicality. The system's cost-effectiveness and versatility make it a valuable tool for early disease detection in underserved regions.

Batyrkhan Omarov et.al. (2021) presented a novel electronic stethoscope integrated with machine learning techniques for real-time detection of heart

abnormalities. This device utilizes a smartphone application, an electronic stethoscope, and machine learning algorithms to classify heart sounds and diagnose patients efficiently. The system demonstrated impressive results with a 93.5% accuracy in detecting normal heartbeats and a 93.25% accuracy in identifying abnormal heartbeats. This technology holds promise for rapid, cost-effective, and non-invasive screening for cardiovascular conditions, enabling timely intervention and reducing the need for more complex and expensive diagnostic procedures. The proposed system has the potential to greatly benefit both healthcare professionals and patients, particularly in remote or underserved areas, by providing early detection of heart-related issues.

Altan G et.al. (2019) discussed data collection techniques, challenges, and preprocessing steps in machine learning. It emphasizes the importance of acquiring reliable datasets and preprocessing methods such as handling missing values, encoding categorical data, and feature scaling. The text also outlines related works on detecting respiratory diseases using machine learning techniques, proposing a less resource-intensive deep learning model for diagnosing respiratory condition.

M. Elhilali et.al. (2019) did a study which introduces a computerized phonocardiogram, utilizing an electronic stethoscope with machine learning techniques to detect heart abnormalities in real time. This system reduces unnecessary echocardiography, enabling efficient and accurate diagnoses. The technology, while simple, holds potential for further enhancements to detect a broader range of cardiac disorders.

M. N. Türker et.al. (2020) did a study on the Advancements in sound quality, telehealth, and computer-aided auscultations are driving modernization in stethoscope technology. Despite electronic stethoscopes' benefits, their adoption among clinicians is slow due to sound differences. A new method introduces an electronic-to-acoustic stethoscope filter, enhancing similarity between recorded acoustic and electronic lung sounds. Validated by clinicians, this filter facilitates transitioning from acoustic to digital stethoscopes and serves as a training tool to assess auditory distinctions between the devices.

Zeenat Tariq et.al. (2022) designed and implemented the Fusion-based Disease Classification (FDC) framework for detecting heart and lung conditions

using audio data. The FDC framework consisted of five stages: data augmentation to enhance detection accuracy, extraction of three key audio features (Spectrogram, MFCC, and Chromagram), conversion of these features into image format, utilization of three specialized convolutional neural network models (FDA-1, FDA-2, FDA-3), and the creation of a fusion network model (FDA-FS) to optimize learning. They employed data augmentation techniques, including noise distortion, time stretching, and pitch shifting, to enhance dataset quality. The fusion model combined the outputs of these three models to improve disease detection. Their results demonstrated high accuracy in classifying heart and lung conditions, particularly when augmented audio data was used.

B T Balamurali et.al. (2021) conducted a comprehensive study to develop a deep learning-based classifier for distinguishing between healthy and pathological cough sounds in children. They used a dataset of cough sounds, split into training and test sets, ensuring that coughs from the same person were in either the training or test set but not both. The audio data underwent preprocessing, including detrending, normalization, and downsampling. Mel-Frequency Cepstral Coefficients (MFCCs) were extracted as audio features for classification. They trained a Bidirectional Long Short-Term Memory (BiLSTM) neural network model for this purpose. The resulting classifier achieved high accuracy, exceeding 84%, in distinguishing between healthy and pathological coughs. Furthermore, it was able to classify specific respiratory conditions with an accuracy exceeding 91%.

Valerie Rennoll et.al. (2021) aimed to address the differences in sound characteristics between acoustic and electronic stethoscopes, which can be a barrier to the widespread adoption of electronic stethoscopes among clinicians. They developed and validated an electronic-to-acoustic stethoscope filter that could mimic the sound of an acoustic stethoscope using recorded lung sounds. The filter was calculated to equalize the sound characteristics of both types of stethoscopes, making them more similar. A panel of clinicians participated in a listening experiment to assess the effectiveness of the filter in increasing the perceived similarity between acoustic and electronic stethoscope lung sounds.

Yoonjoo Kim et.al. (2022) conducted a study to address the subjectivity and variability in human auscultation of respiratory sounds. They explored the

application of machine learning-based AI techniques to accurately analyze respiratory sounds. Several deep learning architectures such as CNN and biLSTM were employed to develop algorithms for recognizing pulmonary diseases from recorded lung sounds. Other methods included optimized S-transform, wavelet signal similarity, and deep belief networks for classification and prediction of respiratory sounds. The researchers also discussed the development of digital stethoscopes, including their capabilities and potential in aiding automatic respiratory sound analysis. The study emphasized the potential of smart stethoscopes to overcome limitations in traditional auscultation and improve the diagnosis and treatment of respiratory conditions.

CHAPTER – 3

AIM AND SCOPE

The Objective of this project is to develop a cutting-edge digital stethoscope that can be seamlessly integrated mobile phones, enhancing portability and accessibility. The device will employ advanced sensors and signal processing techniques to capture heart and respiratory sounds.

The primary objective of this ambitious project is to pioneer the development of a cutting-edge digital stethoscope capable of seamless integration with mobile phones, thereby revolutionizing traditional auscultation practices. By harnessing the power of advanced sensors and sophisticated signal processing techniques, this innovative device will capture respiratory sounds with unparalleled clarity and accurately discern subtle respiratory abnormalities with precision.

Through meticulous engineering and research, the digital stethoscope will be designed to offer unparalleled portability and accessibility, transforming the way healthcare professionals conduct respiratory assessments. Its integration with mobile phones ensures that healthcare providers can carry this essential diagnostic tool with them wherever they go, facilitating timely and comprehensive patient evaluations even in resource-limited or remote settings.

- To design and develop a user-friendly mobile application for Android platform that integrates a digital stethoscope and AI diagnosis capabilities.
- To incorporate advanced signal processing and machine learning algorithms into the digital stethoscope to ensure accurate analysis of heart and respiratory sounds.
- To create a comprehensive database of heart and respiratory sound and continuously improve their accuracy and diagnostic capabilities.

3.1 SCOPE

The project sets out to revolutionize the conventional methods of auscultation by introducing a groundbreaking solution in the form of a compact digital stethoscope seamlessly integrated into a mobile phone case. This innovative approach not only modernizes the way respiratory abnormalities are detected but also significantly enhances the sensitivity and specificity required for accurate diagnoses. By leveraging advanced sensors, sophisticated signal processing techniques, and cutting-edge machine learning algorithms, the digital stethoscope offers real-time analysis of lung sounds, thereby mitigating the risk of misdiagnosis and enabling timely interventions.

At the heart of this innovation lies the integration of state-of-the-art technology into a device that is ubiquitous and indispensable in today's society – the mobile phone. By embedding the digital stethoscope within a phone case, the project ensures accessibility and convenience for both healthcare professionals and patients. The accompanying mobile application complements the hardware with a user-friendly interface, simplifying the interpretation of lung sounds and streamlining the diagnostic process. This integration of hardware and software creates a synergistic platform that empowers healthcare providers with the tools they need to make accurate assessments swiftly and efficiently.

Moreover, the portability of the device mounted on a phone case addresses a significant limitation of traditional stethoscopes. Patients can now carry the digital stethoscope with them to public places, enabling on-the-go assessments and overcoming the constraints imposed by the bulkiness of conventional instruments. This portability not only enhances patient convenience but also extends the reach of respiratory assessments beyond clinical settings, potentially facilitating earlier detection of abnormalities and timely medical interventions.

CHAPTER – 4

MATERIALS AND METHODS

The proposed methodology involves the use of a digital stethoscope to record respiratory sounds of patients with suspected COPD. The recorded sound will be analyzed using deep learning algorithms to detect characteristic sound patterns that are associated with COPD. The proposed method is cost-effective, non-invasive, and can be easily integrated into routine clinical practice. Accuracy of our model ~96.97 percentage. With large datasets of respiratory audio sounds and spectrogram images, we can train deep neural networks without providing lesion-based features to identify COPD condition in patients who are having increased sensitivity and specificity. The main advantage of using this computerized COPD detection system is uniformity in the model outcomes (as a model predicts the same values always on a specific image), high sensitivity, dynamic results generation and high specificity. Furthermore, as an algorithm may have several operational points, the responsiveness and precision is possible to tailor to fit different clinical conditions criteria, such as high sensitivity for a screening system.

4.1 HARDWARE REQUIREMENTS

4.1.1 Traditional Stethoscope



Fig:4.1 Traditional Stethoscope

The above Figure 4.1 is the heart of our device, a standard acoustic stethoscope used by healthcare professionals to listen to internal sounds of the body, like heartbeats and lung sounds. The vibrations produced by internal organ

sounds are detected by the chest piece of the stethoscope, functioning as a resonator. This component comprises two distinct sides: a flat, disk-shaped diaphragm and a concave cup known as a bell. Each side naturally vibrates within specific frequency ranges, which are utilized for various diagnostic purposes (Turker et.al., 2020). It forms the basis for our innovation. The basic framework of a stethoscope, which typically consists of a chest piece with diaphragm and bell. This will be the physical component used to place on the patient's body to capture the sounds. We've exclusively adopted the chest piece, including the diaphragm and bell, from the device for our project

4.1.2 Electret Microphone



Fig:4.2 Electret Microphone

To convert acoustic sound into digital signals, we incorporate an electret microphone. This crucial electronic component captures sound from the traditional stethoscope and converts it into a digital format for further processing. It is equipped with a 3.5-mm stereo plug as shown in Figure 4.2, which can be connected to audio recording devices or a computer for further analysis and recording of the lung sounds.

4.1.3 Android-Based Smartphone with Case



Fig:4.3 Phone Case

An Android-based smartphone serves as the crucial interface for the digital stethoscope project. It functions as the platform for running specialized software and apps designed for audio data processing and visualization. This smartphone acts as the intermediary connecting the traditional stethoscope to the digital realm, allowing for real-time audio analysis, remote consultations, and data storage. The smartphone case as shown in Figure 4.3 acts as the base that holds the stethoscope so that respiratory sounds can be captured from the patients on the go.

4.1.4 Components Assembly

In the process of constructing a digital stethoscope using a phone case, chest piece, and electret microphone, the initial step involves dismantling a traditional stethoscope to acquire the chest piece. Subsequently, the chosen phone case undergoes modification by carving out a section where the chest piece will be attached securely. The chest piece is then affixed to this designated area on the phone case using adhesive or glue. Following this, the electret condenser microphone, preferably equipped with a 3.5mm jack, is prepared by ensuring its operational functionality and extending its connection with soldered wires. The microphone is then integrated into the smartphone's headphone jack or connected via an adapter if the device lacks this feature. Following the hardware setup, the appropriate web application, tailored for stethoscope functionality and AI diagnosis, is developed and integrated onto the smartphone. After calibration and setup, testing is conducted by positioning the chest piece against a surface or the user's chest, with audio feedback relayed through headphones connected to the smartphone. Final adjustments are then made to refine performance, ensuring secure connections and optimal component positioning.

4.2 SOFTWARE REQUIREMENTS

4.2.1 Visual Studio Code

Visual Studio Code (VS Code) is a free, open-source source code editor developed by Microsoft. It has gained significant popularity among developers for its versatility, extensibility, and lightweight design. VS Code is not to be confused with the full Visual Studio IDE, which is a more comprehensive integrated development environment. Visual Studio Code can be helpful for developing, debugging, and maintaining the software components of the project. It supports various

programming languages (e.g., Python, C++) and extensions that can aid in development. Python, with VS Code, serves as the primary programming environment for developing the classification system.

4.2.2 Python

Python is a high-level, versatile, and dynamically-typed programming language known for its simplicity and readability. It's widely used in web development, data analysis, scientific computing, artificial intelligence, and automation. Python's syntax emphasizes code readability, making it an excellent choice for both beginners and experienced developers. The language supports a broad range of libraries and frameworks, like Django and TensorFlow, enhancing its functionality. Python's versatility is essential for data preprocessing, feature extraction, model development, and result analysis.

4.2.3 Android Studio

Android Studio is a software development environment created by Google for building Android apps. It provides tools for designing, coding, testing, and deploying applications on Android devices. Developers use it to create mobile apps with user interfaces, functionality, and compatibility with the Android operating system. It is crucial for building the Android-based digital stethoscope application, which is the user interface for capturing and analyzing respiratory sounds. Android Studio integrates seamlessly with the Android operating system, enabling access to device features such as the microphone for sound recording and playback via the app.

4.2.4 Stream-lit

Streamlit is widely recognized as a leading platform for constructing and launching data-centric web applications using Python. In the context of the Digital Stethoscope project, Streamlit serves as a powerful tool to harness for crafting an intuitive user interface. This interface is instrumental in presenting the outcomes derived from the classification model, distinguishing between COPD and various respiratory ailments. Through Streamlit's capabilities, users benefit from an interactive experience enriched with features like sliders, dropdown menus, and dynamic charts. Such elements facilitate a seamless exploration and comprehension of the diagnosis, enhancing the overall effectiveness of showcasing the project's findings.

4.2.5 Libraries

- **Librosa:** For audio processing, Librosa is indispensable. It helps us handle and analyze audio data effectively.
- **TensorFlow:** TensorFlow aids in creating and training machine learning models, which are essential for sound classification.
- **NumPy:** NumPy is our go-to library for dealing with arrays, enabling efficient data manipulation.
- **Matplotlib:** This library facilitates graphical representation, crucial for visualizing data and results.
- **Pandas:** Pandas is used to manage and analyze data in .csv files, making data processing more streamlined.
- **Seaborn:** For statistical data visualization, Seaborn is employed to create informative and visually appealing plots.
- **Scikit-Learn (SKLEARN):** SKLEARN provides essential tools for machine learning and statistical modeling, helping us build accurate classification models.

4.3 ALGORITHMS USED

4.3.1 Artificial Neural Network

An Artificial Neural Network (ANN) is a computational model inspired by the human brain's neural structure. It consists of interconnected nodes (neurons) organized into layers. ANNs are designed to learn and recognize patterns in data. During training, they adjust connection weights between neurons to minimize errors. ANNs are widely used for tasks like image and speech recognition, natural language processing, and more.

It uses the processing of the brain as a basis to develop algorithms that can be used to model complex patterns and prediction problems. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives signals then processes them and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some

non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold.

4.3.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs) are deep learning models specifically designed for visual data analysis, such as images and audio. Deep learning models like CNN offers numerous advantages compared to traditional machine learning. It automates feature extraction and provides a more generic approach, overcoming limitations often associated with conventional machine learning methods (Alqudah et.al., 2022). They automatically learn hierarchical representations of features through convolutional and pooling layers. In respiratory sound classification, Convolutional Neural Networks (CNNs) are instrumental due to their capability to automatically learn features from audio spectrograms (Yoonjoo Kim et.al., 2021). CNNs utilize convolutional layers to detect patterns and features at different scales within the spectrogram, enabling accurate classification of respiratory conditions such as COPD or asthma. By processing audio data in a hierarchical manner, CNNs excel in capturing intricate relationships, making them pivotal in diagnosing respiratory ailments through sound analysis (Sung Hoon Lee et.al., 2022).

4.3.3 Mel-Frequency Cepstral Coefficients

Mel-Frequency Cepstral Coefficients (MFCC) is a widely used feature extraction technique in the field of speech and audio processing. It is used to represent the characteristics of audio signals, particularly their spectral properties, in a way that is suitable for various machine learning and signal processing applications. Recently, there has been a proposal to utilize these coefficients for the detection and classification of wheezes in respiratory sounds, offering a promising avenue for further exploration in this area (Bahoura et.al., 2013). The aim of this feature analysis is to investigate whether cough sounds exhibit subtle cues that differentiate between healthy individuals and those with pathological conditions, utilizing MFCCs (Balamurali et.al., 2021).

In sound processing, the Mel-Frequency Cepstrum (MFC) is a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a nonlinear Mel scale of frequency. Mel-frequency cepstral coefficients are coefficients that collectively make up an MFC. They are derived from a type of cepstral representation of the audio clip (a nonlinear "spectrum-of-a-spectrum"). The difference between the Cepstrum and the Mel-Frequency Cepstrum is that in the MFC, the frequency bands are equally spaced on the mel scale, which approximates the human auditory system's response more closely than the linearly-spaced frequency bands used in the normal spectrum. This frequency warping can allow for better representation of sound, for example, in audio compression that might potentially reduce the transmission bandwidth and the storage requirements of audio signals. MFCC are obtained by the following steps as shown in the Figure 4.4

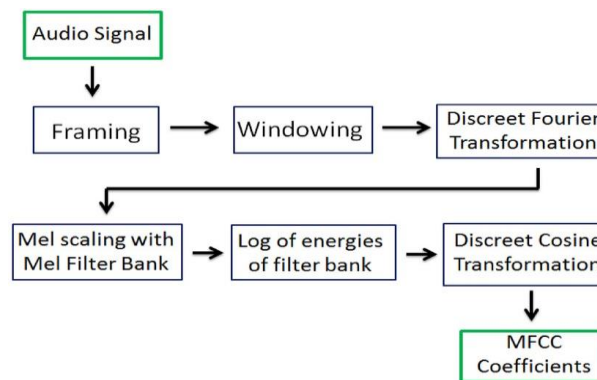


Fig:4.4 MFCC Flowchart

4.4 WORK FLOW

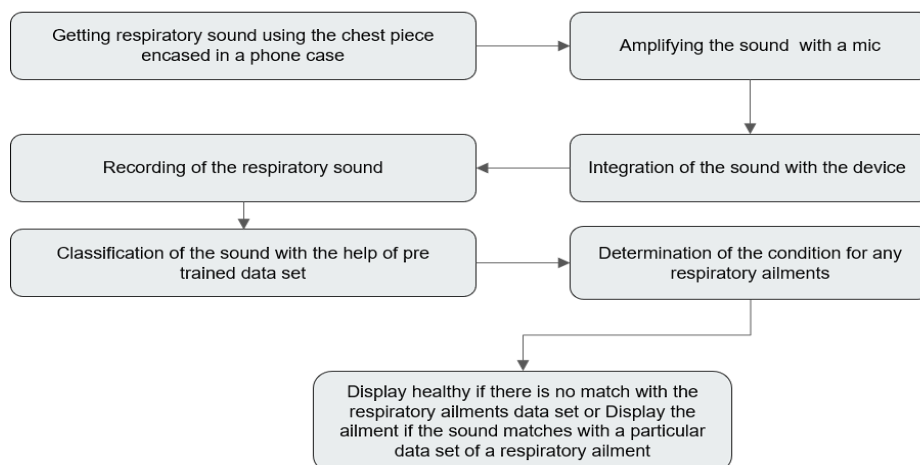


Fig:4.5 Work Flow

The above Figure 4.5 describes the workflow of our project which is elucidated below briefly

- **Respiratory Sound Capture:** Begin by placing the traditional stethoscope's chest piece, which is encased in a phone case, on the patient's body to capture the respiratory sound.
- **Sound Amplification:** Utilize an electret microphone to amplify and convert the acoustic sound into digital signals. This amplification ensures clarity and precision in the recorded sound.
- **Integration with Android-based Device:** Seamlessly integrate the amplified sound into an Android-based device for real-time processing.
- **Respiratory Sound Recording:** Record the captured respiratory sound data to create an audio file for further analysis.
- **Classification using Pre-Trained Dataset:** Employ deep learning models in conjunction with a pre-trained dataset for sound classification. This classification process determines the nature of the respiratory sound, distinguishing between normal and abnormal patterns.
- **Respiratory Ailment Diagnosis:** Based on the classification results, diagnose and determine the presence of respiratory ailments. If the sound matches a specific dataset related to a respiratory ailment, identify the specific ailment.
- **Healthy Status Display:** If no match is found within the respiratory ailments' dataset, display "healthy" to indicate that the patient's respiratory status appears normal.
- **Ailment Display:** In the event that the sound matches a dataset associated with a respiratory ailment, display the corresponding ailment to provide healthcare professionals with valuable diagnostic information.

4.5 SOFTWARE DEVELOPMENT

Developing an AI-based Web Application involves all the below stages

- Audio Acquisition
- Preprocessing
- Creating environment
- Feature Extraction

- Training the model
- Testing the model
- Developing Web Application

4.5.1 Audio Acquisition

- Utilizing the custom-built digital stethoscope, constructed as described earlier, we acquired respiratory sounds for analysis.
- The prepared stethoscope facilitated the recording of high-quality audio data necessary for training and testing our diagnostic models.
- By integrating the stethoscope into the data acquisition process, we ensured consistency and reliability in capturing respiratory sound signals for subsequent analysis.
- This approach enabled us to leverage the digital stethoscope's capabilities to obtain accurate and relevant audio data essential for diagnosing respiratory disorders effectively.

4.5.2 Pre-Processing

- Pre-processing of audio data involves several steps, starting with the extraction of information from CSV and text files.
- Data obtained from different sources, including patient data and CSV files, is combined and organized to ensure comprehensive analysis.
- Visualizations using tools like Seaborn aid in understanding the characteristics of the data, facilitating informed decisions during subsequent processing stages.
- Standardizing the length of audio files to a consistent duration, such as 6 seconds, ensures uniformity and compatibility across the dataset, simplifying analysis and model training.

4.5.3 Creating Environment

- To create a conducive environment for data processing and analysis, it is essential to properly organize and structure audio files.

- Renaming audio files and organizing them into respective folders streamlines the management and retrieval of data during the analysis phase.
- Additionally, editing CSV files to reflect the outcomes of pre-processing tasks ensures that the data is accurately represented and ready for further analysis.
- Installing and importing necessary libraries and dependencies sets up the computational environment required for executing the subsequent steps in the process.

4.5.4 Feature Extraction

- Feature extraction from audio data involves extracting relevant information or characteristics that can be used to distinguish between different respiratory conditions.
- Techniques such as Mel-Frequency Cepstral Coefficients (MFCC) are commonly employed to extract discriminative features from respiratory sound signals.
- These features capture essential aspects of the audio signals, such as frequency components and temporal patterns, which are crucial for training effective machine learning models.

4.5.5 Training Model

- Training machine learning models, including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) networks, is a critical step in the diagnostic process.
- Splitting the dataset into training and testing sets ensures that the model's performance can be properly evaluated and validated on unseen data.
- Using libraries such as TensorFlow for model training provides access to powerful tools and algorithms that streamline the training process and optimize model performance.
- Monitoring metrics such as loss, accuracy, precision, ROC during training allows for iterative refinement of the model architecture and training parameters to improve overall performance.

4.5.6 Testing Model

- After training the model, it is essential to evaluate its performance using independent test data to assess its generalization capabilities.
- Importing audio data and passing it through the trained model enables the generation of predictions for each sample, indicating the presence or absence of respiratory disorders.

4.5.7 Developing Web Application

- The web application allows users to upload audio files for analysis, providing real-time predictions and insights into respiratory health status.
- Integrating the trained model into the web application enables seamless deployment and utilization of state-of-the-art diagnostic tools for respiratory disorders (Devang Sharma et.al., 2020).

CHAPTER – 5

RESULTS AND DISCUSSIONS, PERFORMANCE ANALYSIS

The culmination of our project yields a groundbreaking result in the form of a digital AI stethoscope seamlessly integrated into a phone case, heralding a new era in respiratory assessment technology. This innovative hardware setup represents a paradigm shift in medical diagnostics, offering unparalleled portability, precision, and convenience. Through meticulous engineering and design, the stethoscope attachment embedded within the phone case emerges as a marvel of miniaturization, housing sophisticated microphone and amplifier circuitry meticulously calibrated to capture respiratory sounds with unprecedented fidelity. Placed on the patient's chest region, this attachment, bolstered by the secure mount provided by the phone case, ensures optimal positioning for accurate recordings, setting a new standard for diagnostic accuracy. Moreover, the integration of this hardware setup with smartphones elevates the device's capabilities to unprecedented heights.

5.1 HARDWARE OUTCOME



(a)



(b)

Fig:5.1 Orthogonal Views of The Hardware: (a) Side-View, (b) Top-View

Respiratory sound capture initiates with precise placement of the traditional stethoscope's chest piece, encased within a purpose-built phone case as shown in Figure 5.1, onto the patient's body. This positioning ensures optimal contact for accurate recordings of respiratory sounds from the lungs and airways. Within the chest piece lies an advanced electret microphone, amplifying and converting these acoustic vibrations into crisp digital signals with remarkable sensitivity. This fidelity ensures clarity and precision in the recorded data, vital for accurate diagnosis and monitoring.

Integration with an Android-based device follows seamlessly, leveraging its computational power for real-time processing and analysis. Through this integration, healthcare professionals access recorded respiratory data swiftly, enabling prompt analysis at the point of care. The system's efficiency ensures quick insights into respiratory health, facilitating timely interventions.

Recorded respiratory data is stored within the Android-based device, serving as a valuable resource for longitudinal monitoring and trend analysis. This repository aids in detecting subtle changes in respiratory function over time, optimizing patient outcomes through tailored interventions. Furthermore, it fosters collaboration among healthcare teams, enhancing continuity of care.

Our system also offers robust capabilities for respiratory sound recording, creating high-fidelity audio files for in-depth review and consultation. These files facilitate detailed assessments and ensure seamless continuity of care, fostering collaboration among healthcare professionals. Overall, our approach revolutionizes respiratory assessment, offering unparalleled accuracy, efficiency, and accessibility for optimized patient care.

In summary, our approach to respiratory sound capture and analysis represents a transformative advancement in respiratory assessment technology, offering unparalleled accuracy, efficiency, and accessibility. After completing the hardware aspect of our digital stethoscope, we acquired data from multiple sources, including patients and pre-captured datasets. Subsequently, we developed various models through training and analysis to incorporate them into our product. The analysis of the models is provided on the following page.

5.2 COMPARATIVE ANALYSIS OF MODELS

Table:5.1 Classification Report for Different Models

Models	Classes Predicted	Precision	F1-Score	Accuracy
LSTM	COPD	0.90	0.83	0.81
	Healthy	0.71	0.77	
GRU	COPD	0.82	0.90	0.86
	Healthy	0.98	0.79	
CNN	COPD	0.91	0.94	0.93
	Healthy	0.96	0.90	
ANN	COPD	0.98	0.97	0.96
	Healthy	0.94	0.95	

From the above Table 5.1, comparison of various neural network architectures including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) has been done. It has been determined that Artificial Neural Networks (ANN) consistently exhibit the highest accuracy across different evaluation metrics. Specifically, when analyzing classification results, ANN consistently outperforms other architectures.

Accuracy in deep learning measures the proportion of correctly classified instances out of the total instances, providing an overall assessment of model performance.

Precision quantifies the proportion of true positive predictions among all positive predictions made by the model, focusing on the correctness of positive predictions relative to all predictions labeled as positive.

The F1 score, a harmonic mean of precision and recall, offers a balanced measure of a model's performance by considering both false positives and false negatives, making it particularly useful for imbalanced datasets in deep learning tasks.

The decision to employ ANN as the model of choice for our project is grounded in its ability to effectively capture complex patterns within the data, thus yielding high accuracy in respiratory audio classification tasks.

5.3 ANN MODEL FEATURES

```
Epoch 1/200
1/21 [>.....] - ETA: 14s - loss: 52.8170 - accuracy: 0.3438
Epoch 1: val_loss improved from inf to 6.51822, saving model to saved_models\audio_classification.hdf5
21/21 [=====] - 1s 9ms/step - loss: 30.2085 - accuracy: 0.5145 - val_loss: 6.5182 - val_accuracy: 0.3818
Epoch 2/200
1/21 [>.....] - ETA: 0s - loss: 24.0734 - accuracy: 0.5938
Epoch 2: val_loss improved from 6.51822 to 3.83361, saving model to saved_models\audio_classification.hdf5
21/21 [=====] - 0s 4ms/step - loss: 20.1596 - accuracy: 0.5236 - val_loss: 3.8336 - val_accuracy: 0.3818
Epoch 3/200
1/21 [>.....] - ETA: 0s - loss: 9.2667 - accuracy: 0.5938
Epoch 3: val_loss improved from 3.83361 to 2.66325, saving model to saved_models\audio_classification.hdf5
21/21 [=====] - 0s 4ms/step - loss: 13.1383 - accuracy: 0.5297 - val_loss: 2.6632 - val_accuracy: 0.3818
Epoch 4/200
1/21 [>.....] - ETA: 0s - loss: 10.6746 - accuracy: 0.5625
c:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\engine\training.py:3103: UserWarning: You are saving your model as an HDF5 file. This format is deprecated. We recommend you use the Keras format instead: `model.save('my_model.keras')`
saving_api.save_model(
Epoch 4: val_loss improved from 2.66325 to 0.65215, saving model to saved_models\audio_classification.hdf5
21/21 [=====] - 0s 4ms/step - loss: 11.0825 - accuracy: 0.4992 - val_loss: 0.6522 - val_accuracy: 0.6121
Epoch 5/200
1/21 [>.....] - ETA: 0s - loss: 11.1125 - accuracy: 0.5000
Epoch 5: val_loss improved from 0.65215 to 0.64716, saving model to saved_models\audio_classification.hdf5
21/21 [=====] - 0s 3ms/step - loss: 7.1088 - accuracy: 0.5068 - val_loss: 0.6472 - val_accuracy: 0.6121
Epoch 6/200
1/21 [>.....] - ETA: 0s - loss: 4.7996 - accuracy: 0.5000
Epoch 6: val_loss improved from 0.64716 to 0.63525, saving model to saved_models\audio_classification.hdf5
21/21 [=====] - 0s 3ms/step - loss: 5.1264 - accuracy: 0.5388 - val_loss: 0.6353 - val_accuracy: 0.7333
Epoch 7/200
1/21 [>.....] - ETA: 0s - loss: 4.6849 - accuracy: 0.5000
Epoch 7: val_loss did not improve from 0.63525
21/21 [=====] - 0s 3ms/step - loss: 4.4471 - accuracy: 0.5084 - val_loss: 0.6536 - val_accuracy: 0.6121
Epoch 8/200
1/21 [>.....] - ETA: 0s - loss: 3.5800 - accuracy: 0.6250
Epoch 8: val_loss did not improve from 0.63525
21/21 [=====] - 0s 3ms/step - loss: 3.7287 - accuracy: 0.4810 - val_loss: 0.6824 - val_accuracy: 0.6485
Epoch 9/200
1/21 [>.....] - ETA: 0s - loss: 2.1444 - accuracy: 0.5625
Epoch 9: val_loss did not improve from 0.63525
21/21 [=====] - 0s 3ms/step - loss: 2.5705 - accuracy: 0.5129 - val_loss: 0.7243 - val_accuracy: 0.6121
Epoch 10/200
1/21 [>.....] - ETA: 0s - loss: 3.2379 - accuracy: 0.4062
...
1/21 [>.....] - ETA: 0s - loss: 0.0626 - accuracy: 1.0000
Epoch 200: val_loss did not improve from 0.06971
21/21 [=====] - 0s 3ms/step - loss: 0.1325 - accuracy: 0.9467 - val_loss: 0.0743 - val_accuracy: 0.9636
Training completed in time: 0:00:13.818958
```

(a)

```
test_accuracy=model.evaluate(X_test,y_test,verbose=0)
print(test_accuracy[1])

0.9636363387107849
```

(b)

Fig:5.2 ANN Model Overview: (a) Model Training, (b) Model Accuracy

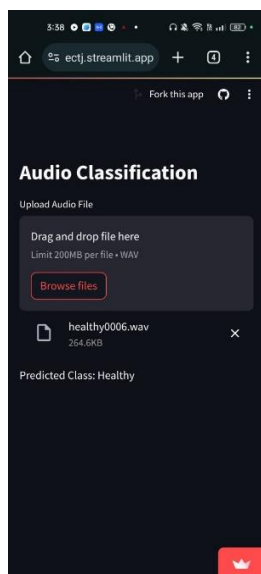
In the process of training our model using the TensorFlow library, we adhered to a standard train-test split methodology, allocating 70% of the data for training and reserving the remaining 30% for testing. This approach ensures that our model is trained on a sufficiently large dataset while also providing a separate set of data for evaluating its performance. As we embarked on constructing our neural network model, we meticulously added layers to enhance its capacity to learn and generalize from the training data. These layers, comprising neurons interconnected in a

hierarchical fashion, allow the model to capture intricate patterns and relationships within the data.

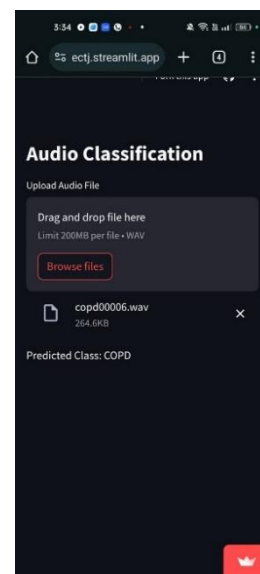
Throughout the training process as shown in Figure 5.2a, we vigilantly monitored the loss and accuracy metrics of our model. Loss quantifies the disparity between the predicted and actual values, while accuracy measures the proportion of correct predictions made by the model. Our initial evaluation yielded an accuracy of 96% as shown in Figure 5.2b, indicating promising performance. However, in scenarios where the accuracy falls short of expectations, we employ several strategies to address this limitation. One such strategy involves adjusting the number of epochs, which denotes the number of times the entire dataset is passed forward and backward through the neural network during training. By increasing the number of epochs, we afford the model more opportunities to refine its parameters and improve its predictive performance.

Upon completion of model training, we conducted rigorous testing using existing data to assess its efficacy in real-world scenarios. This testing phase serves as a critical validation step, providing insights into the model's ability to generalize to unseen data. The achieved accuracy of 96% signifies the model's robustness and reliability in accurately classifying instances within the test dataset.

5.4 APPLICATION INTERFACE



(a)



(b)

Fig:5.3 Application GUI: (a) Healthy Class, (b) COPD Class

The graphical user interface (GUI) showcased above in Figure 5.3 exemplifies the user-friendly interface of our web application, meticulously constructed using Stream-lit, an adaptable framework renowned for its capability in developing interactive data applications. Within this platform, users are seamlessly immersed in our innovative solution, tailored to analyze recorded audio inputs and deliver thorough assessments of respiratory health status. Drawing upon meticulously curated and extensively trained datasets, our application harnesses the power of cutting-edge deep learning algorithms to discern subtle patterns like Cough and Wheezing which are the indicative of compromised respiratory systems. This fusion of advanced technology and user-centric design underscores our unwavering commitment to facilitating positive health outcomes through accessible and impactful solutions.

Integrated seamlessly with a compact stethoscope that plugs directly into smartphones, the application facilitates the capture and analysis of respiratory sounds with ease and convenience. This innovative pairing enables users to access vital health information swiftly and conveniently, empowering proactive management of respiratory well-being. Through thoughtful design choices and streamlined workflows, we aim to empower users with the tools and insights needed to make informed decisions about respiratory health.

At the core of our application lies a robust infrastructure built upon rigorous data science methodologies and best practices. Leveraging meticulously curated datasets sourced from diverse sources, we have painstakingly trained our deep learning models to recognize subtle nuances in respiratory audio recordings. Through extensive experimentation and validation, we have refined our algorithms to achieve high levels of accuracy and reliability in respiratory health assessment.

The versatility of Stream-lit enables us to seamlessly integrate our deep learning models into the application, allowing users to upload audio recordings and receive instant feedback on respiratory health status. Whether it's detecting anomalies in breath sounds or identifying patterns associated with specific respiratory conditions, our application offers comprehensive insights to aid in early detection and intervention.

CHAPTER – 6

SUMMARY AND CONCLUSIONS

In this project, we have proposed an innovative stethoscope, constructed using a chest piece and an Electret microphone encased within a mobile phone case, offers seamless integration with smartphones, facilitating the collection of respiratory audio data. By connecting the digital stethoscope to the audio jack of a smartphone, respiratory sounds can be conveniently recorded and uploaded to our stream-lit web application which is integrated with artificial neural network (ANN)-based deep learning assistive model aimed at aiding medical experts in the early detection of chronic obstructive pulmonary disease (COPD) using respiratory sounds. By leveraging the capabilities of the Librosa machine learning library, particularly features such as MFCC (Mel-frequency cepstral coefficients) and Mel-Spectrogram, we conducted a comprehensive analysis of respiratory sounds to identify patterns indicative of COPD.

Our experiments revealed that the "MFCC" feature outperformed other features within the Librosa library, demonstrating superior accuracy in detecting COPD. Looking ahead, future enhancements to our project could include refining the digital stethoscope design for greater durability and comfort, as well as exploring additional sensor modalities to capture more comprehensive respiratory data. Furthermore, ongoing research could focus on expanding the capabilities of our deep learning model to detect a broader range of respiratory conditions beyond COPD, thereby maximizing its impact on healthcare delivery.

Moreover, integrating our system with a Breath Monitoring System would streamline the process of COPD detection, enhancing its usability and accessibility in clinical settings. Additionally, prioritizing security and privacy considerations will be essential, necessitating the development of robust mechanisms to safeguard sensitive patient data and ensure the system's resilience against potential cyber threats. Overall, these advancements hold the potential to significantly improve the efficiency and accuracy of COPD or other respiratory ailments diagnosis, ultimately benefiting patient outcomes and healthcare delivery.

REFERENCES

- [1] Ahmed J., Vesal S., Durlak F., Kaergel R., Ravikumar N., Remy-Jardin M., and Maier A. 2020. "COPD Classification in CT Images Using a 3D Convolutional Neural Network." In *arXiv [eess.IV]*.
- [2] Alqudah A. M., Qazan S., and Obeidat Y. M. 2022. "Deep learning models for detecting respiratory pathologies from raw lung auscultation sounds." *Soft Computing*, vol. 26 (24), pp. 13405–13429.
- [3] Altan G., Kutlu Y., and Allahverdi N. 2020. "Deep learning on computerized analysis of chronic obstructive pulmonary disease." *IEEE Journal of Biomedical and Health Informatics*, vol. 24 (5), pp. 1344–1350.
- [4] Arts L., Lim E. H. T., van de Ven P. M., Heunks L., and Tuinman P. R. 2020. "The diagnostic accuracy of lung auscultation in adult patients with acute pulmonary pathologies: a meta-analysis." *Scientific Reports*, vol. 10 (1), p. 7347.
- [5] Aviles-Solis J. C., Storvoll I., Vanbelle S., and Melbye H. 2020. "The use of spectrograms improves the classification of wheezes and crackles in an educational setting." *Scientific Reports*, vol. 10 (1), p. 8461.
- [6] Bahoura M., and Ezzaidi H. 2013. "Hardware implementation of MFCC feature extraction for respiratory sounds analysis." In 2013 8th International Workshop on Systems, *Signal Processing and Their Applications (WoSSPA)*, pp. 226–229.
- [7] Balamurali B. T., Hee H. I., Kapoor S., Teoh O. H., Teng S. S., Lee K. P., Herremans D., and Chen J. M. 2021. "Deep neural network-based respiratory pathology classification using cough sounds." *Sensors (Basel, Switzerland)*, vol. 21 (16), p. 5555.
- [8] Brunese L., Mercaldo F., Reginelli A., and Santone A. 2022. "A neural network-based method for respiratory sound analysis and lung disease detection." *Applied Sciences (Basel, Switzerland)*, vol. 12 (8), p. 3877.
- [9] Chowdhury M. E. H., Khandakar A., Alzoubi K., Mansoor S., M. Tahir A., Reaz M. B. I., and Al-Emadi N. 2019. "Realtime smart-digital stethoscope system for heart diseases monitoring." *Sensors (Basel, Switzerland)*, vol. 19 (12), p. 2781.
- [10] Elhilali M., and West J. E. 2019. "The Stethoscope Gets Smart: Engineers from Johns Hopkins are giving the humble stethoscope an AI upgrade." *IEEE Spectrum*, vol.56 (2), pp. 36–41.

- [11] Kim Y., Hyon Y., Jung S. S., Lee S., Yoo G., Chung C., and Ha T. 2021. "Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning." *Scientific Reports*, vol. 11 (1), pp. 17186.
- [12] Kim Y., Hyon Y., Lee S., Woo S.-D., Ha T., and Chung C. 2022. "The coming era of a new auscultation system for analyzing respiratory sounds." *BMC Pulmonary Medicine*, vol. 22 (1), p. 119.
- [13] Lee S. H., Kim Y.-S., Yeo M.-K., Mahmood M., Zavanelli N., Chung C., Heo J. Y., Kim Y., Jung S.-S., and Yeo W.-H. 2022. "Fully portable continuous real-time auscultation with a soft wearable stethoscope designed for automated disease diagnosis." *Science Advances*, vol. 8 (21), p. eabo5867.
- [14] Omarov B., Saparkhojayev N., Shekerbekova S., Akhmetova O., Sakypbekova M., Kamalova G., Alimzhanova Z., Tukenova L., and Akanova Z. 2022. "Artificial intelligence in medicine: Real time electronic stethoscope for heart diseases detection." *Computers, Materials & Continua*, vol. 70 (2), pp. 2815–2833.
- [15] Rennoll V., McLane I., Emmanouilidou D., West J., and Elhilali M. 2021. "Electronic stethoscope filtering mimics the perceived sound characteristics of acoustic stethoscope." *IEEE Journal of Biomedical and Health Informatics*, vol. 25 (5), pp. 1542–1549.
- [16] Seah J. J., Zhao J., Wang D. Y., and Lee H. P. 2023. "Review on the advancements of stethoscope types in chest auscultation." *Diagnostics (Basel, Switzerland)*, vol. 13 (9), p. 1545.
- [17] Sharma D., Sahu S., and Pande D. A. 2020. "Mobile solution for early detection of heart diseases using artificial intelligence and novel digital stethoscope." *International Journal of Engineering Research & Technology (Ahmedabad)*, vol. 9 (5).
- [18] Srivastava A., Jain S., Miranda R., Patil S., Pandya S., and Kotecha K. 2021. "Deep learning based respiratory sound analysis for detection of chronic obstructive pulmonary disease." *PeerJ. Computer Science*, vol. 7, p. e369.
- [19] Tariq Z., Shah S. K., and Lee Y. 2022. "Feature-based fusion using CNN for lung and heart sound classification." *Sensors (Basel, Switzerland)*, vol. 22 (4), p. 1521.
- [20] Turker M.N., Çagan Y.C., Yildirim B., Demirel M., Özmen A., Tander B., Çevik C. 2020. "Smart Stethoscope" *2020 Medical Technologies Congress (TIPTEKNO)*.