Pulmonary Disease Detection using Lung Sound

Puspita Mobarak
dept. EEE
BUET
Dhaka, Bangladesh
2006087@eee.buet.ac.bd

Al-Amin
dept. EEE
BUET
Dhaka, Bangladesh
2006088@eee.buet.ac.bd

Muaz Rahman
dept. EEE
BUET
Dhaka, Bangladesh
2006089@eee.buet.ac.bd

Mohammed Al Hosan
dept. EEE
BUET
Dhaka, Bangladesh
2006090@eee.buet.ac.bd

***Abstract*—The objective of this initiative is to identify pulmonary disorders by analyzing lung sounds. We utilized Mel-Frequency Cepstral Coefficients (MFCC) to extract features and employed a K-Nearest Neighbors (KNN) classifier for illness categorization. The analysis utilized two datasets, and the audio data underwent resampling, normalization, and truncation as part of the preparation stage. The K-nearest neighbors (KNN) classifier was trained using 80% of the dataset and evaluated using the remaining 20%. The evaluation produced a 5x5 confusion matrix. The results indicate the efficacy of the method in identifying bronchitis, COPD, asthma, heart failure, and normal patients. Obstacles were overcome by implementing optimization measures. This experiment demonstrates the capacity of analyzing lung sounds to detect pulmonary diseases, with the possibility of conducting additional research to enhance the accuracy of categorization.**

I. Introduction

Pulmonary illnesses provide substantial global health hazards, necessitating timely identification and diagnosis for optimal control and therapy. Conventional diagnostic techniques can necessitate costly apparatus and intrusive procedures, resulting in delays in both diagnosis and the commencement of therapy. In light of these challenges, non-invasive and cost-effective diagnostic techniques are being studied.

This study focuses on ”Pulmonary Disease Detection using Lung Sound” as an innovative way to early detection. By studying lung sounds, which are indicative of respiratory health, this initiative intends to develop a non-invasive and accessible tool for detecting pulmonary disorders.

The relevance of early diagnosis cannot be emphasized, as it allows for earlier intervention and management, ultimately improving patient outcomes and decreasing healthcare expenditures. Early diagnosis enables healthcare practitioners to commence appropriate treatment options, monitor disease development, and prevent consequences associated with advanced stages of lung disorders.

The methodology adopted in this project comprises the use of Mel-Frequency Cepstral Coefficients (MFCC) for feature extraction from lung sound recordings. These features are then leveraged to train a K-Nearest Neighbors (KNN) classifier for illness categorization. The aims of the project include: - Implementing MFCC for feature extraction from lung sound recordings. - Developing and training a KNN classifier for the classification of lung illnesses. - Evaluating the performance of the categorization model using relevant metrics. - Assessing the feasibility and effectiveness of employing lung sound analysis for pulmonary disease detection.

Identify applicable funding agency here. If none, delete this.

Through this project, we seek to contribute to the advancement of non-invasive diagnostic tools for lung disorders, ultimately improving patient outcomes and healthcare accessibility.

II. Design

A. Problem Formulation

Identification of Scope

The scope of this project comprises the creation and assessment of a system for pulmonary disease identification using lung sound analysis. The expected outputs include the application of Mel-Frequency Cepstral Coefficients (MFCC) for feature extraction and the utilization of a K-Nearest Neighbors (KNN) classifier for disease classification. The research seeks to establish the feasibility and usefulness of employing lung sound analysis as a non-invasive tool for early identification of pulmonary illnesses.

Functionalities

Key functions of the system include audio preprocessing, feature extraction using MFCC, training and testing of the KNN classifier, and evaluation of the classification performance. Additionally, the system should give visualization of extracted features and classification outcomes.

Performance Criteria

Performance metrics used to evaluate the system include accuracy, precision, recall, and F1-score for disease classification. Additionally, the computational efficiency and real-time performance of the system will be considered.

Literature Review

Pulmonary illness detection using lung sound analysis has attracted substantial attention in recent years, with researchers exploring various procedures and techniques to build non-invasive and accessible diagnostic tools. This literature review covers existing studies and improvements in the field, focusing on the employment of signal processing algorithms and electronic stethoscopes for respiratory sound classification and pulmonary illness detection.

One important paper by D. Chamberlain, J. Mofor, R. Fletcher, R. Kodgule, and R. Kodgule presented at the 2015 IEEE Global Humanitarian Technology Conference (GHTC) covers the creation of a ”Mobile Stethoscope and Signal

Processing Algorithms for Pulmonary Screening and Diagnostics." This study underlines the importance of mobile technologies and signal processing algorithms in delivering cost-effective options for lung disease screening and diagnostics. The authors offer a mobile stethoscope integrated with signal processing capabilities aimed at gathering and analyzing lung sounds. Key parts of this research include the design and implementation of signal processing algorithms for the classification and diagnosis of pulmonary diseases based on recorded lung sounds.

Another notable contribution to the topic is the work by Yongpeng Liu, Yusong Lin, Xingjin Zhang, and Zongmin Wang, presented at the 2017 IEEE SmartWorld Conference, titled "Classifying Respiratory Sounds Using Electronic Stethoscope." This study addresses the classification of respiratory sounds using an electronic stethoscope with extensive signal processing capabilities. The authors cover the creation of categorization algorithms built specifically for electronic stethoscope recordings. Their findings highlight the potential of electronic stethoscopes in supporting healthcare workers in the correct diagnosis of pulmonary diseases through respiratory sound classification.

These papers demonstrate the increased interest in adopting electronic stethoscopes and signal processing techniques for lung illness identification. The merging of mobile technologies and modern signal processing techniques offers interesting pathways for non-invasive and accessible diagnostic instruments. By integrating electronic stethoscopes and new classification algorithms, researchers want to better the accuracy and effectiveness of pulmonary illness detection, thereby increasing patient outcomes and healthcare accessibility.

Overall, the examined literature underlines the importance of technical improvements and signal processing techniques in enhancing pulmonary illness identification via lung sound analysis. These research give essential insights and approaches that guide the methodology taken in this project, contributing to the ongoing efforts to develop efficient and accessible diagnostic treatments for pulmonary disorders.

Formulation of Problem

Pulmonary illness identification utilizing lung sound analysis poses various obstacles and constraints that need to be addressed for accurate and reliable diagnosis. One of the key issues encountered is the diverse character of the data resulting from integrating two datasets. These datasets vary in terms of audio file sizes, recording methods, and the positions from which lung sounds were obtained. As a result, there are intrinsic variances in the properties of the lung sounds, making it tough to design a uniform and standardized approach for feature extraction and classification.

Furthermore, changes in the procedures employed to acquire lung sounds contribute to inconsistencies in the results. Different recording approaches, such as utilizing electronic stethoscopes or traditional stethoscopes, may bring changes in sound quality and characteristics, compromising the accuracy of disease classification. Additionally, lung sounds collected from different sides of the lungs may exhibit changes in strength, frequency, and duration, further complicating the analysis procedure.

Another key difficulty is the presence of noise in the data. Environmental noise, movement artifacts, and physiological factors such as heart sounds and breathing patterns might interfere with the quality of lung sound recordings, leading to mistakes in illness identification. Noise reduction and signal processing techniques are crucial to limit the influence of noise and boost the reliability of disease categorization.

Current techniques to pulmonary disease identification employing lung sound analysis suffer significant limitations, mostly originating from the issues stated above. The varied character of the data poses a substantial difficulty in creating strong and generalizable classification models. Traditional machine learning methods, such as K-Nearest Neighbors (KNN), may struggle to successfully learn from diverse and complicated datasets, resulting to unsatisfactory performance in disease classification.

Furthermore, the dependence on manual feature extraction approaches, such as Mel-Frequency Cepstral Coefficients (MFCC), may not capture all significant information included in the lung sound recordings. Deep learning techniques, such as Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), offer potential options for automatic feature learning from raw data. However, these systems require significant volumes of labeled data for training, which may not always be easily available, especially in the case of pulmonary illness diagnosis.

In summary, the challenges and limits in current techniques to pulmonary illness identification utilizing lung sound analysis underscore the need for creative solutions that address data heterogeneity, noise, and changes in recording methodologies. Overcoming these issues will require breakthroughs in signal processing techniques, feature extraction approaches, and machine learning algorithms, ultimately leading to more accurate and trustworthy diagnostic tools for pulmonary disorders.

Analysis

Effectiveness of the Proposed Methodology: The proposed technology for pulmonary illness identification utilizing lung sound analysis, which incorporates Mel-Frequency Cepstral Coefficients (MFCC) for feature extraction and a K-Nearest Neighbors (KNN) classifier for disease classification, displays promising performance. By extracting significant elements from lung sound recordings and applying a simple yet robust classification algorithm, the technology shows potential for accurate disease identification.

Advantages:

- Non-invasive: The methodology offers a non-invasive method for lung illness identification, avoiding the necessity for invasive procedures.
- Expense-effective: Utilizing readily accessible electronic stethoscopes and open-source databases decreases the expense associated with diagnostic equipment.
- Accessibility: The methodology can be simply implemented in diverse healthcare settings, especially in resource-limited areas.

Limitations:

- Data Heterogeneity: Challenges come from combining heterogeneous datasets with variations in audio file sizes, recording methods, and lung sound properties.
- Noise: Environmental noise and physiological factors introduce noise in the data, reducing the accuracy of disease classification.
- Manual Feature Extraction: Reliance on manual feature extraction methods may limit the ability to acquire all significant information included in the lung sound recordings.

Effectiveness Evaluation:

Performance of the System Based on Predefined Metrics: Performance metrics, including accuracy, precision, recall, and F1-score, are used to evaluate the system's performance. The classification model is trained and evaluated using a portion of the dataset, and the results are compared against ground truth labels to determine the effectiveness of the system in accurately categorizing pulmonary illnesses.

Results of the Evaluation: The evaluation findings reveal the system's capacity to classify pulmonary disorders, including bronchitis, COPD, asthma, heart failure, and normal cases, with a considerable degree of accuracy. However, difficulties such as data heterogeneity and noise impair the overall performance of the system, resulting to classification errors and inconsistencies.

Challenges and Mitigation Strategies:

Challenges found during the project include data heterogeneity originating from integrating two datasets, variances in recording methods, and noise in the data owing to ambient conditions and physiological factors.

Propose Mitigation Strategies to Address These Challenges:

- Data Preprocessing: Implement strategies to preprocess the data and solve concerns linked to data heterogeneity, including standardizing audio file sizes, harmonizing recording methods, and reducing noise from the data.
- Feature Engineering: Explore sophisticated feature extraction approaches and automated feature learning methods, such as deep learning, to collect more complete and discriminative features from the lung sound recordings.
- Model Optimization: Fine-tune the classification model parameters and study alternative classification algorithms to increase the robustness and accuracy of illness categorization.
- Quality Assurance: Implement quality assurance measures to assure the reliability and consistency of the lung sound recordings, including periodical calibration of recording equipment and validation of data quality.

By employing these mitigation techniques, the issues discovered during the project can be addressed, thereby enhancing the effectiveness and reliability of the pulmonary disease detection system using lung sound analysis.

B. Design Method

Feature Extraction:

The technique of feature extraction entails gathering relevant information from the raw lung sound recordings to represent them in a way appropriate for machine learning algorithms. In this study, Mel-Frequency Cepstral Coefficients (MFCC) are employed for feature extraction. MFCCs are formed from the short-term power spectrum of the audio signal and represent the properties of the sound, including spectral aspects and temporal dynamics.

III. Implementation

A. *Software Development*

The software development method entails leveraging MATLAB for implementing the full project pipeline, including data preparation, feature extraction, model training, evaluation, and visualization. MATLAB provides a comprehensive platform for signal processing, machine learning, and visualization, making it suited for constructing the pulmonary disease detection system employing lung sound analysis.

B. *Experiment and Data Collection*

Experimental setup and data collection entail acquiring lung sound recordings from open-source databases, such as the ones mentioned before. The recordings are gathered in a controlled environment to assure consistency and quality. Metadata, including patient details and disease classifications, are recorded with the audio files for reference during analysis.

C. *Data Augmentation*

Data augmentation strategies may be performed to increase the diversity of the dataset and improve the generalization of the classification model. Augmentation techniques such as time stretching, pitch shifting, and noise addition can be used in MATLAB to generate additional training samples from the existing dataset.

D. *Data Analysis*

1) **Feature Extraction (MFCC theoretical details:**

   Pre-emphasis: The first phase in the MFCC extraction process is pre-emphasis, which includes applying a high-pass filter to the audio signal to increase high-frequency components. This phase serves to raise the signal-to-noise ratio and improve the effectiveness of future processing steps.

   Frame Blocking: The pre-emphasized signal is then separated into short-time frames using a technique called frame blocking. Each frame typically varies from 20 to 40 milliseconds in duration and overlaps with adjacent frames to provide continuity in the analysis.

   Windowing: A window function, such as the Hamming or Hanning window, is applied to each frame to limit spectral leakage and minimize discontinuities at frame boundaries.

   Fast Fourier Transform (FFT): The windowed frames are then processed through the Fast Fourier Transform (FFT) to compute the power spectrum of each frame. This phase translates the time-domain signal into the frequency domain, providing information about the frequency content of the signal.

Mel Filtering: The power spectrum is then passed through a series of Mel filters, which are triangular-shaped filters spaced equally on the Mel-frequency scale. This process simulates the nonlinear frequency resolution of the human auditory system and helps to capture perceptually relevant frequency ranges.

Log Compression: The output of the Mel filtering step is subjected to logarithmic compression to replicate the nonlinear response of the human ear to sound intensity. This step serves to strengthen the representation of lower-intensity components in the signal.

Discrete Cosine Transform (DCT): Finally, the logarithmically compressed Mel-filtered spectrum is processed through the Discrete Cosine Transform (DCT) to compute the MFCC coefficients. The generated coefficients describe the cepstral properties of the audio stream, capturing crucial elements such as spectrum form and temporal dynamics.

By extracting MFCC coefficients from the lung sound recordings, the feature extraction technique produces a concise and informative representation of the audio signal, appropriate for subsequent classification using machine learning algorithms such as the K-Nearest Neighbors (KNN) classifier.

2) **Feature Visualization:**
Visualizations of the retrieved MFCC coefficients can be constructed using MATLAB's plotting capabilities. These visualizations may include spectrograms, depicting the time-frequency representation of the lung sound recordings, and graphs of the MFCC coefficients over time to highlight their dynamics and variability across different illness categories.
3) **Model Training and Evaluation:**
Model training comprises partitioning the dataset into training and testing sets and building a K-Nearest Neighbors (KNN) classifier using the training data. MATLAB's Statistics and Machine Learning Toolbox contains functions for training and assessing KNN classifiers, including specifying the number of neighbors (K) and the distance measure. The trained classifier is assessed using the testing data, and performance metrics like as accuracy, precision, recall, and F1-score are generated.
4) **Error Analysis:** Error analysis entails reviewing misclassifications made by the trained classifier and discovering patterns or trends in the mistakes. MATLAB's statistical and visualization features can be used to examine classification results, visualize confusion matrices, and discover frequent sources of errors.
5) **Real-Time Performance:**
Real-time performance evaluation examines the computational efficiency and accuracy of the system in processing and classifying lung sound recordings in real-time. MATLAB's profiling tools can be used to monitor the execution time of different components of the system and detect potential bottlenecks that may impair real-time performance.

E. Results

The outcomes of the implementation process include the trained KNN classifier, performance measures such as accuracy, precision, recall, and F1-score, visualizations of extracted features, error analysis findings, and real-time performance evaluation results. These results provide insights into the effectiveness and reliability of the pulmonary disease detection system employing lung sound analysis performed in MATLAB.

IV. Design Analysis and Evaluation

A. Novelty

The proposed technology for pulmonary disease identification utilizing lung sound analysis demonstrates numerous innovative aspects:

1) Integration of MFCC and KNN Classifier: While earlier research have studied various feature extraction and classification strategies for lung illness identification, the integration of Mel-Frequency Cepstral Coefficients (MFCC) and a K-Nearest Neighbors (KNN) classifier in this study offers a novel approach. The use of MFCCs provides a compact and informative representation of the lung sound recordings, while the KNN classifier offers simplicity and interpretability, making it suited for real-time applications in clinical situations.
2) Utilization of Multiple Datasets: By integrating two unique datasets containing lung sound recordings from diverse sources and capturing varied illness situations, this effort uses the diversity and richness of data to boost the robustness and generalizability of the classification model. This approach enables the system to learn from a wider range of auditory patterns associated with different lung disorders, hence boosting its accuracy and effectiveness.
3) Real-Time Performance Evaluation: The evaluation of real-time performance adds a practical dimension to the project, confirming the possibility of implementing the pulmonary illness detection system in clinical settings. By analyzing the system's computing efficiency and response time, this study provides insights into its practical utility and scalability.

B. Design Considerations

Several design factors are needed to address public health, safety, environmental, cultural, and socioeconomic needs:

1) Public Health and Safety: The suggested methodology intends to enhance early identification and diagnosis of lung illnesses, ultimately contributing to better patient outcomes and reducing healthcare burdens. Ensuring the accuracy and reliability of the categorization model is vital to prevent misdiagnosis and maintain patient safety.

2) Environmental Considerations: The use of non-invasive diagnostic techniques, such as lung sound analysis, lowers the environmental effect associated with invasive procedures and diagnostic equipment. Additionally, the incorporation of real-time performance evaluation helps enhance resource use and energy economy in healthcare settings.
3) Cultural and Societal Needs: Cultural and socioeconomic considerations may influence the acceptance and implementation of the proposed methodology in different locations and communities. Consideration of cultural sensitivities and preferences is vital to ensure the accessibility and inclusivity of the lung disease detection system across varied groups.

C. *Limitation of Tools*

Despite its uniqueness and potential, the project may encounter significant restrictions related with the tools and procedures used:

1) MATLAB Limitations: MATLAB, while versatile and frequently used for signal processing and machine learning tasks, may have limitations in terms of computational efficiency and scalability, particularly for real-time applications in resource-constrained contexts. Alternative programming languages and platforms may offer better performance and scalability for deployment in clinical settings.
2) Data Quality and Availability: The efficiency of the suggested methodology significantly relies on the quality and availability of the lung sound recordings utilized for training and testing the classification model. Limitations in data quality, such as noise and variability, may impair the performance and generalizability of the system. Moreover, access to diverse and representative datasets may be limited, providing obstacles in developing a strong and effective classification model.

Despite these limitations, the suggested methodology offers unique methods to overcome the obstacles associated with pulmonary illness identification via lung sound analysis, demonstrating its potential to improve healthcare outcomes and accessibility. Continued research and development efforts are necessary to solve these limitations and further enhance the effectiveness and usability of the suggested methodology.

D. *Impact Assessment*

Assessment of Societal and Cultural Issues

The project's socioeconomic and cultural impact is substantial, as it addresses the global dilemma of enhancing healthcare accessibility and early diagnosis of lung disorders. By establishing a non-invasive and cost-effective technology for pulmonary illness identification utilizing lung sound analysis, the initiative intends to help varied groups, particularly those in resource-limited locations and underserved communities. However, sociological and cultural issues may influence the acceptance and implementation of the proposed methodology. Cultural sensitivities, beliefs, and preferences surrounding healthcare practices and diagnostic methods must be considered to ensure the accessibility and inclusivity of the pulmonary disease detection system across different cultural settings. Additionally, raising awareness and offering education on the necessity of early disease diagnosis and the benefits of non-invasive diagnostic tools can assist increase social acceptance and engagement with the initiative.

Assessment of Health and Safety Issues

Health and safety considerations are crucial in the development and implementation of the lung disease detection system. Ensuring the accuracy and reliability of the categorization model is vital to prevent misdiagnosis and maintain patient safety. Additionally, data privacy and confidentiality must be maintained to preserve patient information and comply with healthcare standards. Furthermore, the real-time performance evaluation of the system is crucial to measure its computing efficiency and response time, contributing to the overall safety and effectiveness of the system in clinical situations. Adequate training and support for healthcare workers using the system are also required to ensure safe and appropriate utilization of the technology.

Assessment of Legal Issues

Legal considerations associated to the initiative essentially focus around data privacy, patient confidentiality, and regulatory compliance. As the project involves the collection and analysis of patient data, ensuring compliance with data protection laws and regulations, such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States or the General Data Protection Regulation (GDPR) in the European Union, is essential to protect patient privacy and confidentiality. Additionally, getting proper ethical approvals and informed consent from people participating in data collection and analysis is important to ensure conformity with legal and ethical norms. Furthermore, attention to applicable regulatory criteria for medical device development and deployment is vital to assure the safety and effectiveness of the pulmonary disease detection system and limit potential legal concerns connected with its usage in clinical practice.

E. *Sustainability Evaluation*

The project's sustainability depends on its long-term impact on healthcare accessibility and resource utilization. By establishing a non-invasive and cost-effective technology for pulmonary illness identification utilizing lung sound analysis, the project hopes to have a lasting impact on increasing early disease detection and reducing healthcare burdens. Sustainability is also measured in terms of resource utilization, including the efficient use of computational resources, data storage, and energy consumption. Moreover, the project's scalability and flexibility to varied healthcare settings and resource-limited environments contribute to its long-term sustainability.

To maintain and update the system, continuous monitoring and evaluation of its performance are needed. This includes conducting frequent assessments of the classification model's accuracy and efficacy, finding areas for improvement, and updating the system accordingly. Strategies for sustaining the system may comprise creating automated updates for software components, including feedback from healthcare experts and consumers, and integrating new datasets to improve the system's resilience and generalizability. Additionally, creating connections with healthcare institutions and stakeholders for continuous support and collaboration can assure the sustained viability of the initiative.

F. *Ethical Issues*

Ethical considerations linked to data gathering, processing, and usage are crucial in the endeavor. The gathering of lung sound recordings must follow to ethical norms, including getting informed consent from participants and preserving data privacy and confidentiality. Ethical rules for research involving human beings, such as those stated in the Belmont Report and Declaration of Helsinki, should be observed to preserve participants' rights and well-being.

Privacy concerns emerge around the collecting, storage, and exploitation of sensitive medical data, such as lung sound recordings. Proper data anonymization and encryption techniques should be utilized to ensure patient privacy and prevent illegal access to sensitive health information. Informed consent must be sought from participants, describing the goal of data collection, how the data will be used, and any potential risks or advantages associated.

Fairness in data analysis and model training is vital to provide impartial and equitable outcomes. Steps should be done to limit bias in the dataset, such as resolving imbalance in illness prevalence and evaluating demographic characteristics to avoid inequities in disease detection. Transparency in the decision-making process, including releasing the algorithm used for disease categorization and offering explanations for classification conclusions, fosters fairness and accountability in the project's ethical conduct.

V. Reflection on Individual and Team work

A. *Individual Contribution of Each Member*

Team Member	Contribution
Puspita Mobarak	Brainstorming, Literature Review, Online Dataset Collection, Coding, Final Presentation
Al-Amin	Methodology Identification, On-field Dataset Collection, Data Extraction, Coding
Muaz Rahman	Literature Review, Online Dataset Collection, Data Extraction, Coding
Mohammad Al Hosan	Methodology Identification, On-field Dataset Collection, Checking Previous Work, Coding

B. *Mode of Teamwork*

The team collaborated closely throughout the project, leveraging each member's strengths and expertise to achieve project objectives. Communication channels such as meetings, emails, and shared documents were utilized to coordinate tasks and share progress updates. Regular team meetings were conducted to discuss project milestones, address challenges, and make decisions collaboratively.

C. *Diversity Statement of Team*

The team comprises members from diverse backgrounds, including engineering, healthcare, and data science. This diversity facilitated interdisciplinary perspectives and enriched the project with varied insights and approaches. Each member brought unique skills, experiences, and cultural perspectives to the team, fostering creativity and innovation in problem-solving.

VI. Future Work

Future work for the project involves various areas targeted at boosting the system's capabilities and addressing limitations:

1) Enhanced Feature Extraction: Investigate improved feature extraction approaches beyond MFCC, such as wavelet transformations or deep learning-based algorithms, to capture more intricate patterns in lung sound recordings.
2) Advanced Classification Algorithms: Explore the use of deep learning techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), for disease categorization to potentially improve accuracy and robustness.
3) Dataset Expansion: Acquire larger and more diversified datasets containing a broader range of lung diseases and patient demographics to boost the model's generalizability and performance.
4) Real-time Implementation: Develop real-time processing capabilities to enable on-the-fly disease detection and diagnosis, supporting timely intervention and treatment in clinical settings.
5) Incorporation with Clinical Systems: Integrate the pulmonary disease detection system with existing clinical systems, such as electronic health records (EHRs) or telemedicine platforms, to streamline workflow and promote seamless incorporation into healthcare practices.

By tackling these areas of future work, the project can continue to evolve and make substantial contributions to the field of pulmonary illness identification and healthcare delivery.

References

1) D. Chamberlain, J. Mofor, R. Fletcher, R. Kodgule, "Mobile Stethoscope and Signal Processing Algorithms for Pulmonary Screening and Diagnostics," in *2015 IEEE Global Humanitarian Technology Conference (GHTC)*, 2015. [Online]. Available: https://ieeexplore.ieee.org/document/7344001
2) Y. Liu, Y. Lin, X. Zhang, Z. Wang, "Classifying respiratory sounds using electronic stethoscope," in *2017 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation*, 2017. [Online]. Available: https://ieeexplore.ieee.org/document/8397496