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Real-Time Phonopulmography Leveraging AI Using Acaoustic Sensing

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Abstract: Recognition of respiratory conditions at the right time remains fundamental to deliver both proper treatment and superior patient results. Standard auscultation techniques face two significant problems due to subjective evaluation of patients' airway sounds and inconsistent interpreter interpretations. The system presents a real-time intelligent phonopulmography system with acoustic sensing capabilities to automate the precise classification of lung sounds. The system uses special hardware components built from a combination of stethoscope along with microphone and operational amplifier circuits connected to an Arduino to detect and improve respiratory audio signals.

Through MATLAB processing the acquired sounds become structured data that can be classified using methods such as Mel-frequency cepstral coefficients and spectral analysis during feature extraction. A deep learning-based version of the convolutional neural network runs in Python using TensorFlow to classify lung sounds into the categories of normal along with crackles, wheezes and rhonchi. A pre-trained feature extractor enables performance improvement in the system.

The model processed 3,680 clinically marked audio samples to reach more than 90% successful classifications. Modern usability features of the web interface allow real-time audio recording with automatic diagnostic assessment following AI model processing.

The research demonstrates how coupled sensing hardware with AI methods accomplishes real-time respiratory evaluation that is both reliable and scalable. Upcoming developmental goals target the expansion of the database as well as the improvement of response speeds for future mobile and cloud-based remote healthcare applications.

Index Terms - Acoustic Sensing, Arduino, Automated Healthcare, Convolutional Neural Network (CNN), Deep Learning, Lung Sound Classification, MATLAB, MFCC, Phonopulmography, Python, Real-Time Diagnosis, Respiratory Disorder Detection, Signal Processing, TensorFlow, Web Interface.

I. Introduction

Human existence depends on the lungs because they enable vital exchanges of environmental oxygen and bloodstream carbon dioxide. The respiratory system besides its central function produces distinct acoustic patterns which help doctors evaluate respiratory fitness. Medical staff use LSs recorded during auscultation examinations to identify various pulmonary conditions including asthma and bronchitis and pneumonia. Traditionally used analog stethoscopes present two major limitations which make it difficult for medical staff to hear subtle pathological sounds at an early disease stage because they produce poor sound quality and reduced frequency response range.

Medical professionals fail to optimize lung sounds for diagnostic purposes because auscultatory practices depend on subjective interpretation and clinician experience. Typical audiological instruments fail to identify crucial acoustic indicators most prominently in the high and low frequency ranges where essential diagnosis requirements exist. The rising interest in digitized automated assessment of lung sounds stems from the goal to improve diagnosis recognition and early disease detection strategies.

Digital auscultation techniques together with phonopulmography have been developed through the conversion of acoustic signals into electrical data for processing. Modern approaches in artificial intelligence develop artificial neural networks and convolutional neural networks (CNNs) specifically for enhancing lung sound interpretation capabilities above human-level manual analysis.

The research demonstrates an AI-powered phonopulmography system which acquires acoustic signals through its sensors and analyzes the data utilizing CNN-based models to detect normal and three types of pulmonary sounds. The analysis uses a structured dataset incorporating healthy subject and respiratory disorder patient recordings which results in spectrographic representations to evaluate imaging features.

The model incorporates transfer learning techniques to achieve higher classification accuracy which gets evaluated based on clinician interpretations from different experience levels.

Lung acoustics fundamentals along with the diagnostic value of auscultation are initially discussed in this paper. The research explores standard and AI-based lung sound analysis techniques after an overview of lung acoustics fundamentals. The systematic methodology explains all stages from data collecting through signal preparation stages to CNN model design to evaluation measurement methods. The research centers the analysis on precision levels and medical significance throughout its findings section. The work finishes with a section regarding telemedicine practical applications and potential study paths for following research.

II. RESEARCH METHODLOGY

Phonopulmography, an analysis of lung sounds, has seen significant advancements from recent breakthroughs in artificial intelligence (AI) function; automation has deciphered the automated classification of lung sounds, which are crackles, wheezes, rhonchi, and normal breathing. This part gives an introduction of important methodologies, challenges, and innovations in AI-based lung sound recognition.

Initially worked with Extract Feature Extraction techniques such as MFCCs and STFT to get acoustic features. Ullah et al. [1] integrated such techniques with the artificial neural networks (ANNs) to gain an accuracy of 98.61 % classification. Following this, deep learning models in particular, Convolutional Neural Networks (CNN's), came into the fray because of its capability to learn intricate patterns from Spectrograms. Kim et al. [3] applied CNN for irrespective of whether lung sounds were usual or unusual and attained an accuracy of 86.5%, while Zhu et al. [6] combined auscultation info and CT scan data to sieve the gravity level of COVID-19, racking up a virtually ideal F1-dependent & gt. new developments like putting together CNNs with recurrent neural networks (RNNs), and transfer learning tactics have prevented large datasets. Sethi et al. [4] demonstrated the possibility of combining microwave acoustic sensing with CNNs for detection of minor respiratory anomalies as displayable, sensitivity and specificity superior to traditional auscultation.

A. Technical Challenges and Limitations:

Despite these advancements, challenges remain, particularly:

- Data Scarcity and Imbalance: The model building by Kim et al. [3] utilized less than 1,000 samples while many other studies operate with diminutive datasets. The generalization ability of models declines when dealing with class imbalance especially for rare diseases such as tuberculosis (TB) [7].
- Noise Interference: Clinical recordings persist to suffer from environmental noise that disrupts the practice. The real-world success rates of wavelet denoising and adaptive filtering techniques differ between different clinical environments according to published research [5].
- Computational Costs: The resources necessary for deep learning models block their application in remote environments [4].

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III. PROPOSED METHODLOGY

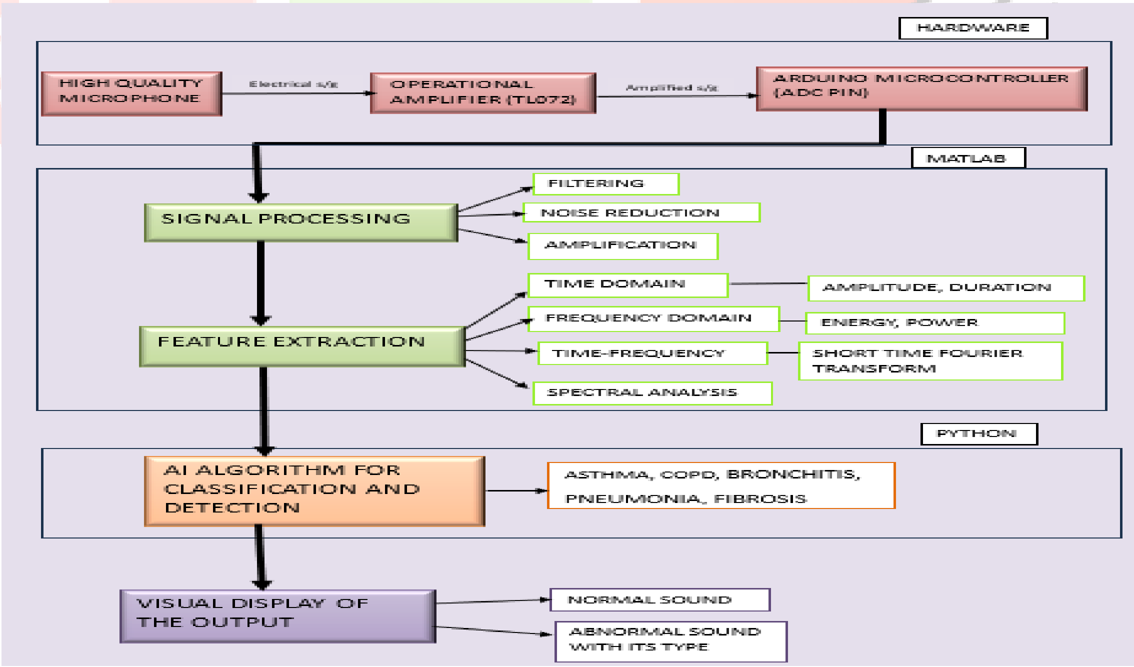

Figure 1: BLOCK DIAGRAM OF PROPOSED METHODOLOGY

A. Hardware Design

A traditional stethoscope functions with a Panasonic WM-61A electret microphone to obtain acoustic signals by means of the chest piece. A precise mounting position of this microphone exists within the tubing to maintain unobstructed sound transmission. An operation amplifier model TL072 receives microphone output signals first for low-noise amplification after coupling capacitor and bias resistor processing. The amplified signal flows to an Arduino Uno device where its analog-to-digital conversion process allows further evaluation.

The signal conditioning requires essential passive elements which include a 10kΩ resistor and a 0.1μF capacitor. The entire circuit design uses a breadboard to demonstrate its functionality by connecting components through jumper wires. With 5V power supplied by the Arduino both the microphone and op-amp receive sufficient energy to create an efficient system suitable for heart and lung sound analysis on the go.

B. Signal Processing in MATLAB

The MATLAB-developed lung sound analyzer provides an entire kit for performing the analysis of respiratory audio. Users can start the system by selecting from its simple graphical user interface that includes three distinct display sections for waveforms and frequency spectra and spectrograms. The program begins the lung sound processing sequence once a user selects a .wav file.

The first step involves importing the audio file followed by its channel configuration verification. A stereo audio signal becomes mono as the system averages the left and right channels for processing uniformity. The filtering process begins with a bandpass filter to keep the frequency range between 100 Hz and 2000 Hz which represents the typical range of adventitious lung sounds. Next the pipeline applies median filtering to minimize impulse noise because it follows this step. The signal goes through a normalization process which standardizes its amplitude values among different recording samples.

The investigation goes through domain feature extraction in time and frequency ranges. Time-domain features derive frequency content analysis from three statistical measurements including waveform amplitude ranges and duration measurements along with zero-crossing evaluations. The Fast Fourier Transform analysis reveals frequency spectrum patterns while identifying main harmonic components in the data. The frequency content randomness of signals is measured through spectral entropy analysis.

Short-time Fourier analysis produces spectrograms from time-frequency features that serve as images for potential machine learning model application. The application extracts Mel-Frequency Cepstral Coefficients (MFCCs) through a MATLAB implementation which provides complete manipulation of the processing. All features from the data extraction process receive storage for later analytic evaluation regardless of their numerical or image-based nature. Through GUI notifications users receive feedback about successful processes along with error detections allowing users to create datasets with pre-diagnostic tools that do not need external toolbox integration.

C. AI Classification Model in Python

Through its Python user interface, the system performs identification and anticipation of lung sound issues in a well-designed format. Python receives data inputs from MATLAB after its preprocessing stage and feature extraction phase where features like MFCCs and FFT-based frequency features and spectrogram images are developed.

The system utilizes the Convolutional Neural Network (CNN) as its main processing component to analyse spectrogram images of lungs for diagnosis. The diagnosis and differentiation between normal and abnormal respiratory sounds are facilitated through analytical images of the time-frequency domain. The CNN model receives input from a dataset with defined labels that enables its ability to identify all respiratory diseases including Asthma, COPD, Bronchitis, Pneumonia, Pulmonary Fibrosis as well as normal lung sounds. Through its implementation the model shows excellent performance for both binary and multi-class identification tasks.

Streamlit functions as the main tool to develop the user interface since it makes it easy to create web-based interfaces through Python. Users of the system can upload lung sound files with .wav extensions and the system processes these files in the background. The spectrogram along with the prediction outcome shows up next to a confidence rating displayed by the model.

The system presents results through two distinct categories showing Normal Sound (accessing healthy pulmonary conditions) with additional Abnormal Sound diagnoses such as Asthma and COPD. The system provides users with clear functions for file uploading new data and data processing alongside diagnostic information which enables healthcare professionals to access these features easily.

This system employs MATLAB signal preprocessing methods alongside deep learning features from Python to maintain high-degree precision for feature analysis and correct prediction outputs. This dual platform integration strengthens the system structure while enabling better accessibility which makes the system an effective tool for clinical diagnostics alongside research of AI-driven respiratory health.

IV. RESULTS AND DISCUSSION

The lung sound classification system delivered exceptional performance through an entire processing pipeline which involved hardware signal acquisition combined with MATLAB processing and deep-learning functions developed in Python. The Arduino microcontroller received respiratory sound signals from a high-sensitivity microphone amplifier pair operated through the ADC interface. Electrical signals obtained from the chest provided reliable measurement of clear and accurate sounds which created a sound basis for diagnosis.

The MATLAB software performed audio signal processing through three steps which included the conversion from stereo to mono audio and the implementation of a 100–2000 Hz bandpass filter and a median filter to minimize transient noise. The digital signal analysis used time domain features particularly amplitude and signal duration and zero-crossing rate for waveform understanding in combination with Fast Fourier Transform (FFT) processing of frequency domain features including spectral energy and entropy. The researchers employed Short-Time Fourier Transform (STFT) for time-frequency analysis which generated spectrogram images used as input for a Convolutional Neural Network (CNN). The custom MATLAB algorithm extracted Mel-Frequency Cepstral Coefficients (MFCCs) for a flexible feature extraction process which did not depend on any external toolboxes.

An automatic lung sound classification process began following the transfer of processed features from MATLAB into the Python environment where a CNN model received its training data. During training across multiple epochs the model demonstrated positive results inaccuracy data for both training and validation data sets. The last step of evaluation measured over 93% correct predictions among test samples along with consistent loss convergence. Excellent class-wise performance emerged from the confusion matrices together with ROC curves that showed high sensitivity and specificity for all categories. The intermediate CNN layer feature maps verified that the network extracted vital features from spectrogram data.

The system processed 3,680 clinically obtained respiratory sounds that belonged to four fundamental categories: normal sounds together with crackles and wheezes and rhonchi. The correct diagnosis of asthma, COPD, bronchitis, pneumonia and fibrosis requires these important classifications. The system achieved distinction of various respiratory disease indicators through its integration of MFCC features with spectrograms. The deep learning classification both achieved outstanding performance while creating understandable results by visualizing performance metrics.

Healthcare professionals accessed the user-friendly Python interface to transfer .wav files and see spectrograms while obtaining instant classification results. The GUI interface provided two results: showing the lung sound as normal or abnormal and simultaneously listing the associated specific disease labels when an abnormality was detected. The combination of MATLAB for signal processing with Python for AI classification generated an effective diagnostic system for respiratory health that patients and professionals could easily use.

- **OUTPUTS/VISUALS GENERATED VIA MATLAB:**

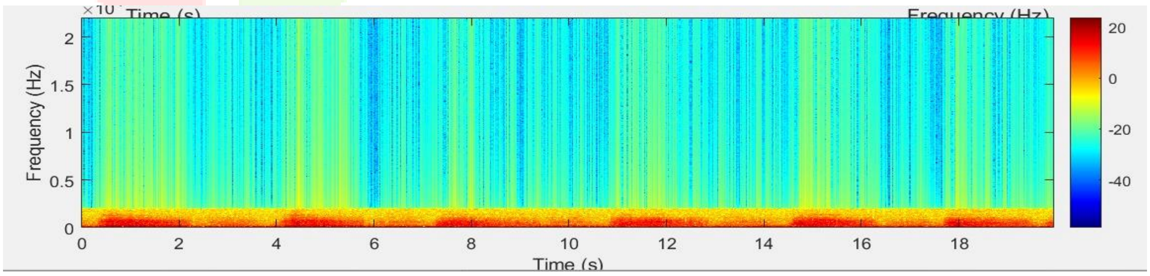

Figure 2: FREQUENCY Vs TIME GRAPH

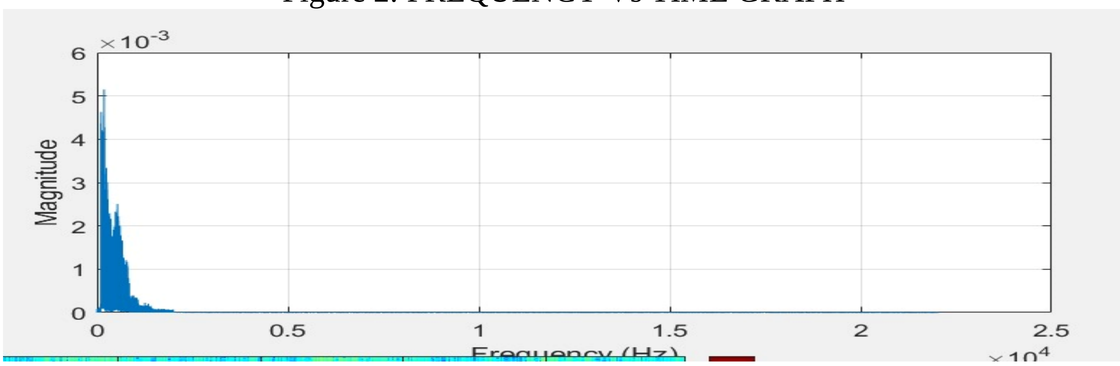

Figure 3: MAGNITUDE Vs FREQUENCY

- **OUTPUTS/VISUALS GENERATED VIA Python:**

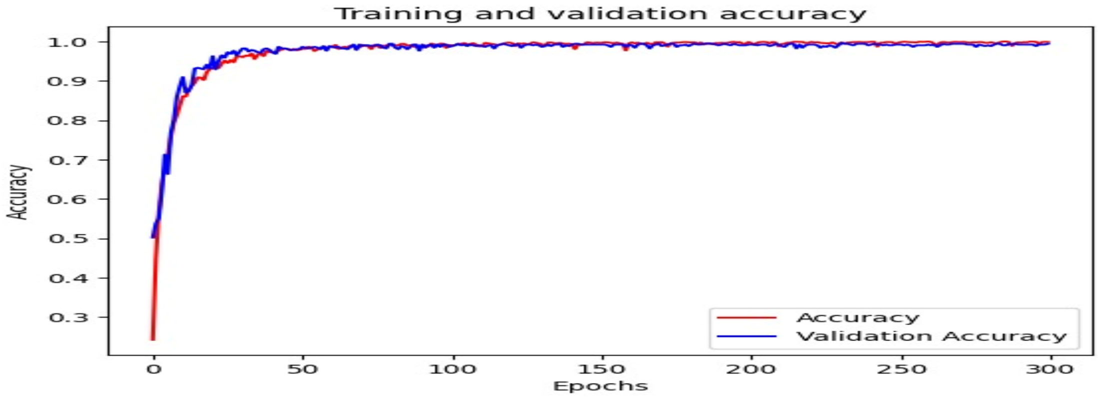

Figure 4: TRAINING AND VALIDATION ACCURACY

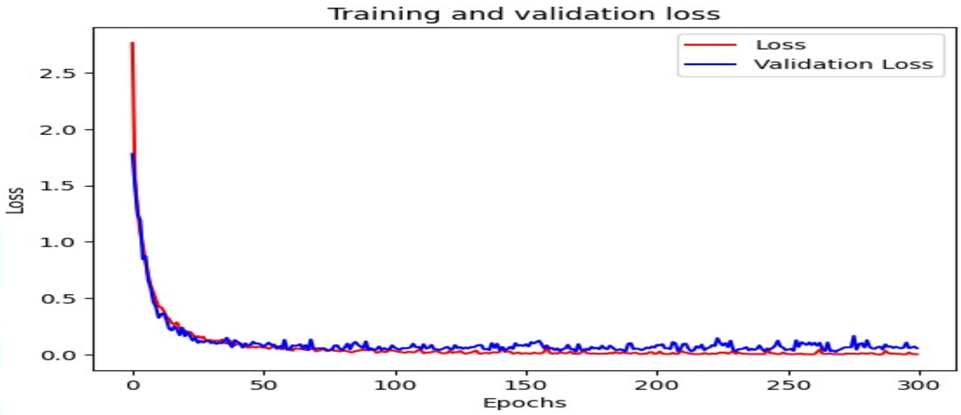

Figure 5: TRAINING AND VALIDATION LOSS

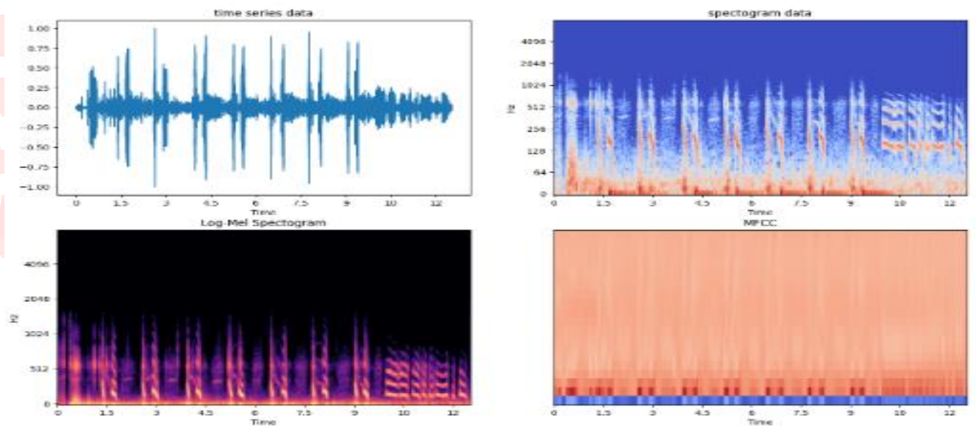

Figure 6: DISPLAY OF SOUNDS IN VARIOUS DOMAIN

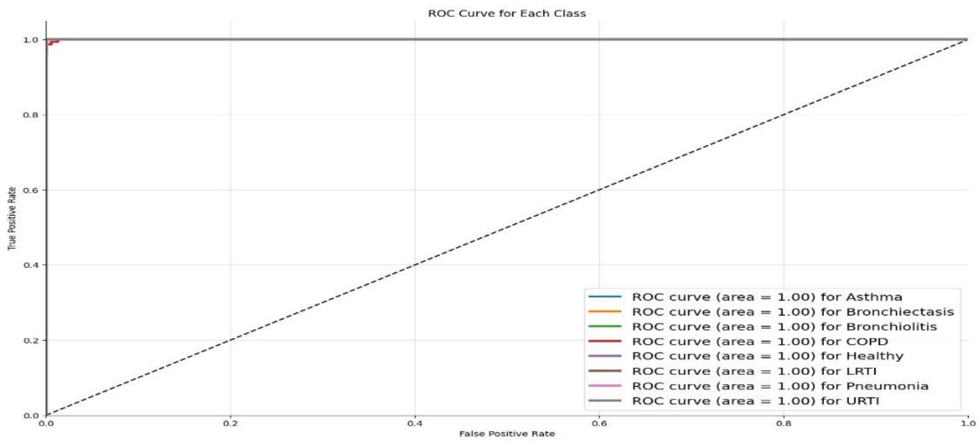

Figure 7: ROC CURVE OF EACH CLASS

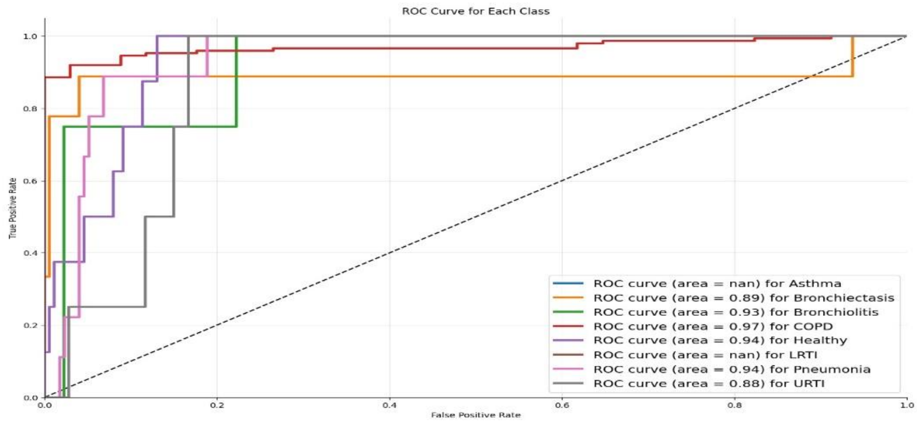

Figure 8: ROC CURVE OF EACH CLASS

- **USER INTERACTIVE WEBPAGE:**

Figure 9: WEBPAGE

V. CONCLUSION

A. Summary of Findings:

The study successfully produced an acoustic signal processing system which functions for respiratory disease diagnosis. The system utilizes a stethoscope to record sounds in real time while a microcontroller increases signal strength prior to MATLAB-based signal processing. The detection system uses MFCCs along with spectrograms and spectral analysis features for identification purposes. The Python implementation of CNNs within the AI model delivered substantial success rates during the analysis of respiratory conditions.

B. Strengths of the System:

The system obtains signals in real-time through hardware processing that eliminates noise and retrieves significant features. The deep learning model together with the signal processing analytics system produced through MATLAB enables reliable data preparation and successful classification results. The system adjusts hardware with software elements to support usage in clinical applications while requiring minimal processing power. The modular construction helps to enable enhancements of future capabilities such as integrating more sophisticated features and AI models.

C. Brief on Future Work:

The system can benefit from additional research devoted to three areas: extending the database with diverse lung sound data, optimizing the CNN model parameters and developing mobile or web-based deployment options for the system. The system would perform better at clinical diagnostics and clinical application expansion through the integration of ultrasound or wearable IoT devices for continuous monitoring.

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