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Optimization of lung sound classification by experimenting with different filtration techniques and LPCC feature extraction

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Abstract-A precise evaluation of lung sounds is crucial for the identification of respiratory diseases. However, the existence of internal disruptions might significantly impede the clarity of lung sounds. This work systematically evaluates the efficacy of four advanced signal preprocessing approaches, using lung sounds obtained from the balanced ICBHI 2017 Challenge dataset. Out of those methods, adaptive filtering was discovered to considerably reduce heart sound peaks by 60-90%, hence enhancing the clarity of lung sounds. Furthermore, this study enhances the input for machine learning classifiers by employing LPCC as a method for extracting features. The performance of Support Vector Machine (SVM) and Random Forest (RF) classifiers were evaluated, with a focus on their suitability for clinical diagnostic systems. The SVM classifier demonstrated its performance achieving a testing accuracy of 75% and a training accuracy of 93%, as opposed to the RF classifier's respective accuracies of 74% and 93%. The results indicate that the use of LPCC feature extraction enhances the effectiveness of the classifier and also confirms the efficacy of the preprocessing procedures. This study significantly enhances the field of computational lung sound analysis by integrating rigorous sound filtering and complex feature extraction techniques. It demonstrates a potential direction for developing accurate, efficient, and clinically relevant diagnostic models.

Keywords: Lung sounds, Adaptive Filtering, LPCC, Random Forest, Support Vector Machine

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1. Introduction

Health is an important element in a human life. An individual can suffer from several types of health issues throughout his lifetime. On them respiratory diseases are becoming one of life threatening diseases. According to the World Health Organization (WHO), it states that, over 7 million individuals worldwide suffer from severe illness or die as a result of the "big five" respiratory diseases such as lung cancer, tuberculosis, acute lower respiratory tract infections, Chronic Obstructive Pulmonary Disease (COPD), and asthma (Levine et al., 2021) . The majority of illnesses associated with a constrained or obstructed respiratory system can be identified by the noises produced when breathing (Pramono, Bowyer and Rodriguez-Villegas, 2017). Variations in lung function brought on by disease may result in alterations in the pattern of lung sounds (Pasterkamp, Kraman and Wodicka, 1997). Thus, it is obvious to see the lung sounds as pertinent indicators of respiratory health. Lung sounds can mainly be categorized as normal and adventitious. Therefore, accurate examination of lung sounds is crucial in the field of respiratory health for the diagnosis of various pulmonary disorders. In healthy individuals, normal breathing noises are audible. Adventitious Lung Sounds (ALSs) are superimposed with the normal respiratory sounds (Jácome et al., 2018).

Due to the advancement in Technologies new Machine Learning technologies are being introduced to the world but still it is very crucial to provide very clear data to the machines for the perfect accuracy. In that mean the respiratory sounds, the major key indicator that is being used to classify the respiratory diseases always presents with heart sounds within it. Where the hearts sounds are presented between the 20-100Hz (Reichert et al., 2008) becomes an internal disturbances for the lung sounds classification tasks in getting the pure breathing sounds for more efficient classification task along with significant sound features.

Therefore, it is importance to filter out the pure breathing sounds and extract significant features from the Lung sounds in order to feed them to the machine learning based computerized lung sound classification tasks. In that mean, the purpose of this study is to evaluate the efficacy of four advanced signal preprocessing techniques on a prominent lung sound database, the ICBHI 2017 Challenge (Nguyen and Pernkopf, 2022) : Wavelet Packet Transform, Adaptive Filtering (Iyer et al., 1986), Time-Frequency Filtering (Pourazad, Moussavi and Thomas, 2006) , and AR/MA Estimation. The goal is to determine which of these audio filtering techniques best enhances lung sound clarity and diagnostic efficacy in clinical settings. Through a thorough experiment-based comparison examination, this work aims to determine the best efficient preprocessing method for real-time lung sound analysis along with the feature engineering methods that can be utilized for the audio signal processing tasks. In that mean as an initial step this paper presents the experiment that was done for LPCC Feature extraction which was practically experimented and compared with two machine learning approaches SVM and RF. Based on the output achieved through this experiment the same preprocessed sounds will be experimented with other feature engineering methods such as Wavelet and MFCC to identify the best feature engineering method to develop a telemedicine applicable model that can be utilized for the dynamic environment.

2. Related Literature

A. Pre-processing

Respiratory sounds (RS) are heard across the chest wall when air moves in and out of the lungs throughout the respiratory cycle. These noises are non-stationary and nonlinear, susceptible to noise contamination, making it difficult for physicians to detect problems (Lal et al., 2023). Preprocessing is crucial for optimizing samples for analysis, reducing storage requirements, and facilitating feature extraction (Zulfiqar et al., 2021). Where these procedures can be employed to ascertain the constituents of the audio signal, presented as numerical data while discerning the audio content and filtering out unnecessary and undesired elements that contain information such as background noise (Chaiyot, Plermkamon and Radpukdee, 2021). As per the studies, the only internal disturbance that can identify from the lung sounds is the heart sounds and few other environmental disturbances due to the difference and quality of the recording instruments. Perturbations may arise in the analysis of lung sounds due to the presence of heart sounds. The majority of heart sounds are found within the frequency range of 20 to 100 Hz (Reichert et al., 2008).

As per a group of researchers' they suggest that the most commonly used denoising techniques are discrete wavelet transform (DWT), singular value decomposition (SVD), and adaptive filtering, which provide robust denoising but can be computationally costly (Li et al., 2020). Similarly, few more researchers have focused on some other techniques such as wavelets, adaptive filtering using a recursive least squares algorithm, time/frequency filtering, reconstruction, AR/MA estimation in the time/frequency domain of wavelet coefficients (autoregressive/mobile average), independent component analysis, and an entropy-based method.

B. *Feature Engineering*

Feature extraction is a crucial step in the creation of effective algorithms for pattern recognition and classification. The classification information is enhanced as a consequence. There are two prevalent categorizations of feature extraction that are employed for LSC systems (Nguyen and Pernkopf, 2022). They are namely features for conventional classifiers and time-frequency classifiers for deep learning. Researchers extract informative feature vectors to represent patterns in specific ways relevant to the task. This is described in the literature as handcrafted or handmade features (Pramono, Bowyer and Rodriguez-Villegas, 2017). From 1938 to 2016, most algorithms for detecting and classifying Adventurous lung sounds were created using manually designed characteristics and were included into the conventional pattern recognition framework. A manually created feature set usually consists of spectral, cepstral, and time-domain attributes in the frequency domain.

There are several types of features that the researchers use in this computational lung sound analysis and speech recognition in audio data and some of them are MFCC (The Mel Frequency Cepstrum Coefficients), Linear Prediction Coefficients (LPCs), Linear Prediction Cepstral Coefficients (LPCCs), and features derived from the Discrete or Continuous Wavelet Transform (DWT/CWT). A comprehensive analysis of features and techniques for categorization has been documented in (Palaniappan, Sundaraj and Ahamed, 2013) review study. Meanwhile various attributes are derived by analyzing the sound properties using different analysis methods outlined in (Reichert et al., 2008).

C. *Performance Analysis*

Aykanat et al. created a cost-effective, user-friendly, and multi-device-compatible electronic stethoscope specifically designed to facilitate data storage on personal computers. The study included two fundamental machine learning algorithms: Support Vector Machines (SVMs) utilizing Mel Frequency Cepstral Coefficient (MFCC) features, and Convolutional Neural Networks (CNNs) utilizing spectrogram pictures. This study found that the CNN and SVM algorithms reached an accuracy rate of 86% (Aykanat et al., 2017) in identifying abnormalities in healthy audio after conducting tests. Moreover, another paper examines the important function of pulmonary auscultation in identifying abnormal lung sounds during clinical examinations. It also explores the possibility of machine learning models to automatically classify these sounds, reducing the need for subjective interpretation by the operator. The ANN and SVM are often employed machine learning classifiers which exhibit accuracy rates ranging from 49.43% to 100% for the identification of abnormal sound types and from 69.40% to 99.62% (Lal et al., 2023) for sickness class categorization.

The majority of CLSA research was published between 2019 and 2021, with 2020 being the most prolific year in this regard, the recent pandemic COVID-19, which is also associated with respiratory illnesses, is likely an explanation of this worry. Consequently, the current state of the art is lacking a technique that can effectively deal with dynamic environments, and no research has been published on this topic where an end user application is introduced using any classifier like Reinforcement Learning that is best for dynamic environment setting. Therefore it is crucial to experiment and identify the best pre-processing technique and feature engineering methods to utilize them in such models.

In addition, even though there are existing intelligent stethoscopes that can transmit lung sounds to computers automatically (Huang et al., 2023) , still a gap exists where it has not yet produced a practical, usable end- product for telemedicine that can automate the classification process, allowing for early disease detection and subsequent treatments.

3. Materials and Methods

This study used a quantitative research strategy and the research was commenced by conducting a pilot survey to ascertain the necessity and utility of a computerized lung sound classification system among medical domain specialists. Upon receiving their feedback and remarks, we comprehended the significance of implementing this filtering methods to the lung sound databases to develop few models that can be implemented in the telemedicine systems for the automatic classification tasks. Initially, a thorough search for the required dataset pertaining to lung sounds from reliable sources was conducted. Subsequently, datasets were successfully obtained by directly contacting the respective authors. This research used ICBHI 2017 dataset (Sun, 2023) where initially it had only 921 lung recordings inclusive of both normal and abnormal with an imbalance between both classes. Later in order to do more precise experiment and to avoid favorable results towards the class that has more samples the dataset was balanced with 1607 recordings through the data augmentation technique. Dataset details and corresponding resources were enclosed in this document for further reference. Meanwhile the dataset used for this research is well-structured and properly labeled, making it suitable for scientific studies.

Then through a deep state of the art analysis four filtering methods such as AR/MA Estimation, Adaptive filtering, Time Frequency Filtering and Wavelet packet transform were experimented using 20- 30 samples from both classes to choose the best filtering methods that suits for the sound recordings utilized in this study. After finding the best filtration techniques it was identified that LPCC, MFCCs and Wavelet are some feature engineering that was used in several studies to extract most significant features from audio signals for the further classification in medical domains. As an initial step LPCC sound features were extracted and experimented and then the model was compared with two machine learning approaches SVM and RF to analyze the performance and accuracy of the model. Following diagram is the flow of the experiment steps followed in this study and the summary of the methodology.

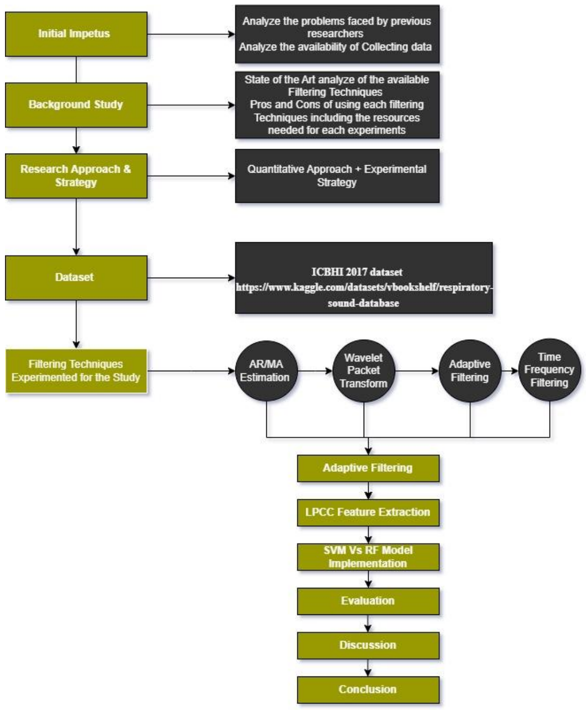

Figure 1. *Methodology*

4. Results & Discussion

This section will provide a detailed and succinct summary of the outcomes.

A comprehensive analysis was conducted and identified the essential audio signal preprocessing techniques required to extract the critical aspects of audio data for use in the classification task. Consequently, it was discovered that the literature employs the following methodologies, which have yielded valuable conclusions.

D. Wavelet packet transform filtering

In this approach it decomposes the respiratory sound signal into different frequency bands, allowing us to target and remove heart sound components. Building upon the work of Bahoura et al., this algorithm identifies and filters out frequencies typically associated with heart sounds (20-100 Hz), thus isolating the respiratory sound signals for further analysis.

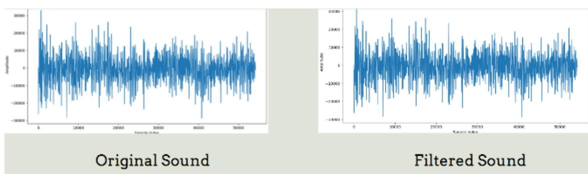

Figure 2. *Wavelet Original Vs. Filtered*

E. AR /MR Filtering (Autoregressive Moving Average)

In this Filtering method, firstly, a band-stop filter was implemented to selectively remove the frequencies associated with heart sounds while preserving the integrity of the respiratory signal. This filter was designed to attenuate frequencies between 20 and 100 Hz, effectively eliminating the interference caused by overlapping heart sound frequencies.

The band-stop filter was constructed using a Butterworth filter design, a widely-used technique known for its stability and efficiency in signal processing applications. By specifying the desired cutoff frequencies and order of the filter, we were able to tailor its characteristics to suit our specific requirements.

Next, band-stop filter was applied the respiratory sound data using the filtfilt function, which performs zero-phase filtering to minimize phase distortion and ensure accurate temporal alignment of the filtered signal. This step was crucial in preserving the temporal dynamics of the respiratory signal while effectively suppressing the unwanted heart sound components.

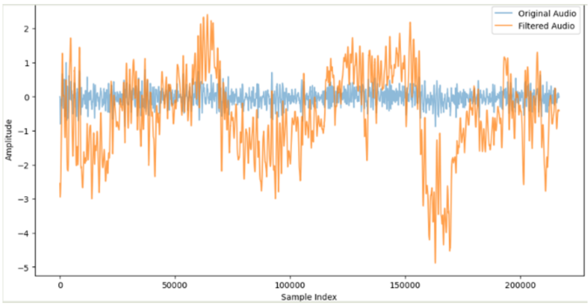

Figure 3. *AR/MR Filtering*

F. Time Frequency Filtering

In this filtering method, two primary filtering techniques such as High-Pass Filtering and Notch Filtering were used where High-pass filtering was applied to attenuate low-frequency components, which often include baseline drift and artifacts associated with heart sounds. In the meantime Notch filtering was utilized to suppress specific frequencies known to correspond to heart sounds. By selectively attenuating these frequencies, the effectiveness of the filtering techniques was assessed through visual inspection of spectrograms, which provided insights into signal clarity and noise reduction.

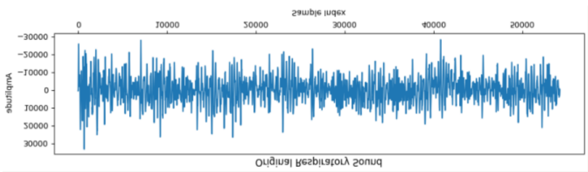

Figure 4. *Time Frequency Original*

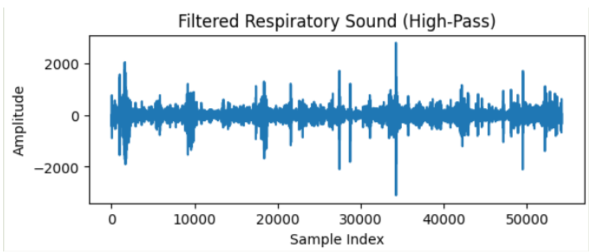

Figure 5. *Time Frequency Filtered*

G. *Adaptive Filtering*

This method provided more clear output compared to the other three methods utilized in this study. It was able to reduce the heart sounds with the average of 75% where this filtering technique was finalized to proceed with the next steps of developing an agent for computerized lung sound classification tasks.

Bandpass filters are used to selectively pass a range of frequencies while attenuating frequencies outside the specified range. Here, the low and high cutoff frequencies for the bandpass filter are defined (low - 20 Hz, high - 100 Hz), determining the frequency range of interest for the filtering process. Before applying the adaptive filter, the input audio signal is normalized. Normalization ensures that the signal's amplitude values fall within a consistent range, typically between 0 and 1. Following is the graphical representation of the output we got through this filtering method before and after the filtration.

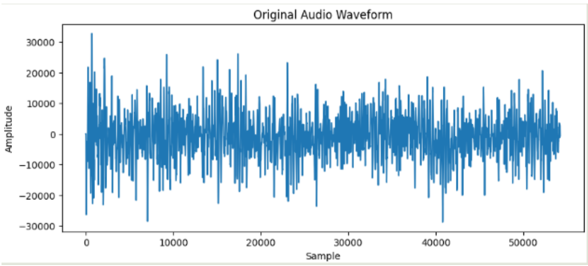

Figure 6. *Raw Lung Sound*

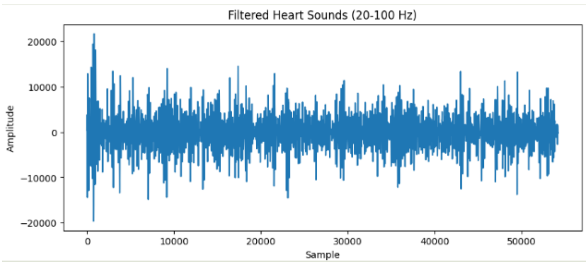

Figure 7: *Filtered Heart Sound*

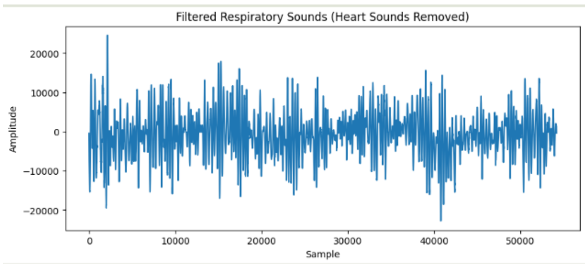

Figure 8. *Pure Lung Sounds*

After observing positive results from adaptive filtering compared to other three methods where this filter reduced the heart sounds to the peak of 90%, all audio samples were preprocessed using this technique. LPCC sound features were then extracted from the filtered samples, which had a sampling rate of 4000Hz. The first machine learning technique used to train the data was SVM. This method achieved a training accuracy of 93% and a testing accuracy of 75%. Next, the same samples were trained using Random Forest, which resulted in a training accuracy of 93% and a testing accuracy of 74%. In comparison, SVM provided more accurate predictions for this database compared to RF. The chart below provides a concise overview of the comparison between SVM and RF.

ML Classifier	Label	Precision	Recall	F1-Score	Accuracy
SVM	Normal	0.79	0.85	0.82	0.75
	Abnormal	0.66	0.56	0.60	
RF	Normal	0.84	0.77	0.80	0.74
	Abnormal	0.61	0.70	0.65	

5. Conclusion

This study presents the most precise filtering method that can be utilize to filter out the internal disturbances from the lung sounds out of the traditional four filtering methods AR/MA Estimation, Adaptive filtering, Time frequency filtering and Wavelet packet transform filtering. In addition to a quantitative analysis of the signals, this was validated by the use of both visual and auditory examinations. Experts in the field of medicine examined the outputs of all four filtering methods and confirmed that the sounds coming from the lungs could be heard clearly with only a small amount of interference from the heart in adaptive filtering compared to the other three. The results of adaptive filtering are superior to those of the other traditional methods where it reduces the disturbance to an average of 75%. In addition to this, Adaptive Filtering was able to successfully eliminate white Gaussian noise, minimize interference from vocal sounds, and reduce measurement errors. Meanwhile time frequency filtering yields superior results in terms of computational expenses and speeds. Further, the SVM classifier generates superior outcomes when utilized in conjunction with LPCC sound features in the ICBHI 2017 Balanced Database, compared to the RF classifier.

6. Limitations and Future Works

Since there are some other sound feature extractions methods like MFCCs and Wavelets prevails in literature, those features also can be extracted and compared with these machine learning techniques and the best out of those three-feature extraction mechanism can be utilized for further analysis. Meanwhile, since lung sounds are something that can be changed based on generations, some other ML classifier that work well with a dynamic environment can also be implemented and tested to embed with real world applications.

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