LUNG DISEASE RECOGNITION METHODS USING AUDIO BASED ANALYSIS WITH MACHINE LEARNING

Dr. R.Radhakrishnan[1], Swathika D[2], Unnathi N[3], Vidyasree R[4], Yachitha A[5]

[1]Professor, [2,3,4,5]UG scholars, Department of Electronics and Communication Engineering,

Adhiyamaan College of Engineering (AUTONOMOUS), Hosur

ABSTRACT

This project focuses on the development of a system for analyzing lung sounds to classify respiratory diseases using deep learning techniques.The workflow includes data acquisition, preprocessing, feature extraction using spectrogram analysis and MFCCs, and classification using a CNN developed with PyTorch. Matlab and Audacity are utilized for preprocessing and feature extraction. The system is designed for robustness against variations in input data, ensuring reliable performance in real-world applications. By leveraging advanced machine learning techniques, this project aims to assist in the early detection and diagnosis of respiratory diseases, contributing to improved patient care and healthcare efficiency.

Keywords: Respiratory disease, MFCC, Preprocessing, feature extraction, classification, early detection, medical diagnostics.

I INTRODUCTION

Lung diseases such as pneumonia, asthma, COPD, and lung cancer are significant health concerns worldwide, contributing to high mortality and morbidity. Early and accurate detection is crucial for better patient care and reducing the strain on healthcare systems. Traditional diagnostic approaches, including X-rays, CT scans, and pulmonary function tests, require advanced equipment and expert analysis, making them less accessible in under-resourced areas. Recently, audio-based techniques have gained attention for diagnosing lung diseases. By examining respiratory sounds like wheezes, crackles, and irregular breathing patterns, machine learning models provide a promising solution for early detection. This approach enhances clinical assessments by offering a non-invasive, cost-effective, and accessible method for identifying respiratory conditions.

II.LITERATURE SURVEY

Lee et al, “Noise Suppression in Lung Sound Recordings”- 2018,Wavelet transform helps to isolate noise components by analyzing signals at various frequency levels, while adaptive filtering dynamically adjusts to filter out unwanted sounds like heartbeats and environmental noise. Wang et al, “Pre- Processing Methods for Improved Lung Sound Diagnosis”-2019, Normalization adjusts signal amplitude for consistency, while bandpass filtering removes frequencies outside the lung sound range, reducing ambient and bodily noise. Brown & Davis, “Wavelet Transforms in Lung Sound respiratory patterns indicative of diseases. Johnson et al, “Feature Extraction Techniques for Lung Sound Analysis”-2021, Various methods like Mel- frequency cepstral coefficients (MFCCs), spectral entropy, and statistical features are explored to analyze lung sounds. MFCCs capture frequency- based features, essential for distinguishing between normal and abnormal lung sounds, while spectral entropy assesses signal randomness. Smith et al, “Automated Classification of Respiratory Sounds”- 2022, In this, the authors develop a machine learning model using convolutional neural networks (CNNs) to classify respiratory sounds. They preprocess recordings through noise reduction and segment the sounds into manageable time windows, then extract spectrogram-based features to feed into the CNN.

III.EXISTING SYSTEM

Traditional lung auscultation involves using a stethoscope to listen to lung sounds, allowing clinicians to assess the respiratory system by placing the stethoscope on various parts of the chest. By interpreting sounds such as wheezes, crackles, and other anomalies, clinicians can identify potential respiratory conditions. This approach,however, relies heavily on the clinician's experience and subjective judgment, which may vary between practitioners. Automated lung sound analysis offers a more objective and technology-driven approach, utilizing high-fidelity recording devices like digital stethoscopes and sensors to capture detailed sound data. To ensure sound clarity, preprocessing techniques, such as digital noise reduction and filtering, are employed to eliminate irrelevant noise. Feature extraction then analyses both time-domain and frequency-domain characteristics.

1VDISADVANTAGES

1. **Noise:** Respiratory acoustic samples often have significant background noise, which complicates and hinders accurate analysis.

2. **Imbalanced Data:** The distribution of audio samples across different respiratory diseases is often uneven, leading toimbalanced dataset.

3. **Extraction:** Effective feature extraction enhances model efficiency.

4. **Algorithm Choice:** Selecting the appropriate algorithm is essential for acheieving the desired results.

5. **Dataset selection:** Obtaining and maintaining high-quality noise-free datasets,proper preprocessing of training data is essential to ensure accurate and generalizable results.

V PROPOSED METHODOLOGY

The proposed lung sound analysis system provides a structured and efficient method for diagnosing respiratory diseases by analyzing and classifying lung sounds. It follows a systematic approach, including data acquisition, preprocessing, feature extraction, and classification. Initially, lung sounds are recorded using high-quality digital stethoscopes or specialized audio devices to capture diverse sound patterns associated with both normal and abnormal conditions. The clarity of these recordings is essential, as precise input data significantly influences the accuracy of the analysis.After data collection, preprocessing is performed to remove background noise and enhance the quality of lung sounds. This step ensures that subtle respiratory signals remain distinguishable. Feature extraction is then carried out using spectrogram analysis and Mel Frequency Cepstral Coefficients (MFCCs). Spectrograms visually represent frequency distribution over time, highlighting spectral and temporal patterns of lung sounds. MFCCs, on the other hand, break down sounds into frequency components, allowing for the identification of key characteristics needed for classification. Using these extracted features, the system categorizes lung sounds by comparing them to established patterns of healthy and pathological conditions. This aids healthcare professionals in performing quick and non-invasive respiratory assessments. The classification process is driven by

Convolutional Neural Networks (CNNs), which are deep learning models specialized in processing structured data, such as images. These networks employ convolutional layers to detect essential features, pooling layers to reduce dimensionality, and fully connected layers for final classification. To implement this model, PyTorch, an open-source deep learning framework, is used. PyTorch enables efficient neural network training through its dynamic computation graphs, making it well-suited for both research and practical applications. Its user-friendly APIs allow seamless training on large datasets, enhancing the reliability and effectiveness of the lung sound analysis.

VI BLOCK DIAGRAM

This refers to the process of listening to lung sounds using a stethoscope or electronic devices. These sounds are key to diagnosing conditions like asthma, pneumonia, or bronchitis. After capturing the lung sounds, conditioning improves the quality of these sounds. Transceiver is responsible for sending and receiving the lung sound data between different components of the system. It ensures that the sound data collected from the patient is transferred to the processing unit for further analysis. the system's "messenger" that helps the different parts of the project communicate with each other by transferring the lung sound data efficiently. This seamless data transfer enables real-time analysis and ensures accurate classification of respiratory conditions. Lung sounds are often accompanied by background noise, such as heartbeats, breathing sounds, or external environmental noise. This module applies filters to clean up the lung sound data by removing unwanted noise. A filter is like a tool that helps us focus only on the important lung sounds and ignores the rest. For example, a digital filter could be used to reduce noise and keep only the essential lung sound that the system needs for analysis. The final step involves the **user interface** (UI), which presents the analysis results to healthcare providers in an easy-to- understand format. This may include visualizations of the lung sounds, the results of the classification, and recommendations for further testing or treatment. By providing this information in a clear, actionable format, the system empowers healthcare providers to make informed decisions and offer personalized care to their patients.

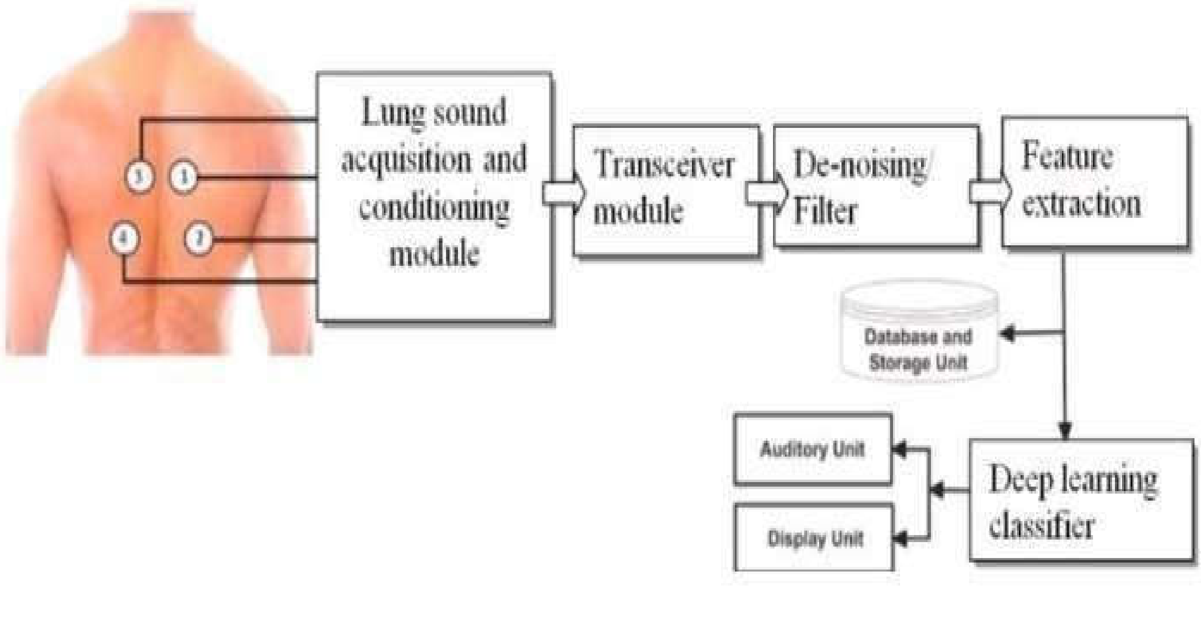


Fig 1: Basic block diagram of Proposed system

VII ADVANTAGES

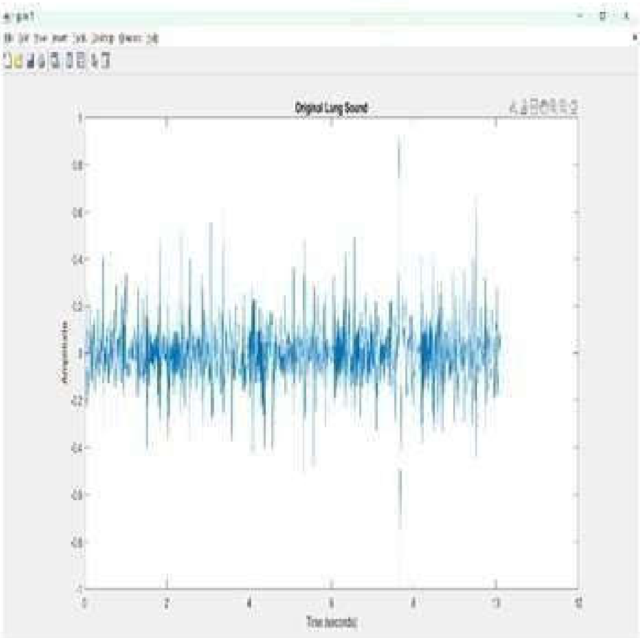
1. **Pre-processing of lung sound signals:** Preprocessing audio files contains functions like trimming the audio to a consistent duration,removing regains of silence,and resampling audio files to a consistent sample rate.
2. **Lung-heart sound methods:** LS and HS heavily overlap in both frequency and time,making it difficult to separate the mixed signal(LHS) using traditional BSS techniques.
3. **Artifact removal methods:** Audio artifact removal aims to substract noise from the sound signals while improving the intelligibility and quality of the sound signal.Deep learning-based on audio diagnosis techniques usually present artificial noises.
4. **Early Detection and Diagnosis:** By analyzing subtle changes in lung sounds,the system can prtentially detect lung sounds at an early stage,even before more pronounced symptoms appear.Early detection is crucial for improving patients outcomes,allowing for timely interventions and treatments that could prevent disease progression.
5. **Deep learning methods:** MFCC was also commonly used with Recurrent Neural Networks(RNNs),machine learning and ensemble learning,as well as other feature-based methods that have been infrequently used with machine learning and ensemble methods.

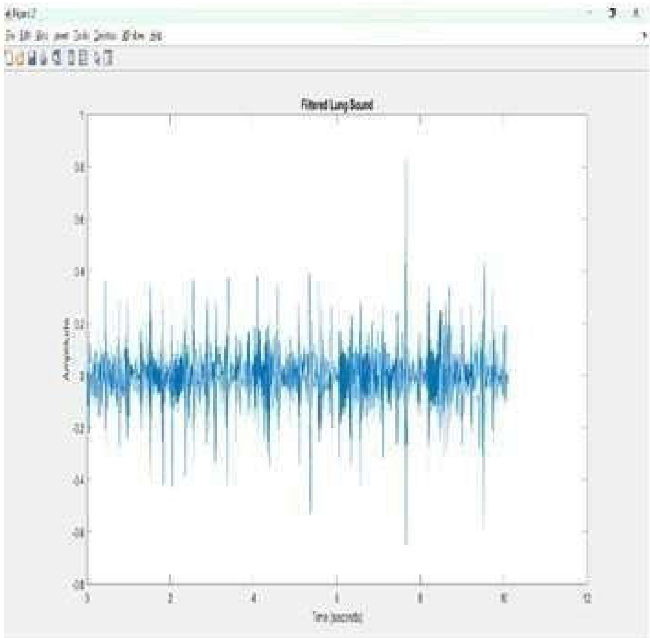
VIII APPLICATION

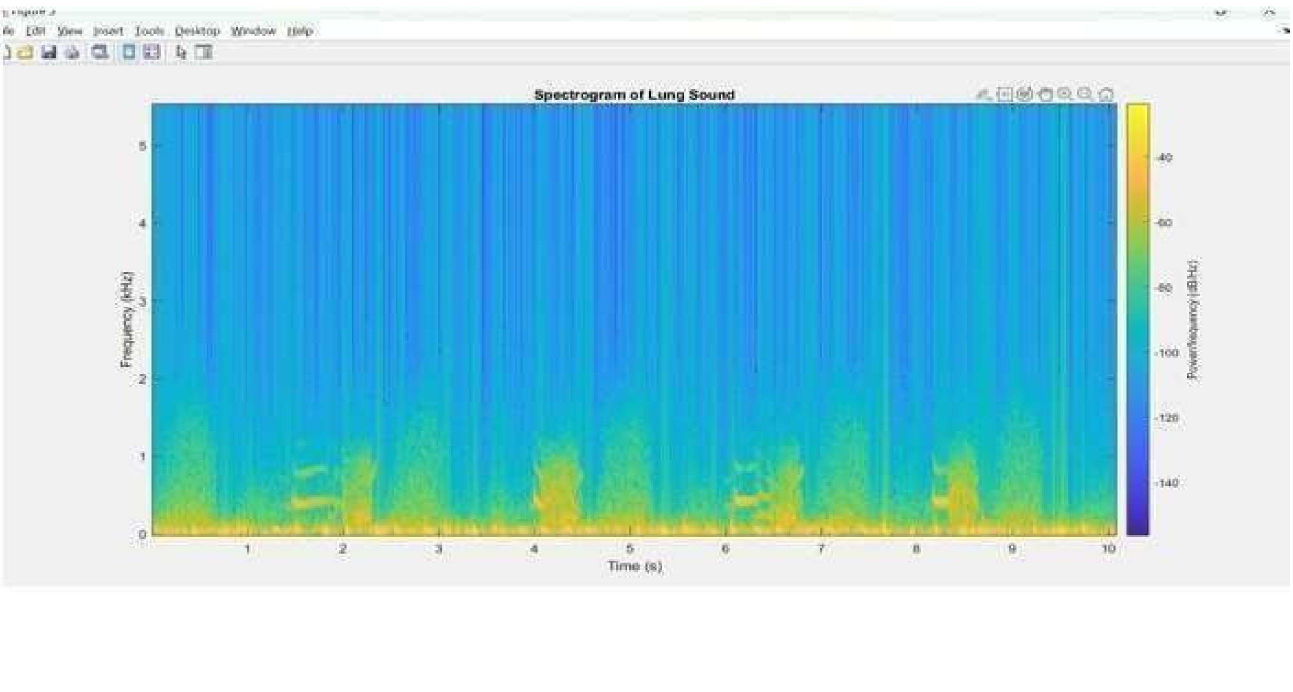
1. **Early Detection of Lung Diseases:** The system can be used to detect the early onset of lung diseases such as asthma, pneumonia, COPD, or even lung cancer. By analyzing subtle changes in lung sounds, it can identify patterns that may indicate the presence of disease even before noticeable symptoms appear.
2. **Chronic Disease Monitoring:** For patients with chronic respiratory diseases like asthma, COPD, or pulmonary fibrosis, the system can be used for continuous monitoring of lung function. Patients can record their lung sounds regularly, and the system can track changes over time.
3. **Telemedicine and Remote Diagnosis:** Audio-based analysis can be integrated into telemedicine platforms, enabling remote consultation between patients and healthcare providers.
4. **Screening for High-Risk Populations:** The system can be used for population-level screening, particularly for high-risk groups such as the elderly, smokers, or individuals with a family history of lung diseases. Regular screening with audio-based analysis can help identify individuals at risk of developing conditions like COPD or lung cancer.
5. **Smart Healthcare Devices and Wearables:** The system can be integrated into wearable devices like smartwatches or chest patches equipped with microphones to continuously monitor a patient's respiratory health. The wearable devices would record respiratory sounds and send the data to a cloud- based platform where machine learning models analyze it in real-time.
6. **Emergency Situations and Ambulance Services:** Ambulances and emergency services can use the system to evaluate the respiratory health of patients in critical situations, such as asthma attacks, cardiac arrest, or suspected pneumonia.
7. **Educational Tools for Medical Training:** Audio-based lung sound recognition can be used as a teaching tool in medical education

8. **Patient Self-Management and Health Tracking:** Patients with chronic respiratory conditions can use the system as a self-management tool, allowing them to track their symptoms and progress over time.

IX RESULT







The spectrogram image of a lung sound would display sound intensity across time and frequency (vertical axis). Each point in these plots show how much of each frequency is present at a given time, represented by colour intensity. Spectrogram features for a healthy lung sound includes low frequency (below 300Hz), smooth texture, absence of high frequency components and temporal stability. Spectrogram features for a unhealthy lung sound includes high frequency bands (400-1600Hz) based on severity, long duration, irregular patterns, intensity variations and noisy texture.

Fig: Lound disease classification output

The above figure illustrates the results of training and testing the CNN for classifying lung sounds into categories.The implementation leverages PyTorch for model development, optimization, and evaluation. The results demonstrate the accuracy and loss trends over epochs, validating the model's performance in recognizing distinct respiratory conditions. The results demonstrated in the figure provide a strong foundation for deploying the model in practical scenarios, such as automated diagnosis systems. The model's ability to generalize across unseen data can be further evaluated by testing it on a separate validation set, which helps in assessing its real world applicability. Fine-tuning of hyperparameters such as the learning rate and batch size could also be explored to optimize performance.Moreover,techniques like cross-validation can be employed to ensure robustness and mitigate overfitting.The results demonstrated in the figure provide a strong foundation for deploying the model in practical scenarios,such as automated diagnosis ststems.Ultimately,this CNN-based approach offers an efficient and reliable tool for classifying lung sounds,aiding in early detection and management of respiratory diseases.

X.CONCLUSION

The lung sound classification project aims to create a reliable system for detecting respiratory diseases by analyzing lung sounds. Using CNNs, the system is designed to classify lung sounds into categories such as healthy, wheezing, crackles, stridor, and squawk etc. The project involves multiple stages, including data acquisition, where lung sound recordings are collected, followed by preprocessing to clean and prepare the data. Feature extraction techniques, such as MFCCs and spectrogram analysis, are applied using MATLAB to convert raw audio into meaningful features suitable for model training. The project then uses PyTorch to implement and train the CNN model, optimizing it through techniques like hyperparameter tuning, loss function adjustments, and data augmentation. Evaluation metrics such as accuracy, precision, recall, and F1-score are employed to assess the model's performance. The system demonstrates the potential of machine learning in medical diagnostics, providing a cost-effective tool for early detection of lung diseases. Future work could focus on improving model robustness and developing a real-time deployment for clinical use, enhancing healthcare delivery.

XI.FUTURE SCOPE

The future scope of lung disease recognition using audio-based analyses with machine learning holds immense potential for transforming healthcare. Astechnology advances, these systems could integrate with multi-modal diagnostic tools, combining audio data with imaging, clinical history, and genetic information for more accurate and personalized diagnoses. Real- time, wearable monitoring devices will enable continuous tracking of respiratory health, alerting patients and healthcare providers to early signs of disease exacerbations or complications. Enhanced machine learning models, including deep learning and AI-driven approaches, will improve the system's accuracy, enabling the detection of even more subtle or complex lung conditions. Furthermore,the expansion of these methods to global health initiativies could bring affordable and accessible lung disease setection to underserved populations,especially in rural or low-pressure areas.Overall,the integration of these technologies into everyday healthcare could revolutionize early diagnosis,chronic disease management,and patient care,making lung disease recognition more efficient,accessible,and effective worldwide.

XII REFERENCE

1 K. Rajesh Kumar & M. Vijayakumar 2023, “Optimization of Cognitive Femtocell Network via Oppositional Beetle Swarm Optimization Algorithm”, Intelligent Automation & Soft Computing, vol. 36, no.1, pp. 819-832, DOI: 10.32604/iasc.2023.030961, ISSN: 1079-8587 (Print), ISSN: 2326-005X (Online).

2 Johnson, D., Patel, R., & Singh, S.(2021), “Feature extraction techniques for lung sound analysis: A review of current methodologies and future directions”, Medical Data Analysis, 9(1), 112-130.

3 Brown, E., & Davis, L. (2020), “Wavelet transforms in lung sound classification: An application for early diagnosis of respiratory diseases”, IEEE Transactions on Biomedical Engineering, 67(5), 789-799.

4 Wang, F., Zhao, Y., & Chen, X. (2019), “Pre-processing methods for improved lung sound diagnosis: A systematic review”, International Journal of Medical Informatics, 128, 1-11.

5 Lee, H., Park, J., & Kim, M. (2018), “Noise suppression in lung sound recordings for accurate diagnosis of respiratory conditions”, Journal of Acoustical Society, 144(6), 3208-3215.

6 Nguyen, H., & Tran, T. (2023). Real-time classification of lung sounds using convolutional neural networks. Journal of Biomedical Informatics, 133, 104151.

7 Gonzalez, A., & Morales, J. (2020), “A comparative study of time frequency representations for lung sound classification”, Journal of Sound and Vibration, 474, 115-130.

8 Abeyratne, U. R., Swarnkar, V., & Setyati, A. (2013), “Cough sound analysis can rapidly diagnose childhood pneumonia”, Annals of Biomedical Engineering, 41(11), 2448-2462.