Pulmonary Ailment Classification using Phonopneumography

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Abstract: Lung auscultation is one of the most popular diagnostic modalities used by the pulmonary experts to analyze the condition of the respiratory system. When auscultating various areas on the anterior and posterior sides of the chest, lung sounds can be detected. Lung sounds are indicative of different anatomical flaws in the lungs and provide accurate prognoses regarding respiratory health, resulting in more trustworthy medical tool for identifying respiratory disorders. According to a recent study conducted by the world health organization (WHO), approximately ten million (M) people die each year as a result of respiratory diseases. In order to analyze respiratory sounds on a computer, we developed a cost-effective and easy-to-use Algorithm that can be used with any device. Employed two types of machine learning algorithms; Gammatone Cepstrum Coefficients Features in a Convolutional Neural Network and Since using GTCC and STFC features with a CNN-LSTM algorithm. We prepared four data sets for CNN-LSTM algorithm to classify respiratory audio: (1) healthy versus pathological classification; (2) rale, rhonchus, and normal sound classification; (3) singular respiratory sound type classification; and (4) audio type classification with all sound types.

Index Terms: **Respiratory Disease classification, Pulmonary disease classification, Lung disease classification, Lung disease classification based on lung sounds.**

I. INTRODUCTION

Respiratory diseases are the leading causes of death and disability worldwide, with the poorest regions having the greatest disease burden. Ageing and risk factors such as smoking, environmental pollution, and body weight also play a key role in this issue. Chronic respiratory diseases, including asthma, account for 7% of all deaths worldwide and are the third leading cause of death. Between 1990 and 2017, the number of deaths due to chronic respiratory diseases increased by 18%. Pneumonia kills millions annually, particularly among children under 5 years old. Over 10 million people develop tuberculosis (TB), which is the most common lethal infectious disease. Lung cancer kills 1.6 million people each year and is the deadliest cancer globally. Respiratory diseases make up five of the 30 most common causes of death: COPD, lower respiratory tract infection, tracheal, bronchial, and lung cancer, TB, and asthma. Over 1 billion people suffer from acute or chronic respiratory conditions. Lung diseases significantly affect people's social, economic, and health lives. Social deprivation is the most important factor affecting death and disability rates, with the highest rates seen in the poorest regions. Lower mortality rates are seen in more affluent countries due to better access to health services and improved treatments. The treatment of lung diseases is of great importance in the medical field, and research is ongoing for early diagnosis and intervention in respiratory diseases. However, 45% of WHO Member States report having less than one physician per 1000 population, which can lead to mistakes. Finding new ways to help doctors save time is a priority, and automatic and reliable tools can help diagnose more people and reduce errors due to work overload.

II. LITERATURE SURVEY

Yi Ma, Xinzi Xu, and Yongfu Li. Lungrnl: An improved adventitious lung sound classification using non-local block resnet neural network with mix up data augmentation. In Interspeech, pages 2902–2906, 2020.Their method employs a non-local block ResNet neural network along with mixup data augmentation to improve classification accuracy. By leveraging advanced neural network architectures and data augmentation techniques, their research aims to facilitate more precise diagnosis of respiratory conditions, offering potential benefits for medical applications. This innovation could significantly enhance automated diagnostic systems by providing more reliable assessments based on lung sound analysis, thus potentially improving patient care and medical outcomes in respiratory health.

III. PROPOSED SYSTEM

A) Sound Analysis and Pattern Recognition:
Employing framing and windowing techniques for effective preprocessing of respiratory sound data. Conducting in-depth analysis through Linear Predictive Coefficient (LPC) extraction to identify distinct features indicative of respiratory health. Utilizing advanced classification algorithms such as Multi-layer Perceptron (MLP) for precise differentiation between healthy and abnormal respiratory sounds.
B) Real-Time Monitoring and Data Integration:
Establishing a seamless real-time data acquisition system to continuously capture respiratory sound signals. Integrating collected data into the analysis pipeline for immediate processing, ensuring swift detection of anomalies.
C) Dynamic Model Adaptation and Refinement:
Implementing adaptive learning mechanisms to enable the classification model to evolve and improve its accuracy over time. Incorporating feedback loops to adjust model parameters and accommodate variations in respiratory conditions and sound patterns.
D) Instant Notification and Alerting System:
Integrating an instantaneous alert system triggered by the classification model upon detection of irregular respiratory patterns. Employing efficient communication protocols to promptly notify healthcare professionals, facilitating timely interventions.
E) Seamless Communication Infrastructure:
Developing robust communication protocols to ensure reliable transmission of alerts between the classification system and healthcare providers. Implementing low-latency communication channels to enable swift responses to respiratory abnormalities.
F) Localization and Characterization of Respiratory Abnormalities:
Enhancing the classification model to not only detect abnormalities but also localize and characterize them within the respiratory system. Providing detailed insights into the nature and location of abnormalities to guide targeted treatment strategies and clinical decision-making.

IV. MODEL BUILDING

A) Dataset Preparation:
Various datasets were utilized, including ICBHI 2017, comprising recordings from multiple sources. Dataset sizes ranged from 38 recordings to 17930 sounds from 1630 subjects. Data augmentation techniques were employed to increase dataset sizes and improve model generalization. Features like MFCC, spectrogram images, and statistical features were extracted from respiratory sound data for classification.

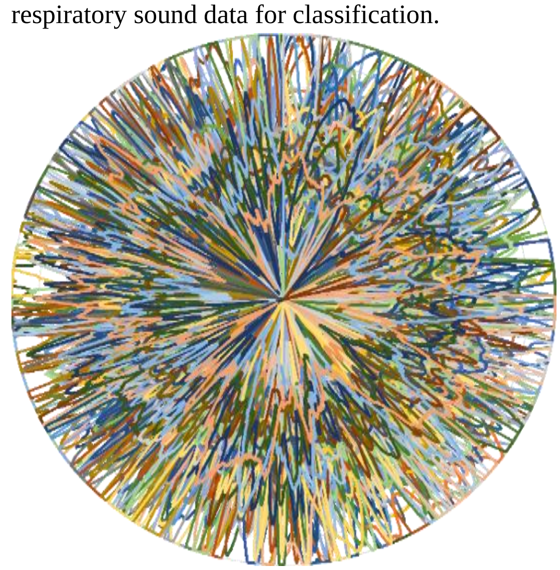

Fig 1.1: 200 Audio clips of healthy class

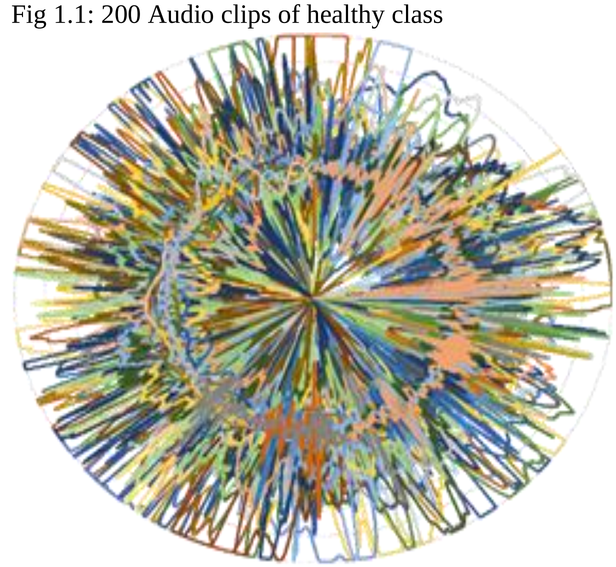

Fig1.2:200 Audio Clips of non-healthy

B) Model Configuration:

Developed an automated tool to distinguish healthy respiratory sound from and non-healthy ones that come from respiratory infection carrying patients, where GTCC-based features are employed. Using over 6800 clips, we obtained the highest accuracy of 99.22%.

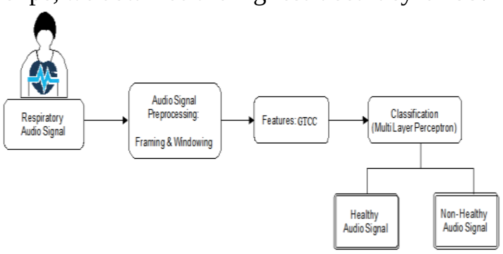

Fig 2: Block diagram for proposed work

C)Model Accuracy:

In this, the traditional machine learning methods like Artificial Neural Networks (ANN) and k-Nearest Neighbors (k-NN) initially dominated lung sound analysis, offering high classification accuracy. Despite their effectiveness, these methods faced challenges such as computational complexity and the need for extensive datasets. Recent advancements focused on hybrid machine learning algorithms, like Genetic Algorithm (GA)-based ANN, aiming to boost accuracy. Real-time systems emerged, showcasing promising accuracy rates, yet further refinement is needed for widespread clinical adoption. Proposed hierarchical approaches aim to streamline diagnosis, particularly in resource-limited settings. Automated tools leveraging Generalized Time-Correlation Coefficient (GTCC)-based features demonstrated exceptional accuracy, laying the groundwork for efficient lung sound analysis systems.

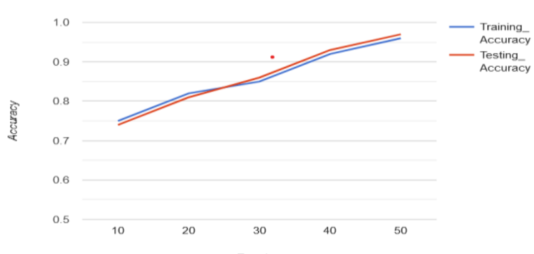

Fig 3: Accuracy

D)Model Evaluation:

After Training with CNN-LSTM algorithms, the evaluation of the trained model is done on validation dataset to assess its generalization capabilities. Calculate metrics such as precision, recall, and F1 score to quantify the model's accuracy in identifying and localizing faults. Use these metrics to iteratively refine the model if necessary.

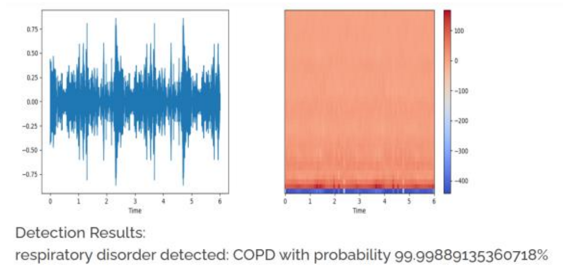

Fig 4: Validation and Testing

E) Architecture:

The parallel-pooling structure was employed in order to boost classification performance in the proposed CNN architecture. In the CNN architecture, an average-pooling layer and a max-pooling layer are connected in parallel in order to boost classification performance. The deep features are utilized as the input of the Linear Discriminant Analysis (LDA) classifier using the Random Subspace Ensembles (RSE) method. They reported a highest accuracy of 83.2% for the healthy class and an overall accuracy of 71.15%.

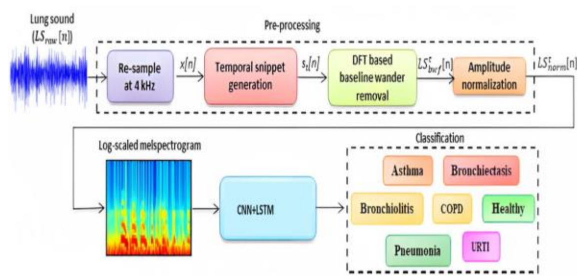

Fig 5: Architecture

V. CONCLUSION

Looking at the audio content, it is difficult to classify respiratory sounds. In our research, a system is presented for distinction of healthy and non-healthy lung sounds which is very important prior to further diagnosis of the type and severity of infection. We have performed our experiments using a publicly available dataset and evaluations indicate that the highest accuracy of 99.22% with an AUC value of 0.9993 is obtained. Automated adventitious sounds detection or classification provides a promising solution to overcome the limitations of conventional auscultation. Finally identifying the nature and severity of infection from the breath sounds.

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