Diagnosing Respiratory Conditions Via Lung Sounds using CNN-LSTM

Prof. Shah S. N.[1], Mr. Pawar R.B.[2], Ms. Raut A.S.[3], Ms. Jadhav S.N.[4]
[1]*Assistant Professor,Computer Department, Sharadchandra Pawar College of Engineering and Technology Someshwarnagar, India*
[2,3,4] *Student,Computer Department, Sharadchandra Pawar College of Engineering and Technology Someshwarnagar, India*

***Abstract*—Respiratory diseases rank among the foremost causes of mortality globally. While traditional lung auscultation is effective, it is hindered by limitations such as interference from background noise and reliance on the expertise of healthcare professionals. Recently, machine learning has emerged as a promising approach for the automated analysis of lung sounds, enhancing diagnostic accuracy and reducing the time required for diagnosis. This study is dedicated to the development of an automated system for lung sound classification, utilizing GTCC-based features in conjunction with a Multi-Layer Perceptron (MLP) classifier. Our system, trained on a comprehensive dataset comprising over 6,800 audio clips, achieved an impressive classification accuracy of 99.22%, underscoring its potential to facilitate the early detection of respiratory diseases.**

***Keywords*— Machine Learning, Lung Sound Analysis, GTCC Features, Deep Learning, Respiratory Diseases.**

I. INTRODUCTION

Respiratory illnesses rank among the leading causes of death and disability globally, with the heaviest impact seen in the poorest regions. Research identifies several major risk factors, including aging, tobacco use, environmental pollutants, and excess body weight. Chronic respiratory conditions pose a significant global public health issue, affecting approximately 65 million individuals. In 2017 alone, chronic obstructive pulmonary disease (COPD) was responsible for around 3.91 million deaths, representing 7% of all deaths worldwide and ranking as the third most common cause of death. Between 1990 and 2017, deaths from chronic respiratory diseases increased by 18%, rising from 3.32 million to 3.91 million.

Asthma, the most prevalent chronic disease among children, affects 14% of children worldwide. Pneumonia remains a major killer, particularly of children under five years old, claiming millions of lives each year. Tuberculosis (TB) continues to affect over 10 million people annually, with approximately 1.4 million deaths each year, highlighting its status as one of the deadliest infectious diseases. Lung cancer, the most fatal cancer type, causes about 1.6 million deaths each year. Overall, chronic respiratory diseases are linked to about 4 million premature deaths annually.

Among the top 30 causes of death worldwide, five are respiratory diseases: COPD ranks third; lower respiratory tract infections are fourth; tracheal, bronchial, and lung cancers come sixth; TB is twelfth; and asthma ranks twenty-eighth. Cumulatively, over 1 billion people live with either acute or chronic respiratory conditions.

Children, especially those under the age of five, are disproportionately affected by respiratory illnesses, with pneumonia being the leading cause of death in this age group. Each year, about 9 million children under five pass away, emphasizing the urgent need for more effective interventions. Despite the lungs being a vital organ, they are especially vulnerable to airborne pathogens and environmental damage. The consequences of respiratory diseases are not limited to health; they also affect social and economic well-being. Evidence suggests that social deprivation significantly contributes to both mortality and disability, with the poorest regions bearing the greatest burden. Meanwhile, wealthier countries tend to report lower mortality rates, owing to better access to healthcare services and more advanced treatment technologies.

Because of the extensive impact of respiratory diseases, improving their treatment and management is a critical goal in medicine. Ongoing research aims to enhance early detection and intervention methods. Accurate diagnosis of these conditions requires both medical expertise and time. However, WHO statistics indicate that 45% of its Member States have fewer than one physician per 1,000 people, falling short of the recommended ratio. Given the existing strain on healthcare professionals, the possibility of diagnostic errors rises. Therefore, developing automated and dependable tools to assist doctors has become essential. Enhancing diagnostic systems can lead to earlier and more accurate identification of patients, ultimately helping to reduce mistakes resulting from excessive workloads.

II. METHODOLOGY

Respiratory conditions are commonly identified through diagnostic techniques such as spirometry and lung auscultation. Spirometry, which evaluates the volume of air inhaled and exhaled during breathing, is widely regarded as an effective tool for identifying abnormalities in both the upper and lower respiratory tracts. However, its accuracy depends significantly on patient cooperation, making it prone to potential errors. Furthermore, conventional spirometry devices are typically confined to clinical environments due to their high cost, the need for regular calibration, and difficulties in guiding patients through the procedure.

Auscultation, another standard method, involves using a stethoscope to listen to internal body sounds, generally performed on the front and back of the chest. In recent years, it has gained recognition for its usefulness in detecting pulmonary issues and irregularities. Yet, its success largely hinges on the clinician's experience and skill. Issues such as low-quality equipment or background noise can lead to misinterpretations or false-positive results, underlining the limitations of traditional practices.

These limitations have created an opportunity for the advancement of automated lung sound analysis systems. By incorporating technology and automation, these tools offer the potential to enhance diagnostic precision and streamline the process of detecting respiratory diseases.

System Architecture

Input Data: The system processes lung sound recordings, which undergo initial preprocessing steps including wavelet-based smoothing, artifact elimination, and normalization.

Preprocessing: To enhance signal clarity, smoothing techniques are applied to reduce noise and remove artifacts. Z-score normalization ensures that all signals have a standardized dynamic range, improving consistency across the dataset.

Deep Learning Framework: The architecture integrates 1D Convolutional Neural Networks (CNNs) with Bidirectional Long Short-Term Memory (BDLSTM) units to effectively analyze both spatial and temporal aspects of lung sound signals.

- CNN Component: The CNN layers are responsible for extracting spatial characteristics from the input signals. This is achieved through a series of operations including convolution, batch normalization, ReLU activation, dropout for regularization, and max-pooling for dimensionality reduction.
- BDLSTM Component: The Bidirectional LSTM layers handle temporal dependencies by analyzing signal patterns in both forward and backward directions. This dual perspective helps capture complex variations over time, with hidden units storing relevant sequential information.

Training and Evaluation: The model is trained using a tenfold cross-validation strategy to ensure generalization and robustness. Stochastic Gradient Descent (SGD) is employed for optimization. Model performance is assessed using key metrics such as accuracy, sensitivity, precision, and F1-score.

III. ALGORITHMS

Evaluation: The proposed model's performance is benchmarked against existing methods, including MFCC-based Inception networks. A detailed analysis is conducted to assess classification accuracy across multiple respiratory conditions, such as asthma, pneumonia, and chronic obstructive pulmonary disease (COPD). This comparison helps evaluate the effectiveness and robustness of the model in real-world diagnostic scenarios.

Feature Extraction: To extract meaningful patterns from lung sound recordings, two types of audio features are utilized:

- Gammatone Cepstral Coefficients (GTCC): These coefficients capture critical auditory cues by mimicking human auditory processing, offering valuable insights into abnormal respiratory sounds.

- Short-Time Fourier Coefficients (STFC): STFC helps reveal the frequency content of the sounds over time, enabling the detection of subtle variations characteristic of different lung conditions.

Together, these features form a rich representation of lung acoustics, essential for accurate classification.

Model Design: A hybrid deep learning model combining Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) units is implemented:

- CNN Layers: Responsible for extracting spatial features from spectrogram representations of lung sounds, capturing localized patterns in the input data.
- LSTM Layers: Designed to learn temporal dependencies in the sequential sound data, capturing dynamic changes over time.

This architecture is optimized to balance high accuracy with computational efficiency, making it suitable for practical applications where resource constraints are a concern.

IV. RESULT AND DISCUSSION

Performance Evaluation: The effectiveness of the proposed CNN-LSTM model was thoroughly assessed using a tenfold cross-validated confusion matrix, which mapped predicted classifications against actual respiratory conditions. This hybrid architecture—combining Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) units—consistently outperformed individual CNN or LSTM models, demonstrating superior diagnostic capability across a range of lung sound categories.

The model achieved an impressive overall classification accuracy of 98.85%, indicating a strong ability to differentiate between diverse respiratory disorders.

Class-wise precision results included:

- Normal: 98.80%
- Asthma: 95.60%
- Pneumonia: 98.80%
- Bronchitis (BRON): 100%
- Chronic Obstructive Pulmonary Disease (COPD): 99.00%
- Heart Failure (HF): 100%

For comparison, the standalone models yielded lower precision scores:

- CNN-only model: 96.88% (average precision)
- LSTM-only model: 92.15% (average precision)

These findings clearly demonstrate the strength of integrating CNN's spatial feature extraction capabilities with LSTM's temporal sequence learning, allowing the hybrid model to more effectively capture complex audio patterns in lung sounds.

In addition to high precision, the model delivered strong performance across multiple evaluation metrics—F1-score, sensitivity, specificity, and overall precision—proving its reliability even when handling imbalanced data across different respiratory conditions.

Importantly, the system maintained consistent accuracy despite challenges such as background noise and varying recording environments. This robustness suggests that the model is well-suited for deployment in practical settings, including remote diagnostics and mobile health applications, where medical expertise and resources may be limited. These findings affirm the model's potential for real-world clinical integration.

V. LITERATURE SURVEY

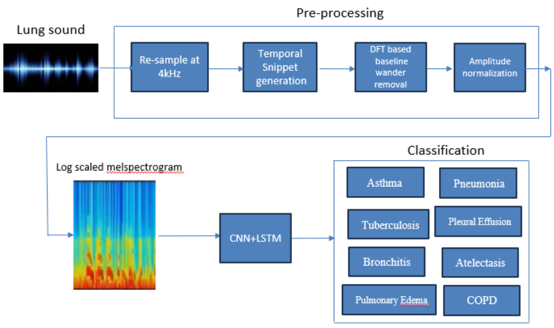
A literature review is a text of a scholarly paper, which includes the current knowledge including substantive findings, as well as theoretical and methodological contributions to a particular topic. Literature reviews use secondary sources, and do not report new or original experimental work.

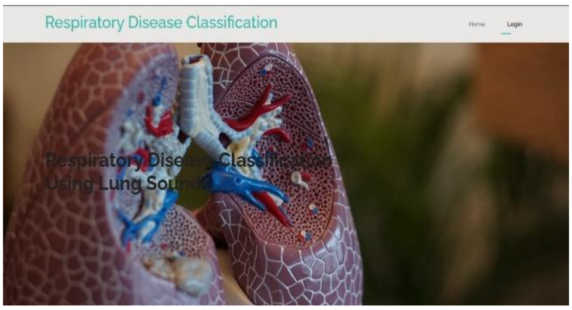
1. Paper Name: Investigating into segmentation methods for diagnosis of respiratory diseases using adventitious respiratory sounds. Author: Liqun Wu and Ling Li
2. Paper Name: A Respiratory Sound Database for the Development of Automated Classification.Author: B. M. Rocha, D. Filos, L. Mendes, I. Vogiatzis, E. Perantoni, E. Kaimakamis, P. Natsiavas, A. Oliveira, C. Jácome, A. Marques, R. P. Paiva, I. Chouvarda, P. Carvalho, N. Maglaveras
3. Paper Name: Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning.Author: Yoonjoo Kim, YunKyong Hyon, Sung Soo Jung, Sunju Lee, Geon Yoo, Chaeuk Chung & Taeyoung Ha

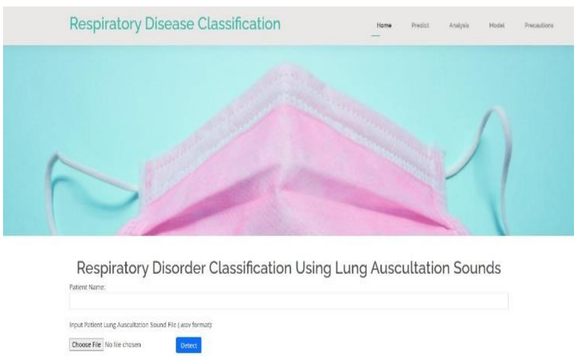
4. Paper Name: Performance evaluation of lung sounds classification using deep learning under variable parameters.Author: Zhaoping Wang and Zhiqiang Sun

5. Paper Name: Detecting COVID-19 and community acquired pneumonia using chest CT scan images with deep learning . Author: Shubham Chaudhary , Sadbhawna , Vinit Jakhetiya , Badri N Subudhi , Ujjwal Baid, Sharath Chandra Guntuku

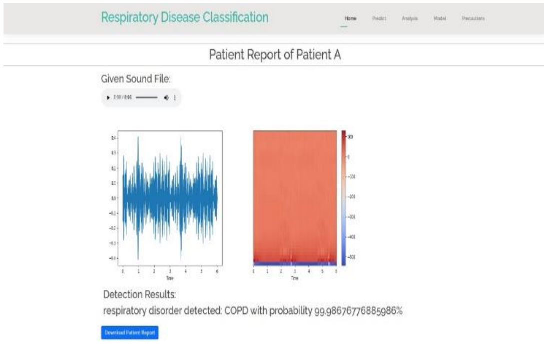
VI. SYSTEM ARCHITECTURE

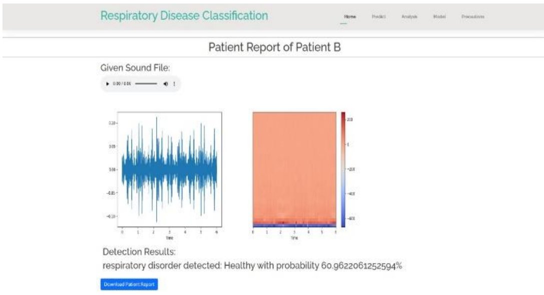


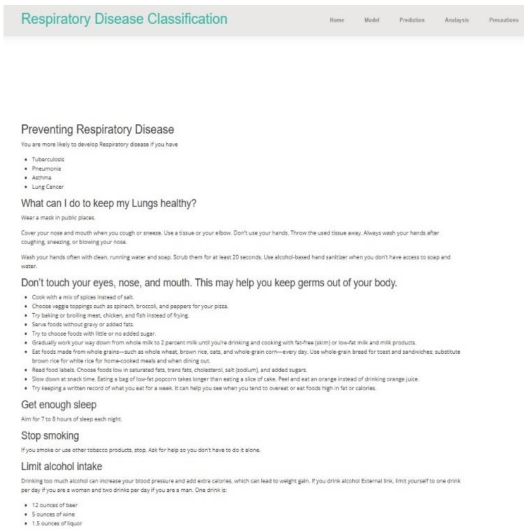




VII. RESULT







VIII. ADVANTAGES

1. Improved Accuracy: Advanced technologies, like AI or automation, enhance precision, leading to better quality outcomes and fewer deviations or mistakes.
2. Quick Diagnosis: Rapid identification of issues ensures timely solutions, reducing downtime or delays in critical situations.
3. Reduced Human Error: Automated systems minimize the impact of fatigue, oversight, or inconsistencies that can occur with human involvement.

4. Cost-Effective: Streamlined processes optimize resource allocation and operational efficiency, leading to significant cost savings over time.

IX. CONCLUSION

This project develops a cost-effective and accurate system for automatic lung sound classification using CNN-LSTM, combining GTCC STFC feature extraction to analyze respiratory sounds. The CNN extracts key sound patterns, while LSTM captures temporal changes, improving diagnostic accuracy. This system helps medical professionals detect respiratory conditions early with low cost solution and is suitable for clinical and remote healthcare applications. Future improvements include better clinical validation, real-time optimization, and enhanced dataset diversity to make the model more reliable and effective..

REFERENCES

[1] Liqun Wu and Ling Li, “Investigating into segmentation methods for diagnosis of respiratory diseases using adventitious respiratory sounds”

[2] B. M. Rocha1, D. Filos, L. Mendes, I. Vogiatzis, E. Perantoni, E. Kaimakamis, P. Natsiavas, A. Oliveira, C. Jácome, A. Marques, R. P. Paiva, I. Chouvarda, P. Carvalho1, N. Maglaveras, “A Respiratory Sound Database for the Development of Automated Classification”

[3] Yoonjoo Kim, YunKyong Hyon, Sung Soo Jung, Sunju Lee, Geon Yoo, Chaeuk Chung & Taeyoung Ha, “Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning”.

[4] Zhaoping Wang and Zhiqiang Sun, “Performance evaluation of lung sounds classification using deep learning under variable parameters”

[5] Rajesh Kumar Tripathy and Ram Bilas Pachori , Shaswati Dash , Adyasha Rath, Ganapati Panda,” Automated Detection of Pulmonary Diseases From Lung Sound Signals Using Fixed Boundary-Based Empirical Wavelet Transforms”

[6] Shubham Chaudhary , Sadbhawna , Vinit Jakhetiya , Badri N Subudhi , Ujjwal Baid, Sharath Chandra Guntuku., “Detecting COVID-19 and community acquired pneumonia using chest CT scan images with deep learning”

[7] Jyotibdha Acharya , Student Member, IEEE, and Arindam Basu, Senior Member, IEEE,” Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient Specific Model Tuning”

[8] Diego Perna ,” Convolutional Neural Networks Learning from Respiratory data”

[9] Sangeetha Balasubramanian, Periyasamy Rajadurai, “Machine Learning-Based Classification of Pulmonary Diseases through Real-Time Lung Sounds”.

[10] Victor Basu, Srinibas Rana,” Respiratory diseases recognition through respiratory sound with the help of deep neural network.”

[11] Implications for global food security,” in Plant Nutrition and Food Security in the Era of Climate Change. Amsterdam, The Netherlands: Elsevier

[12] Q. Wang, X. Zhu, Y. Ni, L. Gu, and H. Zhu, “Blockchain for the IoT and industrial IoT: A review,” Internet Things.