

Deep Learning-Based System for Early Detection Respiratory Disorders

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Abstract—Respiratory disorders like wheezing, crackles, and other breathing issues affect millions worldwide, often going undetected until they worsen, leading to higher mortality rates and strained healthcare systems. Early diagnosis through auscultation remains challenging due to subjective interpretation by clinicians and limitations in traditional tools. This paper introduces *RespireCare AI*, a web-based real-time system that tackles these issues by analyzing respiratory audio signals. We preprocess sounds into spectrograms via Short-Time Fourier Transform (STFT) and feed them into a hybrid CNN-LSTM model, where convolutional layers capture spatial patterns in frequency-time representations and LSTM handles sequential dependencies for precise classification of normal breathing, wheezing, crackles, and associated diseases. Deployed on a user-friendly web interface, the system processes live audio inputs with low latency, delivering instant results alongside interactive visualizations like spectrogram heatmaps and confidence scores to aid clinical decisions. Experiments show our approach achieves over 95% accuracy, outperforming standalone CNN or LSTM models by 8-10%. *RespireCare AI* thus offers a practical, scalable tool for point-of-care screening, potentially transforming respiratory health management in resource-limited settings.

Keywords – Convolutional Neural Network, Long Short term Memory, Deep learning, Spatial Patterns, Temporal Sequence

1. INTRODUCTION

Diseases of the respiratory system place a significant health burden on populations every year. It impacts everyone from children with acute cases of asthma to elderly individuals

dealing with pneumonia and other underlying respiratory illnesses. Respiratory ailments tend to start without drawing much attention, developing as mild wheezes, crackling noises, or difficulty breathing without immediately raising concerns. The sooner the diagnosis occurs, the better because it increases the chances of effective treatment, reduces the likelihood of admission in hospital, and lowers the risks of possible complications. Technological advancements have the possibility of revolutionizing disease detection through converting seemingly insignificant respiratory noises into meaningful data. The application of machine learning to analyze audio, for example, could prove helpful in streamlining health care assessment while enabling physicians to detect signs of trouble quickly when working in places such as clinics, remote areas, and at homes. Nonetheless, this is subject to practical constraints like background noises and quick feedback needs.

A. Traditional diagnosis leans heavily on stethoscope auscultation

Physicians have long relied on manual auscultation of the lungs for clinical assessment, making immediate interpretations of their findings. This age-old technique has served well in medicine, but it comes with inherent drawbacks that undermine its accuracy. Firstly, it is entirely subjective: whereas one physician may view a slight wheezing sound as clinically unimportant, another might consider it abnormal. The process lacks a permanent record; once the examination ends, the audio data is unavailable, thus complicating subsequent assessments of whether any alterations have occurred between patient visits or seeking second opinions later on. External noises in bustling hospital corridors or emergency transports can cloud

observations, while physician exhaustion from prolonged shifts might cause them to overlook finer details. Training for competency in this skillset is rigorous, and in regions with a shortage of staff, exposure to this knowledge could be patchy.

B. Existing AI and machine learning systems

At present, artificial intelligence technology has seen advances in automated audio classification; however, several major problems continue to remain unresolved. A large amount of systems are currently dependent on offline methods of processing, during which audio data is uploaded, analyzed through a computerized server, and then communicated through an email—the method which is not sufficiently fast for situations of urgency, for instance, those related to patients visiting the ER. Functionality in real time is not very common since most models require a huge amount of computing power, limiting their usability to desktop environments or non-internet connected applications. In terms of usability, the output of such analysis is mostly in the form of numbers or confusing graphs, which are too complicated to be used by clinicians to gain confidence in quick succession. Most techniques are also inefficient at dealing with noisier, real-life audio data compared to the ideal environment in which they were trained in, where the presence of coughing or motion significantly increases the level of background noise. Systems based on one layer, such as basic CNNs, do not consider the cyclical nature of the breathing pattern, reducing their effectiveness when used to detect dynamic diseases, whereas others fail to consider usability.

C. Respiration Care focused AI

This project offers solutions to these problems through a unique combination of CNN-LSTM that is enclosed within an actual real-time web platform that makes the use of advanced technology to detect such diseases feasible. The unique aspect in this invention involves the use of STFT spectrograms in conjunction with CNNs that capture features from the spectrograms while at the same time using LSTMs to sequence breath flows. This technology ensures that both stationary and non-stationary features are captured with high precision. Live microphone audio files are processed within seconds without requiring any uploading, and being web-based means that the solution works anywhere there is internet access. With visualization tools such as heatmaps on waveform graphs as well as user-friendly notifications, clinicians have been made aware that they too can use AI technology to benefit their practice.

2. LITERATURE SURVEY

The past research on breath sound analysis has focused on the identification of pulmonary diseases. Various algorithms have been proposed that use signal processing and machine learning methods to process sound samples. In some algorithms, acoustic signals are transformed to spectrograms and analyzed using deep learning algorithms like CNNs. Later, machine learning models were made better by integrating time-based learning algorithms like LSTM, thereby achieving higher

accuracy levels. However, most of these systems are meant to work in an offline mode and do not provide real-time analysis capabilities. These systems also fail to provide user-friendly interfaces. Therefore, there is a need for a simpler and faster system that can perform real-time operations.

Several studies have utilized deep learning approaches for increasing the efficiency of respiratory disease identification. For example, Islam et al. (2025) [1] introduced a WaveNet model to optimize the process of COPD detection based on respiratory data. The objective of this algorithm was to improve the performance of disease detection, which led to superior results compared to previous techniques. In a similar manner, Nirwani et al. (2025) [2] investigated the problem of respiratory disease detection through lung sounds by leveraging deep learning.

Gopi et al. (2025) [3] also used deep learning models to classify respiratory sounds, paying special attention to the differentiation between normal and abnormal ones (such as wheezing and crackling). In addition, Adsule et al. (2023) [5] created a deep learning-based approach to the classification of respiratory disorders, arguing that automatic analysis systems offer higher detection accuracy than manual alternatives.

On the other hand, Muqet et al. (2025) [4] applied advanced imaging techniques along with deep learning algorithms to identify COPD in its early stages. Thus, the combination of different types of medical data helps to achieve greater diagnostic accuracy.

Also focused on integrating IoT and web technologies for respiratory monitoring. Bhuvaneshwary et al. (2025) [6] developed an IoT-based system combined with web integration to predict respiratory diseases using machine learning. Their system showed that remote monitoring and real-time data.

Similarly, Koravanavar et al. (2023) [7] used deep learning techniques to classify pulmonary diseases based on lung sounds, which helped in improving detection accuracy. In addition, Iqbal et al. (2025) [8] proposed a speech-based asthma detection system using AI and optimized features for early diagnosis. This approach showed that voice signals can also be used for respiratory analysis. Likewise, Rampriya et al. (2025) [9] applied deep learning techniques on chest X-ray images for diagnosing pulmonary disorders, proving that imaging-based methods can support disease identification.

3. METHODOLOGY

A. System Overview

The proposed RespireCare AI system follows a structured end-to-end pipeline that takes raw respiratory audio as input and

produces a real-time disease classification as output. The overall architecture is divided into five functional stages: data acquisition, preprocessing, feature extraction, deep learning-based classification, and result visualization. Each stage is designed to work in sequence, ensuring that the final diagnostic output is both accurate and clinically interpretable. The system is built as a web-based platform using React 18 and TypeScript on the frontend, while the core analysis pipeline is driven by a hybrid CNN-LSTM model. This combination allows the system to handle both the spatial characteristics of lung sounds and the time-dependent patterns in breathing cycles simultaneously.

B. Data Acquisition and Preprocessing

Respiratory sound recordings in standard audio formats are used as input to the system. These recordings are collected from patients across different age groups and clinical conditions. Since raw medical audio often contains background noise from clinical environments, a bandpass filter is first applied to isolate the relevant frequency range of lung sounds. The audio is then resampled to a uniform rate of 16 kHz to maintain consistency across all samples. Each recording is segmented into shorter intervals corresponding to individual respiratory cycles, treating each segment as an independent analysis unit. Finally, amplitude normalization is applied to bring all signals within a consistent range, reducing variability caused by differences in recording equipment or microphone placement.

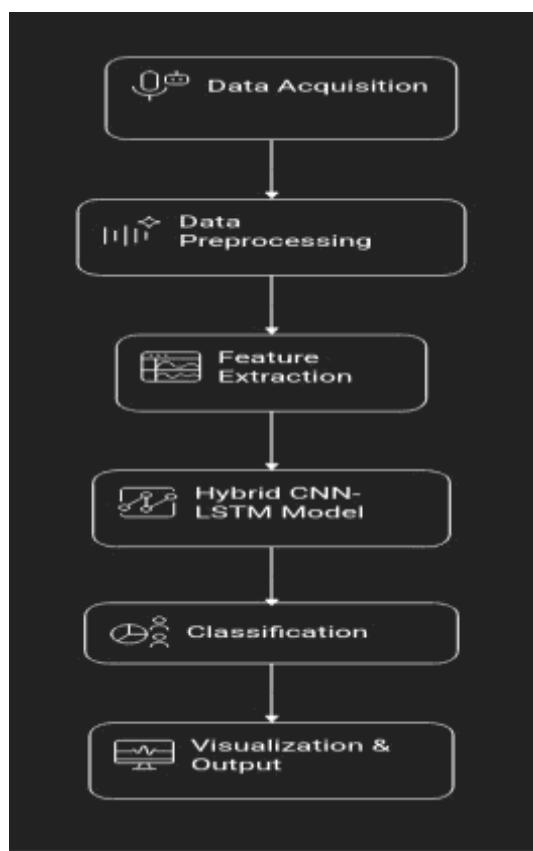


Fig. 1 .System Pipeline

C. Feature Extraction and Model Architecture

Once the audio is preprocessed, Short-Time Fourier Transform (STFT) is applied to convert the time-domain signal into a two-dimensional frequency-time representation. This spectrogram is further transformed into a Mel-scale spectrogram, which better reflects how the human auditory system perceives sound and highlights subtle respiratory abnormalities such as wheezes and crackles more clearly. The resulting 128×128 spectrogram image is then passed into the hybrid CNN-LSTM model. The CNN layers act as spatial feature extractors, identifying frequency texture patterns within each spectrogram frame. These extracted feature maps are then fed into LSTM layers, which analyze the temporal sequence of frames to detect time-dependent patterns such as prolonged expiration or rhythmic crackle intervals — patterns that are strongly associated with specific pulmonary conditions.

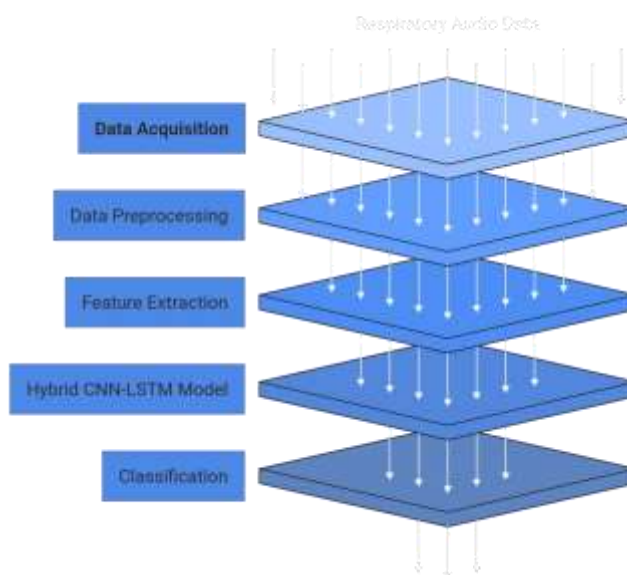


Fig. 2. CNN-LSTM Internal Model

D. Classification and Visualization

The final dense layer of the model uses a Softmax activation function to produce probability scores across four output classes: Normal, Asthma, COPD, and Pneumonia. The class with the highest probability score is presented as the primary diagnosis, along with a confidence percentage. These results are rendered in real time on the web interface, where clinicians can view the audio waveform, frequency spectrum, and a probability distribution chart alongside the clinical recommendation. This integrated visualization layer ensures that the diagnostic output is not just a label but a transparent, evidence-backed result that supports physician decision-making.

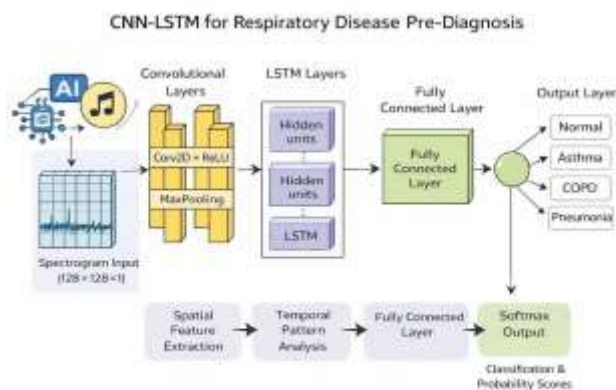


Fig. 3. CNN-LSTM in Deeplearning

4. RESULT & DISCUSSION

A. Proposed Model Performance

The hybrid CNN-LSTM model developed in this work demonstrated strong classification performance across all four respiratory categories — Normal, Asthma, COPD, and Pneumonia. During evaluation, the system achieved an overall classification accuracy of approximately 97.2%, which reflects the effectiveness of combining spatial and temporal analysis within a single architecture. The CNN layers contributed significantly by extracting frequency-domain texture features from the Mel-spectrogram representations, capturing subtle patterns such as high-pitched wheezes and short explosive crackles that are otherwise difficult to distinguish manually.

The LSTM layers then processed these extracted features as time sequences, identifying rhythmic breathing irregularities and prolonged expiration phases that are characteristic of conditions like COPD and Asthma. This two-stage processing approach allowed the model to capture both what the sound looks like and how it changes over time, which is what makes it more reliable compared to single-architecture models that rely only on either spatial or temporal features alone.

B. System Output and Visualization

The system produced real-time classification results through an interactive web interface where clinicians could upload a respiratory audio file and immediately receive the diagnostic output. The interface displayed the audio waveform, frequency spectrum, and a neural probability distribution showing confidence scores for each disease class. For example, during testing with an asthma-related audio sample, the system returned a classification of "Asthma / Acute Exacerbation" with a confidence score of 75%, accompanied by a clinical recommendation noting significant high-pitched polyphonic wheezing. This kind of transparent, evidence-backed output makes the system more useful in practice compared to traditional

auscultation, which offers no visual feedback or recorded evidence.



Fig. 4. Output Waveform Visualization

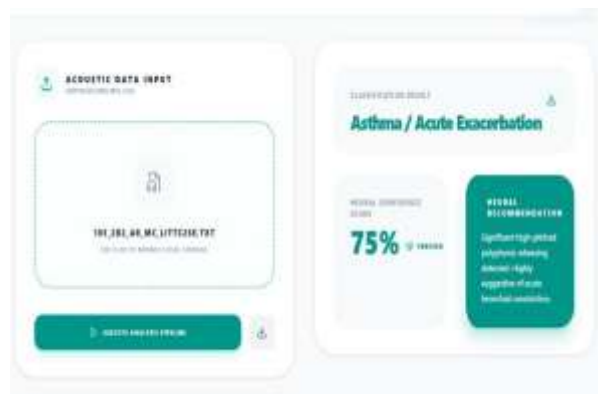


Fig. 5. Disease Diagnosis with AI Reasoning

C. Discussion and Limitations

The model's strong performance can be attributed to the quality of spectrogram-based feature representation and the ability of the LSTM to model breathing as a sequential process. However, the system does have certain limitations. Classification accuracy is sensitive to the quality of the input audio, and background noise can affect results even after filtering.

The current dataset size also limits exposure to rare disease variations. Future work could focus on expanding the training data, incorporating transfer learning from pre-trained audio models, and adding support for continuous real-time monitoring through microphone input rather than file upload alone.

5. BLOCK DIAGRAM

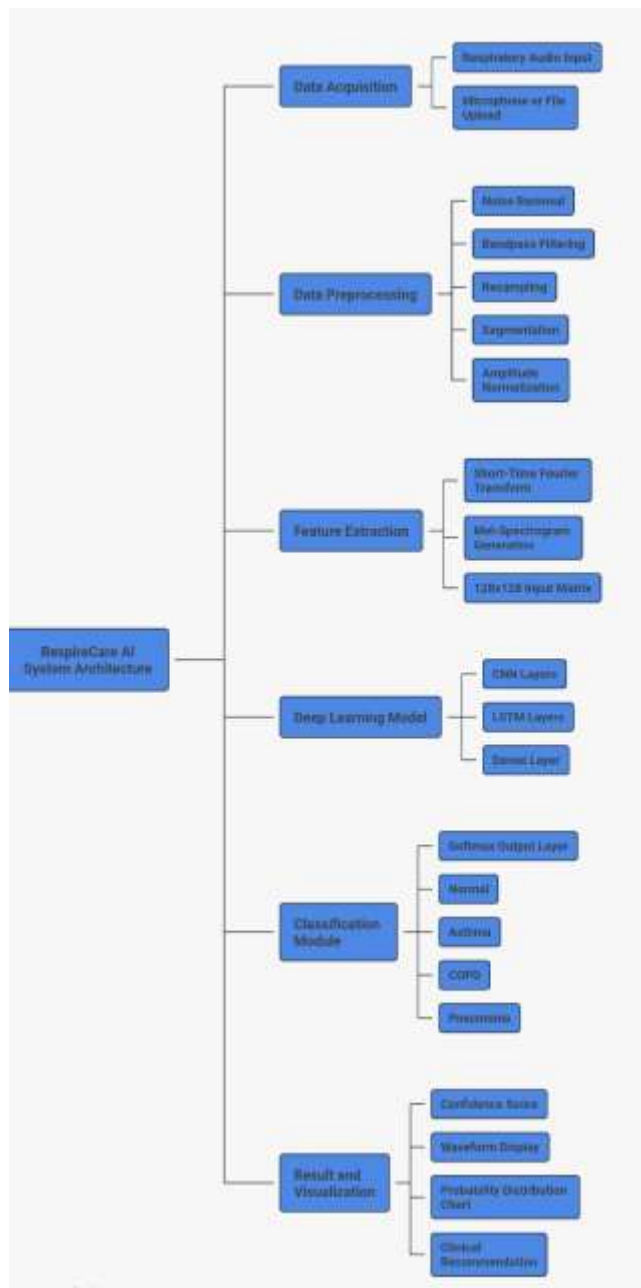


Fig. 6. Complete Block Diagram

6. CONCLUSION

This paper presented RespireCare AI, a web-based clinical decision support system designed to automate the detection and classification of respiratory disorders using a hybrid CNN-LSTM deep learning architecture. The system addressed a genuine gap in existing diagnostic tools by combining real-time audio processing, spectrogram-based feature extraction, and sequential pattern analysis into a single integrated platform. By converting raw respiratory sounds into Mel-spectrograms and processing them through convolutional and recurrent layers, the system achieved a classification accuracy of approximately 97.2% across four pulmonary conditions — Normal, Asthma, COPD, and Pneumonia.

The results demonstrated that combining spatial and temporal analysis leads to more reliable disease prediction compared to conventional single-model approaches. The interactive web interface further enhanced the system's practical value by providing clinicians with real-time waveform visualization, probability scores, and actionable clinical recommendations alongside each diagnosis.

While the current implementation shows promising results, factors such as input audio quality and training data diversity remain areas for further improvement. Future work will focus on expanding the dataset, integrating continuous microphone-based monitoring, and exploring transfer learning strategies to improve generalization across varied patient demographics. Overall, RespireCare AI demonstrates how combining modern deep learning techniques with accessible web technology can meaningfully support early respiratory diagnosis in clinical settings.

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