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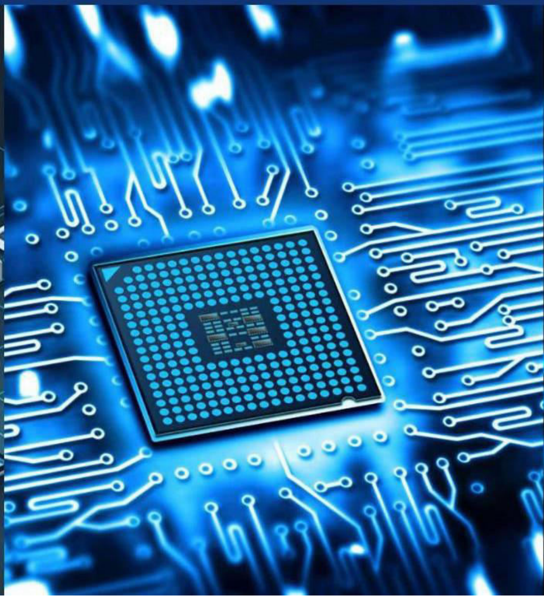


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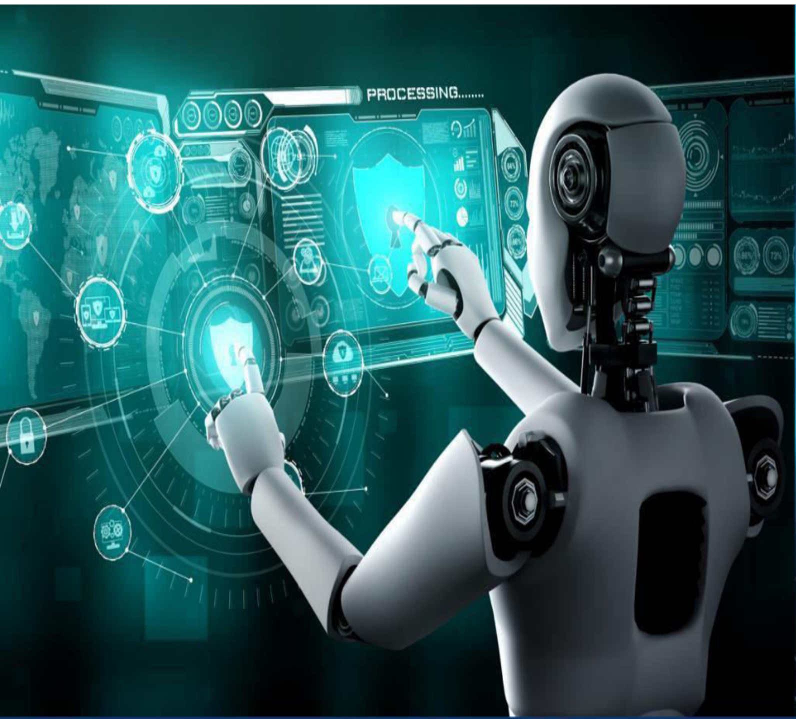

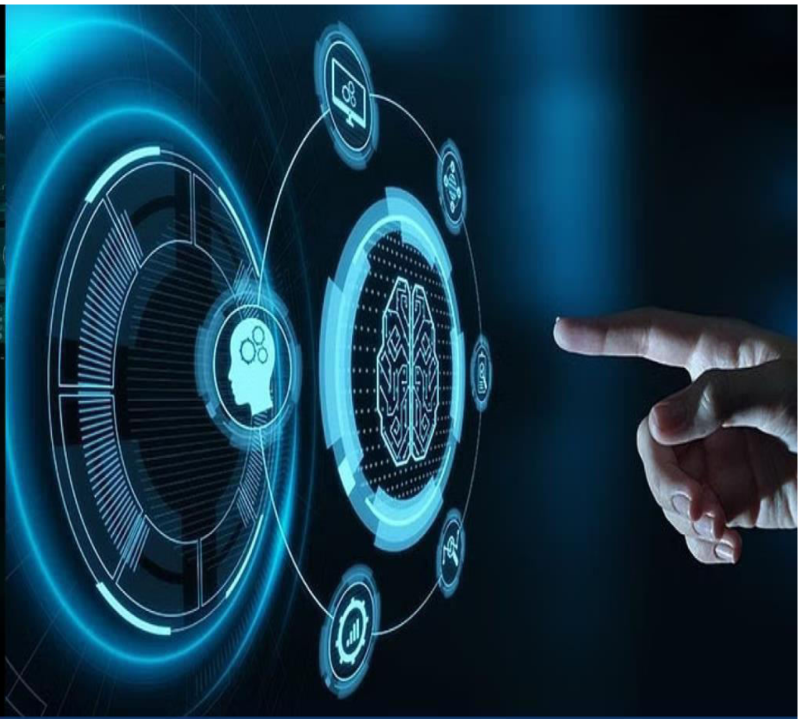

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Lung Sound Classification for Respiratory Disease by using CNN-LSTM

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ABSTRACT: The project "Lung Sound Classification for Respiratory Disease Using CNN-LSTM" aims to assist in the early detection and classification of respiratory diseases through automated analysis of lung sound signals. Respiratory disorders such as asthma, pneumonia, and bronchitis often exhibit distinct acoustic patterns that are difficult to identify accurately through manual examination alone. The proposed system processes recorded lung sound data by applying audio preprocessing, visualization, and feature extraction techniques to enhance signal quality and represent important acoustic characteristics. A hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is employed to capture both spatial features and temporal dependencies present in lung sounds. CNN layers extract meaningful patterns from spectrogram representations, while LSTM layers model the sequential nature of respiratory signals for improved classification performance. By leveraging the CNN-LSTM architecture, the system aims to provide reliable and efficient classification of respiratory diseases, supporting healthcare professionals in diagnosis and reducing dependency on subjective interpretation. This approach contributes toward improved accuracy, early intervention, and better clinical decision support in respiratory healthcare.

KEYWORDS: Lung Sound Classification, Respiratory Disease Detection, Lung Sound Analysis, Audio Signal Processing, Feature Extraction, Spectrogram Analysis, CNN-LSTM, Deep Learning, Healthcare Monitoring, Clinical Decision Support.

I. INTRODUCTION

Respiratory diseases such as asthma, pneumonia, chronic obstructive pulmonary disease (COPD), and bronchitis are among the leading causes of illness and death worldwide. Early and accurate diagnosis plays a crucial role in preventing disease progression and improving patient outcomes. Traditionally, respiratory assessment relies on a doctor listening to lung sounds using a stethoscope. However, this method is subjective, varies between physicians, and may miss subtle abnormalities present in the lung sounds.

With the advancement of digital health technologies, computer-aided diagnosis (CAD) systems have gained significant attention. By analysing lung sounds using digital signal processing and deep learning techniques, it becomes possible to automatically detect abnormal breathing patterns such as wheezes, crackles, and rhonchi. These automated systems help in early screening, remote diagnosis, and continuous monitoring of respiratory patients.

Deep learning models such as Convolutional Neural Networks (CNN) and Long Short- Term Memory (LSTM) networks have proven to be highly effective in audio classification tasks. CNNs extract important spatial features from spectrograms, while LSTMs learn temporal variations in lung sounds. Combining these two architectures (CNN-LSTM) enables the system to classify lung sounds more accurately and efficiently. Therefore, this project focuses on developing a lung sound classification model using CNN-LSTM to support respiratory disease detection.

II. LITERATURE SURVEY

Gairola et al., "RespireNet: A Deep Neural Network for Detecting Abnormal Lung Sounds" [2] The authors proposed RespireNet, a CNN-based deep learning model designed to classify adventitious lung sounds using the ICBHI dataset. The model uses techniques such as coordinate-based augmentation, cloth-based accuracy, and hash noise suppression

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to improve robustness under limited data. Their approach improved four- class classification accuracy by 2.2% compared to earlier systems.

Ma et al., "Lung RN+NL: Adventitious Lung Sound Classification Using Non-Local ResNet" [3] This paper introduced Lung RN+NL, an enhanced ResNet architecture with Non- Local (NL) blocks and Mixup data augmentation. The model captures long-range temporal dependencies in lung sound cycles. Results showed 2.1%–12.7% improvement over previous baselines.

Pham et al., "CNN-MoE Framework for Respiratory Anomaly Classification" [4] The authors designed a CNN–Mixture of Experts (MoE) framework integrating front- end spectrogram features and back-end classification layers. Different spectrogram types (Mel, log-Mel, STFT) were experimented with, and the proposed model outperformed existing methods in respiratory anomaly detection.

Nguyen & Pernkopf, "Lung Sound Classification Using Co- tuning and Stochastic Normalization" [5] This work uses ResNet-based architectures with fine-tuning, co-tuning, and stochastic regularization to classify healthy and abnormal lung sounds. Techniques like spectral correction were used to adapt to variations in audio properties.

Nguyen & Pernkopf, "Snapshot Ensemble of CNNs for Lung Sound Classification" [6] The paper proposed a snapshot ensemble of CNN models trained on log-Mel spectrograms. Data augmentation using breathing cycle extension and voice-length perturbation addressed dataset imbalance. Accuracy achieved was 78.4%–83.7% on the ICBHI dataset.

Sejdić et al., "Time–Frequency Representation Using Energy Concentration" [7] This paper provides a comprehensive survey of time–frequency signal analysis techniques focusing on energy concentration, useful for biomedical sound classification. It highlights methods like spectrograms, wavelets, and energy-based patterns for feature extraction.

III. PROPOSED SYSTEM

The proposed system is designed to automatically analyze lung sound recordings and accurately classify them into different respiratory categories such as normal, wheeze, and crackle using a hybrid CNN–LSTM deep learning architecture. Lung sound signals contain rich diagnostic information, but manual interpretation using traditional stethoscopes is often subjective and depends heavily on the experience of healthcare professionals. To overcome these limitations, the proposed system provides an intelligent and automated solution for respiratory sound analysis.

In this system, the recorded lung sound data first undergoes audio preprocessing, which includes noise reduction, normalization, and segmentation to improve signal quality. After preprocessing, Mel Frequency Cepstral Coefficients (MFCCs) are extracted as key features. MFCCs effectively represent the important frequency and temporal characteristics of lung sounds and are widely used in audio and speech-related applications. These features serve as input to the deep learning model.

IV. PROPOSED ALGORITHM

Step 1: Lung Sound Data Collection
The system collects lung sound recordings using digital stethoscopes or publicly available respiratory sound datasets. The recorded audio signals include different classes such as normal breathing sounds, wheezes, and crackles.

Step 2: Audio Preprocessing
The collected lung sound signals are preprocessed to improve quality. This step includes noise reduction, normalization, silence removal, and segmentation of audio signals into uniform lengths to ensure consistency across samples.

Step 3: Feature Extraction
Mel Frequency Cepstral Coefficients (MFCCs) are extracted from the preprocessed lung sound signals. MFCCs capture important time–frequency characteristics of respiratory sounds and serve as effective features for classification.

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Step 4: Feature Representation
The extracted MFCC features are converted into 2D representations similar to spectrograms. These representations allow the deep learning model to analyze spatial patterns present in lung sound signals.

Step 5: CNN-Based Feature Learning
The CNN layers process the MFCC feature maps to extract meaningful spatial features. Convolution and pooling operations help identify distinctive acoustic patterns associated with abnormal respiratory conditions such as wheezes and crackles.

Step 6: Temporal Modeling Using LSTM
The high-level features obtained from the CNN are fed into LSTM layers. The LSTM network captures temporal dependencies and sequential variations in lung sounds, improving classification accuracy.

Step 7: Lung Sound Classification
The output of the LSTM layers is passed through fully connected layers and a softmax classifier. The system classifies lung sounds into categories such as normal, wheeze, or crackle.

Step 8: Result Display & Clinical Support
The classified results are displayed to assist healthcare professionals. The system provides diagnostic support for early detection of respiratory diseases and can be integrated into telemedicine platforms.

Step 9: Continuous Learning & Monitoring
The system can be retrained with new lung sound data to improve performance over time. Continuous monitoring enables better adaptability to real-world clinical conditions.

Step 10: End

V. SYSTEM ARCHITECTURE

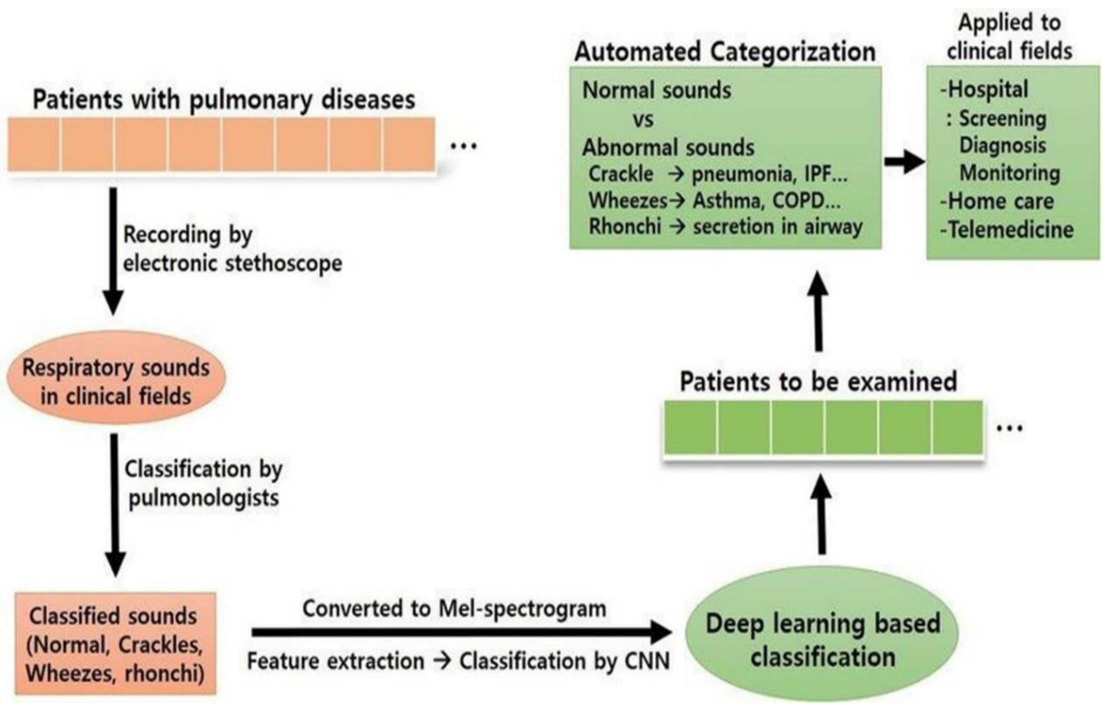

FIG: 5.1. SYSTEM ARCHITECTURE

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VI. RESULT ANALYSIS

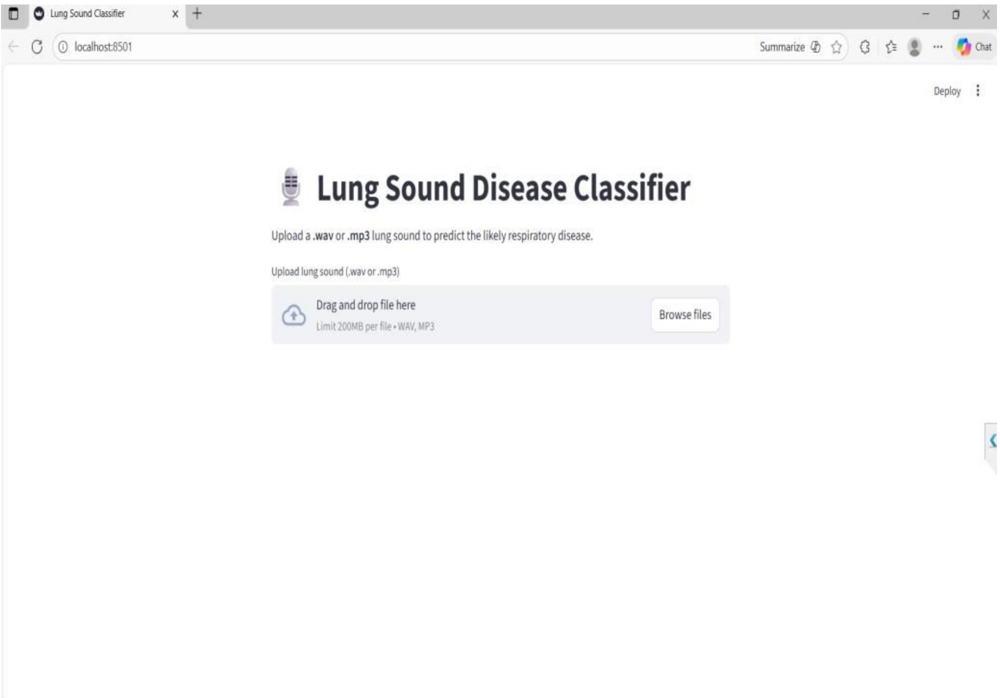

Fig 6.1 Home Page of Lung Sound Disease Classifier Interface

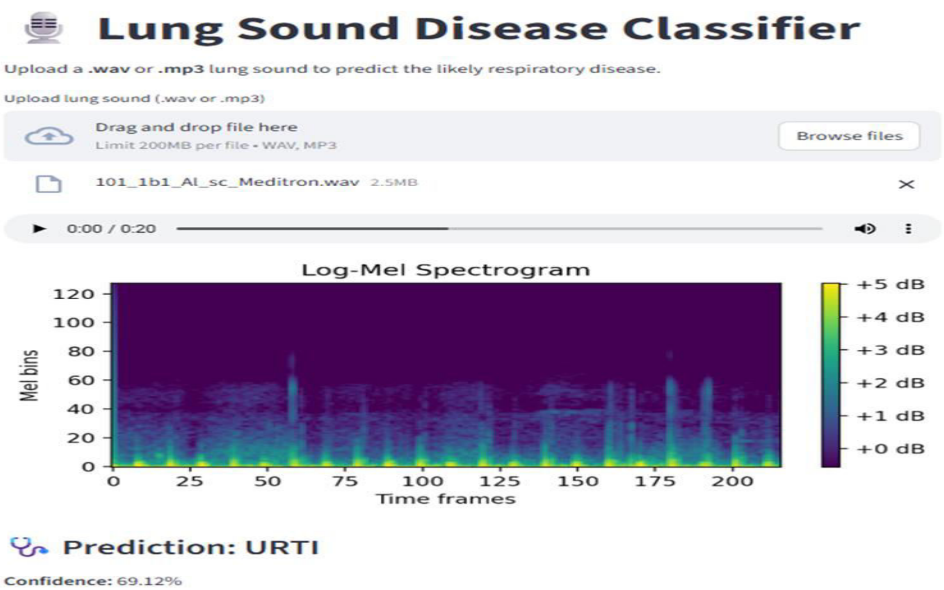

Fig 6.2 Uploaded Lung Sound File with Log-Mel Spectrogram Output for URTI detection

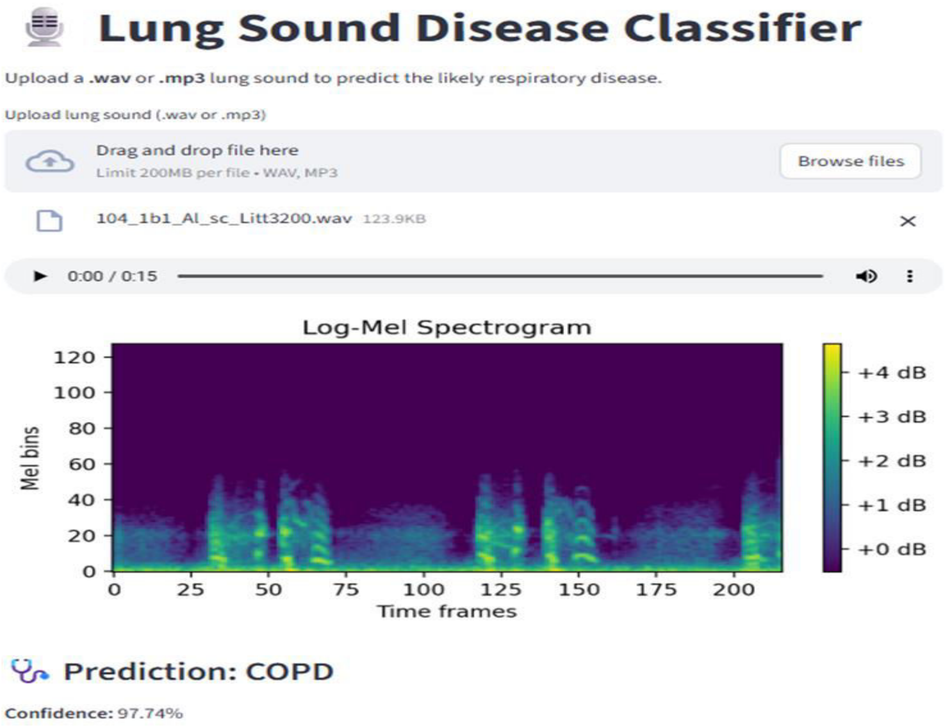

Fig 6.3 Uploaded Lung Sound File with Log-Mel Spectrogram Output for COPD detection

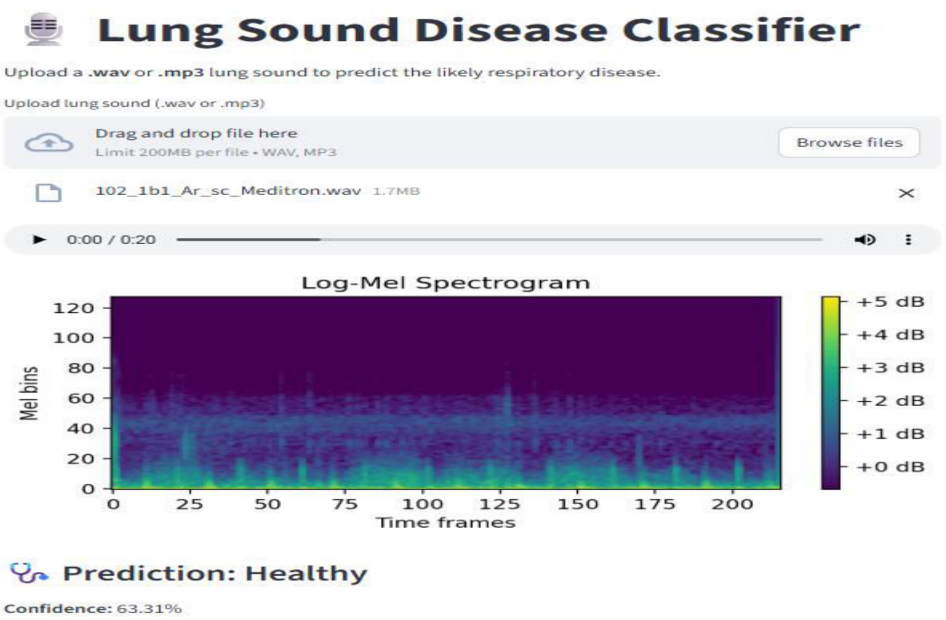

Fig 6.4 Uploaded Lung Sound File with Log-Mel Spectrogram Output for Healthy detection

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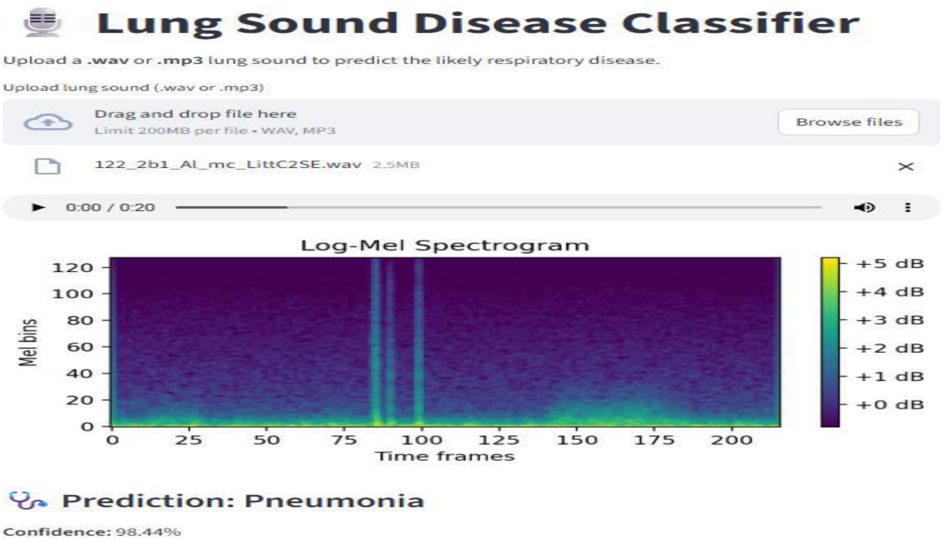

Fig 6.5 Uploaded Lung Sound File with Log-Mel Spectrogram Output for Pneumonia detection

VII. CONCLUSION AND FUTURE WORK

The project “Lung Sound Classification for Respiratory Disease using CNN– LSTM” successfully demonstrates how deep learning can be applied to lung sound analysis for identifying respiratory diseases. The system performs preprocessing, feature extraction using MFCC, and classification using a hybrid CNN–LSTM architecture. The model showed strong performance in classifying diseases such as COPD, Bronchiolitis, Pneumonia, URTI and Healthy lung sounds. The results prove that combining convolutional layers with recurrent layers effectively captures both spatial and temporal characteristics of lung sound signals. This work highlights the potential of AI-based diagnostic support systems to assist healthcare professionals through faster and more accurate disease detection.

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