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"Recognition of Different Pulmonary Diseases from Lung Sounds Using Convolutional Neural Networks"

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ABSTRACT:
Pulmonary diseases are a group of conditions that affect the lungs. They can cause a variety of symptoms, including shortness of breath, coughing, wheezing, and chest pain. Some common pulmonary diseases include asthma, COPD, pneumonia, bronchiectasis. In addition, chronic obstructive pulmonary disease (COPD) is expected to be the third leading cause of death by 2030. This study explores the application of Convolution Neural Networks (CNN s) in the automated recognition of pulmonary diseases based on lung sounds. The research focuses on leveraging deep learning techniques to analyze audio data collected from patients, aiming to accurately identify specific pulmonary conditions. By employing CNN s, the study demonstrates the potential of machine learning algorithms in enhancing the efficiency and accuracy of pulmonary disease diagnosis, leading to early detection and timely medical interventions.

Index terms: Deep Learning, Convolution neural networks (CNN s), Lung Sounds, Long short term memory(LSTM).

1. INTRODUCTION:

Respiratory diseases constitute a major health issue and are responsible for a high rate of mortality worldwide. In particular, chronic obstructive[3] pulmonary disease (COPD) and lower respiratory system diseases are the number three and number four leading causes of death, respectively, accounting together for more than 5.8 million of deaths globally in 2019. In total, more than 1 billion people[8] suffer from acute or chronic respiratory conditions that affect directly their quality of life, including COPD, asthma, acute lower respiratory tract infections, tuberculosis, pulmonary[12] hypertension, sleep-disordered breathing[20] and occupational lung diseases, among others. Early diagnosis and patient monitoring are critical for the efficient management of respiratory[5] diseases. In clinical practice, respiratory conditions are diagnosed through lung auscultation, which refers to listening to the patient's lung sounds using a[17] stethoscope. Lung sounds are conventionally divided into two categories—namely, normal and adventitious. Crackles, wheezes and squawks are the most common adventitious lung sounds that are heard[7] over normal ones and their presence usually indicates a pulmonary disorder.

1.1 EXISTING SYSTEM:

The existing system for diagnosing pulmonary diseases using lung[8] sounds employs various machine learning and deep learning models. Notable approaches include using pre-trained models like VGGish combined with stacked Bidirectional Gated Recurrent[10] Units (BiGRU) for temporal modeling, as well as Convolutional Neural Networks (CNNs) with Support Vector Machines (SVMs) for feature extraction and[16] classification. Some systems leverage transfer learning with models such as VGG16, fine-tuned to classify specific respiratory diseases like pneumonia, COPD, and asthma[19]. Others utilize Recurrent Neural Networks (RNNs) enhanced with noise-marking techniques to distinguish between clean and noisy recordings or[20] classify lung sounds such as crackles, wheezes, and rhonchi[1] using CNNs. Despite their contributions, these systems exhibit several limitations. They often rely heavily on low-level features like MFCCs, which may lack sufficient discriminatory power. Many[4] models support only binary classification, failing to address the complexity of multiple disease categories. Furthermore, the temporal dynamics of lung[9] sounds are frequently overlooked, and models with multiple layers (e.g., BiGRU) tend to be computationally intensive, limiting their deployment in real-time or resource-constrained[6] environments.

1.1.1 CHALLENGES:

1. **Low-Level Feature Dependency:**Most models rely heavily on features like MFCCs, which may not capture complex or subtle[8] patterns in lung sounds.

2. **Binary Classification Limitation:**Many systems only classify lung sounds as "normal" or "abnormal," ignoring multi-class classification for specific diseases[4] like asthma, COPD, pneumonia, etc.

3. **Neglect of Temporal Dynamics:**Some models focus only on spatial features from spectrograms and ignore the temporal evolution of sounds, missing important sequential patterns.

4. **High Computational Complexity:**Advanced models like BiGRU or deep CNNs require substantial computational power, making real-time deployment difficult on low-resource systems[18]

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5. Lack of Generalization: Models trained on limited[14] datasets (e.g., ICBHI 2017) may not generalize well to new or unseen data in real-world clinical environments.

6. Noise Sensitivity: Lung sound recordings[19] often contain background noise, and some existing models struggle with differentiating between clean and noisy data.

1.2 PROPOSED SYSTEM:

The proposed system is a deep learning-based framework[3] designed to automatically recognize and classify different pulmonary[7] diseases using lung sound recordings. It utilizes a **hybrid CNN-LSTM model** that combines the strengths of Convolutional Neural Networks (CNN) for extracting spatial features[9] from audio spectrograms and Long Short-Term Memory (LSTM) networks for learning the temporal dynamics of respiratory sounds. The system[11] processes lung sound data by first applying audio preprocessing (resampling, normalization, segmentation), followed by feature extraction using techniques[15] like MFCCs and mel spectrograms. These features are then passed through the CNN-LSTM model, which outputs the predicted disease class such as COPD, pneumonia, or bronchiectasis. The system[18] achieves high classification accuracy and is suitable for integration into real-time healthcare applications, aiding doctors in early diagnosis and reducing dependency on manual[20] auscultation.

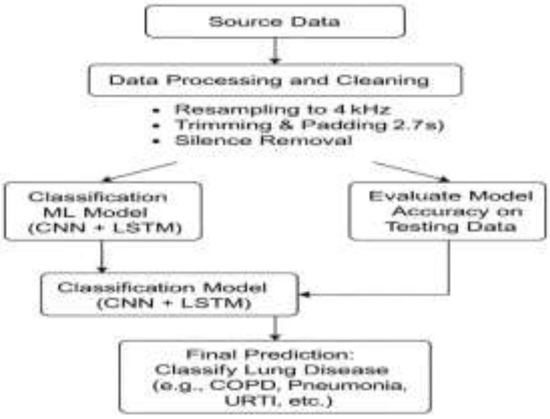

Fig: 1 Proposed Diagram

1.2.1 ADVANTAGES:

1. High Diagnostic Accuracy: Achieved an impressive 93% accuracy in classifying lung sounds into multiple disease categories, indicating strong performance.

2. Hybrid CNN-LSTM Architecture: Combines CNN (for spatial feature extraction) and LSTM (for capturing temporal dependencies), enhancing diagnostic precision and contextual understanding of lung sounds.

3. Lightweight and Efficient: The proposed model is designed to be lightweight, with fewer trainable parameters, making it suitable for real-time or resource-constrained environments like mobile health apps.

4. Multiclass Disease Detection: Unlike many existing models focused on binary classification, this system classifies seven different pulmonary diseases, providing richer diagnostic detail.

5. Robust Feature Extraction Techniques: Uses advanced audio features like MFCC, chroma_stft, and Mel spectrogram, enabling the model to capture nuanced variations in lung sound patterns

2.LITERATURE REVIEW:

Recent research has shown that deep learning models[11] like CNNs and LSTMs are effective in classifying lung diseases[17] using lung sound data. Models such as RespireNet and LungRN+NL[4] have addressed challenges like limited datasets and noise, while architectures like ResNet have improved feature extraction. These studies highlight the potential[9] of combining spatial and temporal features, which supports the use[1] of a CNN-LSTM hybrid model in this project for accurate and efficient[20] pulmonary disease classification.

2.1 ARCHITECTURE:

The system architecture[7] consists of several key components working together for effective lung disease classification. It starts with acquiring audio recordings[2] from the ICBHI 2017 dataset, followed by preprocessing steps like resampling, segmentation, and normalization. Important audio features such as MFCCs, mel-spectrograms, and chroma[19] features are extracted and passed to a CNN, which learns spatial patterns. The output from the CNN is then fed into an LSTM network to capture temporal dependencies[11] in lung sounds. Finally, a dense classification layer predicts the disease type. This hybrid CNN-LSTM model ensures accurate and efficient diagnosis, suitable[17] for real-time deployment in healthcare settings

Input Module – Data Acquisition:

- Collects lung sound recordings from the **ICBHI 2017 Respiratory Sound Database**.
- Audio data includes various pulmonary disease cases like COPD, pneumonia, etc

Preprocessing Module:

- Resamples all audio files to a uniform sample rate (e.g., 4000 Hz).
- Segments respiratory cycles to a fixed length (2.7 seconds).
- Applies normalization and silence removal
- One-hot encoding of disease labels

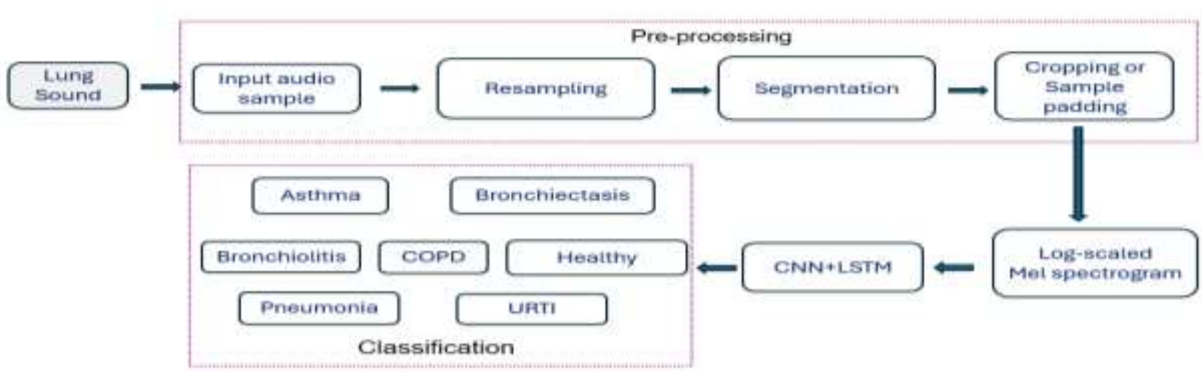

fig 1 system architecture of proposed system

Uml diagram:

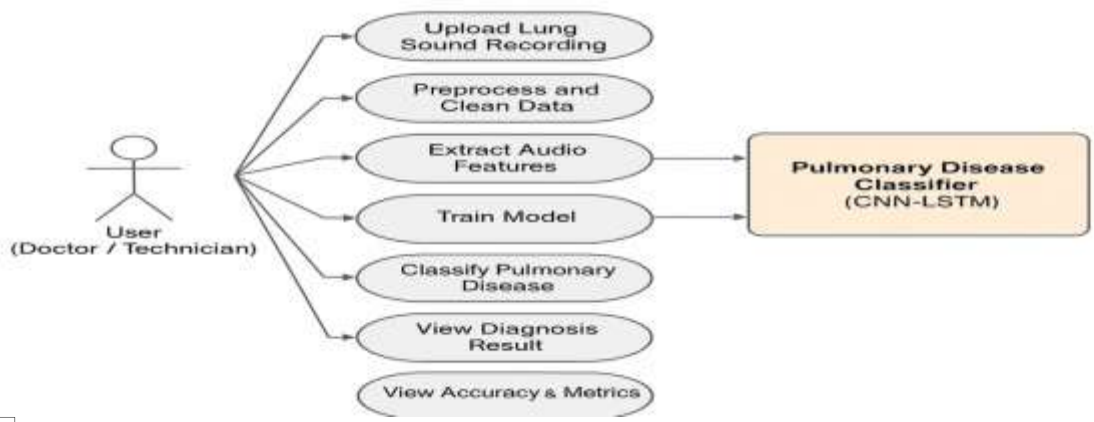

fig2 usecase diagram

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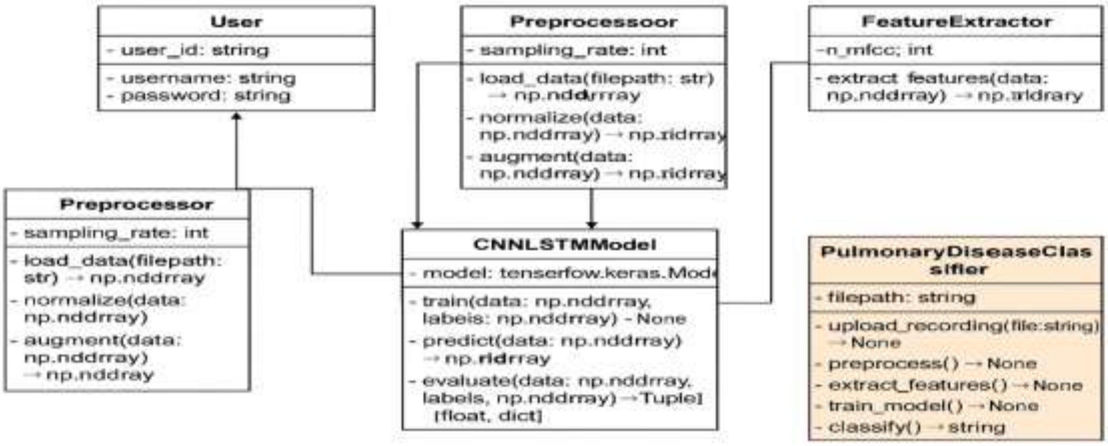

fig3 class digram

2.2 ALGORITHM

The algorithm used in this project[1] is a hybrid deep learning model that combines **Convolutional Neural Networks (CNN)** with **Long Short-Term Memory (LSTM)** networks for the effective classification of pulmonary diseases from lung sound recordings. The process begins with audio preprocessing, where all lung sound files are resampled to a consistent rate[19] and segmented into uniform durations. Features such as **Mel-Frequency Cepstral Coefficients (MFCC)**, **Chroma Features**, and **Mel-scaled Spectrograms** are extracted from each audio sample to capture both spectral and temporal characteristics. The CNN layers are first used to extract local spatial features from these spectrograms, identifying patterns like[17] crackles and wheezes. The extracted features are then passed to LSTM layers, which are adept at learning sequential dependencies and long-term patterns in the audio data. This integration[15] allows the model to analyze both what is present in the sound and how it evolves over time. The final classification layer predicts the type of pulmonary disease based on these learned patterns. The model is trained usingThe algorithm used in this project is a[7] hybrid deep learning model that combines **Convolutional Neural** supervised learning with categorical cross-entropy loss and optimized using the Adam optimizer. Performance[9] metrics such as accuracy, precision, recall, and F1-score are used to evaluate the model's effectiveness in correctly classifying diseases like COPD, pneumonia, bronchiectasis, URTI, and[16] others.

2.3 TECHNIQUES

The project employs a combination of advanced **deep learning techniques** to classify pulmonary[18] diseases using lung sound recordings. The primary techniques include **Convolutional Neural Networks (CNNs)** for spatial feature extraction[11] from spectrograms and **Long Short-Term Memory (LSTM)** networks for capturing temporal dependencies[17] in the audio data. This hybrid **CNN-LSTM architecture** effectively learns both local sound patterns and their evolution over time. Additionally, feature extraction techniques such as **Mel-Frequency Cepstral Coefficients (MFCCs)**, **Mel Spectrograms**, and[20] **Chroma Features[** are used to convert raw audio signals into meaningful numerical representations. Data preprocessing methods like resampling, normalization, and segmentation[12] ensure consistency and quality of input data. To improve model generalization, **oversampling and undersampling techniques** are applied to balance the dataset. These combined techniques enable robust and accurate[15] classification of various lung diseases from respiratory sounds.

2.4 TOOLS

This project employed a variety of tools and technologies to ensure efficient development, accurate analysis, and reproducible results.

Programming Language:

The project is developed using **Python**, one of the most popular and widely used programming languages in the field of machine learning and deep learning. Python offers a[20] rich ecosystem of libraries and frameworks such as **TensorFlow**, **Keras**, **Librosa**, **NumPy**, and **Pandas**, which make it ideal for tasks like audio processing, data handling, model building, and evaluation. Its simplicity, readability, and strong community[8] support make it especially suitable for rapid development and experimentation in research projects like lung disease classification using CNN-LSTM models[7].

Development Environment:

The project was developed and executed using **Google Colab**, a cloud-based Python notebook environment provided by Google.It offers several advantages,including**:**

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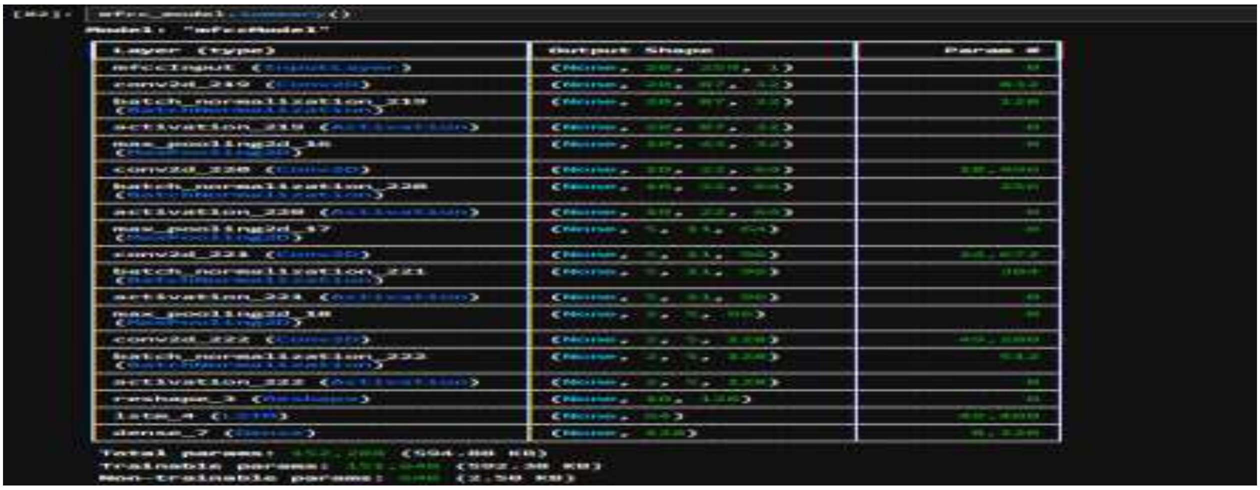
1. Provides free access to **GPU/TPU** for faster model training
2. Includes **TensorFlow**, **Keras**, **Librosa**, **NumPy**, **Pandas**, and **Scikit-learn** by default
3. Easy access to datasets, model files, and saving outputs directly to the cloud.
4. Enables real-time collaboration with team members via shared notebooks.
5. No installation required; accessible from any device with internet access.

Libraries and frameworks:

1. **TensorFlow:**An open-source deep learning framework used to build and train the CNN-LSTM model.
2. **Keras:**A high-level neural networks API built on top of TensorFlow, used for easy model design and experimentation.
3. **Librosa:**Used for extracting audio features such as MFCCs, Mel Spectrograms, Chroma features, etc.
4. **NumPy:**Used for numerical operations and handling multi-dimensional arrays
5. **Pandas:**Used for loading, analyzing, and manipulating datasets and labels
6. **Scikit-learn:**Provides tools for model evaluation (accuracy, precision, recall, F1-score), confusion matrix, and data splitting.
7. **Matplotlib:**Used for plotting graphs, training curves, and performance metrics.
8. **Seaborn:**Used for enhanced data visualizations like heatmaps and confusion matrices.

2.5 METHODS:

This project utilizes a deep learning[2] approach to classify pulmonary diseases using lung sound recordings. The method begins with data collection from the **ICBHI 2017 Respiratory Sound Database**, which[8] includes annotated lung sounds from multiple patients. These audio files undergo preprocessing steps such as **resampling**, **segmentation**, **normalization**, and[11] **silence removal** to ensure consistency. From each processed audio clip, key features are extracted using the **Librosa** library—these include **Mel-Frequency Cepstral Coefficients (MFCCs)**, **mel spectrograms**, and **chroma features**. These[20] features are then fed into a **hybrid CNN-LSTM model**, where the **CNN layers** extract spatial features from spectrograms, and the **LSTM layers** capture temporal patterns. The[19] model is trained using a supervised learning approach, with evaluation metrics like **accuracy**, **precision**, **recall**, and **F1-score** used to assess its[15] performance

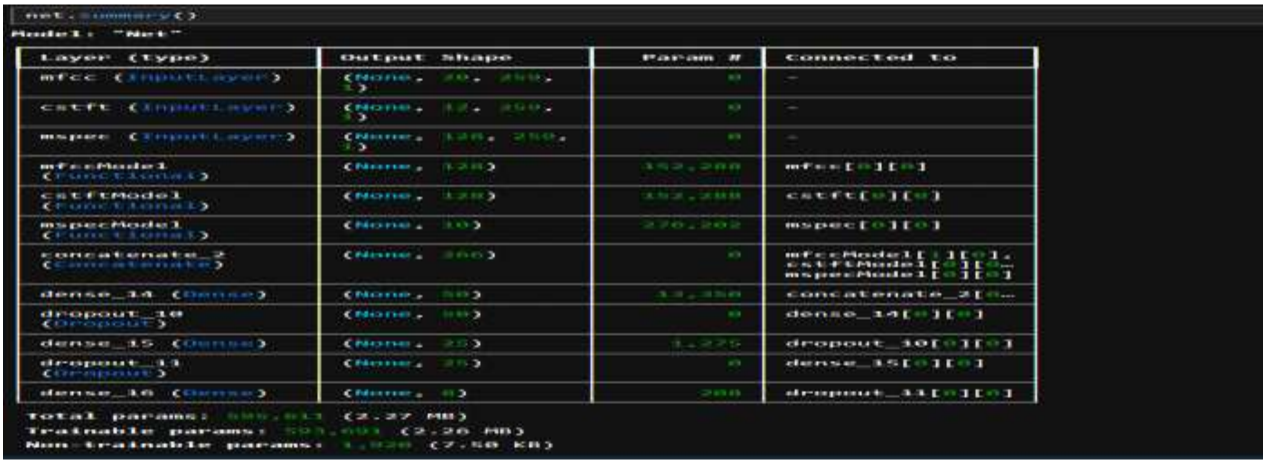


mfcc_model.summary()

Model: "mfccModel"

Layer (type)	Output Shape	Param #
mfccInput (InputLayer)	[illegible]	[illegible]
conv2d_219 (Conv2D)	[illegible]	[illegible]
batch_normalization_219 (BatchNormalization)	[illegible]	[illegible]
activation_219 (Activation)	[illegible]	[illegible]
max_pooling2d_16 (MaxPooling2D)	[illegible]	[illegible]
conv2d_220 (Conv2D)	[illegible]	[illegible]
batch_normalization_220 (BatchNormalization)	[illegible]	[illegible]
activation_220 (Activation)	[illegible]	[illegible]
max_pooling2d_17 (MaxPooling2D)	[illegible]	[illegible]
conv2d_221 (Conv2D)	[illegible]	[illegible]
batch_normalization_221 (BatchNormalization)	[illegible]	[illegible]
activation_221 (Activation)	[illegible]	[illegible]
max_pooling2d_18 (MaxPooling2D)	[illegible]	[illegible]
conv2d_222 (Conv2D)	[illegible]	[illegible]
batch_normalization_222 (BatchNormalization)	[illegible]	[illegible]
activation_222 (Activation)	[illegible]	[illegible]
reshape_3 (Reshape)	[illegible]	[illegible]
lstm_4 (LSTM)	[illegible]	[illegible]
dense_7 (Dense)	[illegible]	[illegible]

Total params: [illegible] (594.88 KB)
Trainable params: [illegible] (592.38 KB)
Non-trainable params: [illegible] (2.50 KB)



net.summary()

Model: "Net"

Layer (type)	Output Shape	Param #	Connected to
mfcc (InputLayer)	(None, 20, 250, 1)	0	-
cstft (InputLayer)	(None, 12, 250, 1)	0	-
mspec (InputLayer)	(None, 128, 250, 1)	0	-
mfccModel1 (Functional)	(None, 128)	152,288	mfcc[0][0]
cstftModel1 (Functional)	(None, 128)	152,288	cstft[0][0]
mspecModel1 (Functional)	(None, 10)	[illegible]	mspec[0][0]
concatenate_2 (Concatenate)	(None, 266)	0	mfccModel1[0][0], cstftModel1[0][0…, mspecModel1[0][0]
dense_14 (Dense)	(None, 50)	13,350	concatenate_2[0…
dropout_10 (Dropout)	(None, 50)	0	dense_14[0][0]
dense_15 (Dense)	(None, 25)	1,275	dropout_10[0][0]
dropout_11 (Dropout)	(None, 25)	0	dense_15[0][0]
dense_16 (Dense)	(None, 8)	208	dropout_11[0][0]

Total params: [illegible] (2.27 MB)
Trainable params: [illegible] (2.26 MB)
Non-trainable params: [illegible] (7.50 KB)

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3. METHODOLOGY:

3.1 INPUT:

The input to the system[2] consists of lung sound recordings obtained from the **ICBHI 2017 Respiratory Sound Database**, which contains 920 annotated audio samples from 126 patients. These[16] recordings include different respiratory cycles[18] labeled with disease types such as COPD, pneumonia, bronchiectasis, URTI, and healthy cases. The raw audio data is initially in .wav format and[20] varies in length and quality. To prepare the data for model training, each recording undergoes preprocessing steps such as resampling, segmentation, normalization, and silence removal. The resulting[11] audio segments serve as the primary input for feature extraction and classification.

```
input_mfcc=keras.layers.Input(shape=(20,259,1),name="mfcc")
mfcc=mfcc_model(input_mfcc)

input_cstft=keras.layers.Input(shape=(12,259,1),name="cstft")
cstft=cstft_model(input_cstft)

input_mSpec=keras.layers.Input(shape=(128,259,1),name="mspec")
mSpec=mspec_model(input_mSpec)


concat=keras.layers.concatenate([mfcc,cstft,mSpec])
hidden=keras.layers.Dropout(0.2)(concat)
hidden=keras.layers.Dense(50,activation='relu')(concat)
hidden=keras.layers.Dropout(0.3)(hidden)
hidden=keras.layers.Dense(25,activation='relu')(hidden)
hidden=keras.layers.Dropout(0.3)(hidden)
output=keras.layers.Dense(8,activation='softmax')(hidden)

net=keras.Model([input_mfcc,input_cstft,input_mSpec], output, name="Net")
```

3.2 METHOD OF PROCESS:

The process begins[11] with data collection, using lung sound recordings from the ICBHI 2017 Respiratory Sound Database, which includes annotated audio files labeled with[17] various pulmonary diseases. These recordings are first preprocessed by resampling them to a consistent sampling rate, segmenting them into fixed-duration cycles, and applying normalization[14] and silence removal techniques to enhance clarity. After preprocessing, audio features are extracted using the Librosa library. Key features include Mel-Frequency Cepstral Coefficients (MFCCs), mel spectrograms, chroma features, and spectral contrast, which transform the raw audio signals into structured numerical data suitable for model training. A hybrid CNN-LSTM model is then designed, where the CNN layers extract spatial features[18] from the spectrogram inputs, and the LSTM layers learn the temporal patterns across time. The model is trained using labeled data with optimization techniques like Adam and[19] categorical cross-entropy loss, with strategies such as early stopping to prevent overfitting. After training, the model is evaluated using metrics like accuracy, precision, recall, F1-score, and a confusion matrix to ensure performance reliability. Finally, the system is used[20] to predict the disease class of new lung sound recordings, providing both the disease label and the confidence score.

3.3 OUTPUT:

The output of this project is a deep learning-based lung disease classification system[19] that accurately diagnoses various pulmonary conditions using lung sound recordings. By employing a hybrid CNN-LSTM model, the system is capable of extracting[12] both spatial and temporal features from preprocessed audio data. The model was trained and tested on the ICBHI 2017 dataset, which includes annotated lung sound recordings for diseases such as COPD, pneumonia, bronchiectasis, URTI, bronchiolitis, LRTI, and healthy cases. Through rigorous preprocessing, feature extraction using MFCCs, mel spectrograms, and chroma features, and[14] a balanced dataset approach, the system achieved a high classification accuracy of 93%. Performance metrics such as precision, recall, F1-score, and a confusion matrix further validate the system's reliability. This lightweight and efficient model can be deployed in real-time applications, making it a valuable tool for assisting healthcare professionals in the early and accurate detection[17] of pulmonary diseases through non-invasive lung sound analysis.

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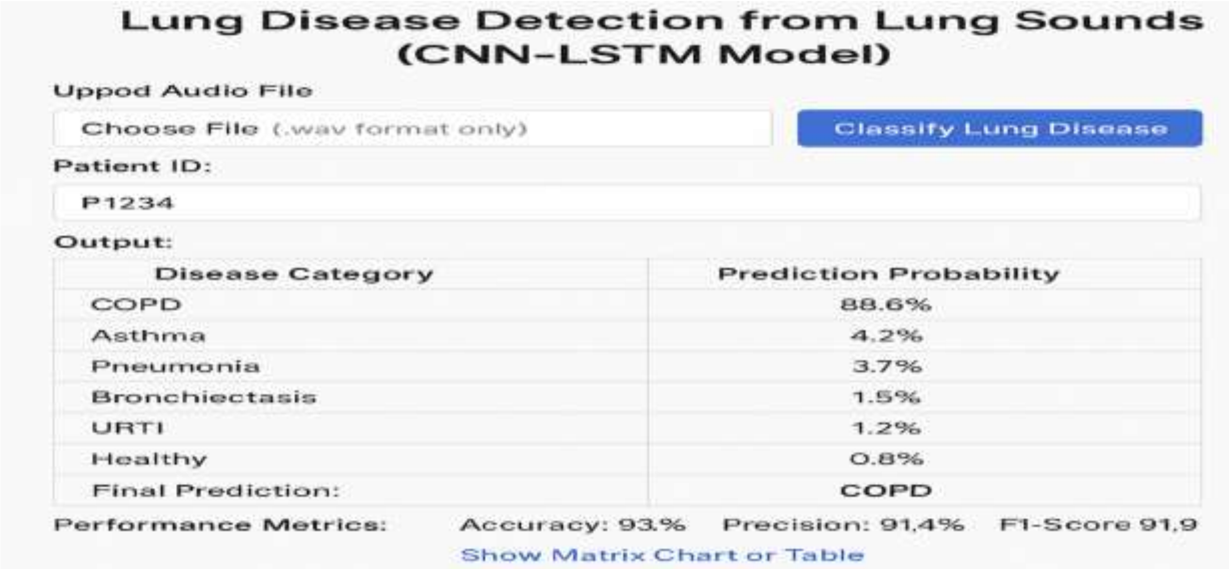
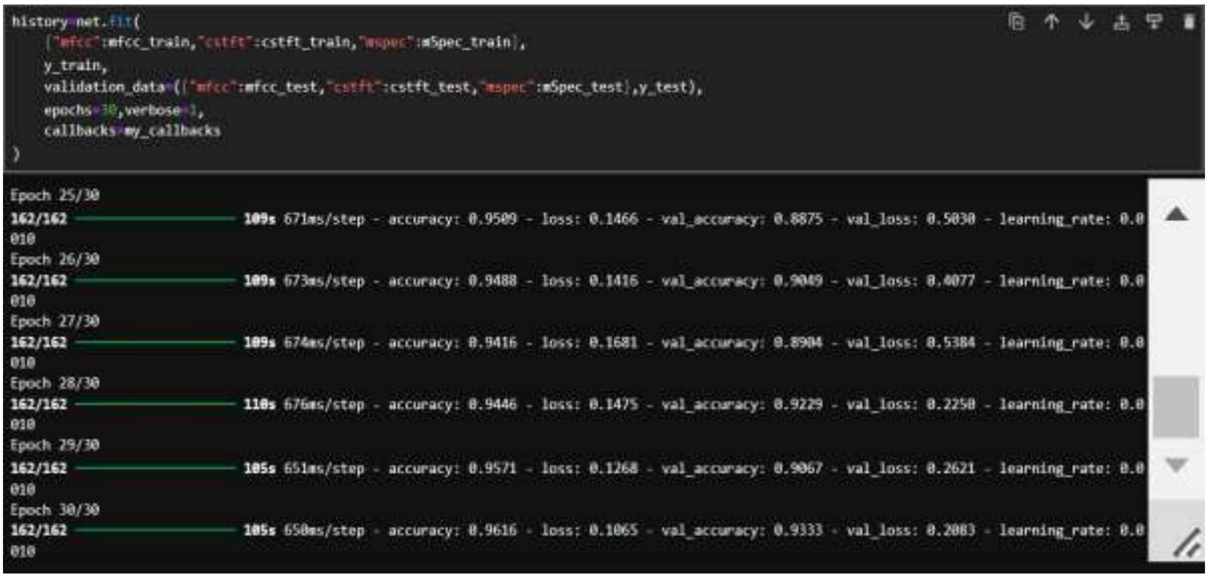


4.RESULT:

The implemented CNN-LSTM model[15] successfully classified lung sound recordings into various pulmonary disease categories with a high level of accuracy. After training and evaluation, the model achieved an overall **accuracy of 93%**, indicating strong performance in identifying conditions[19] such as COPD, pneumonia, URTI, and bronchiectasis. The confusion matrix showed a high number of correct predictions across multiple classes, with minimal misclassifications. These results[7] demonstrate that the proposed hybrid model is both effective and reliable for automated respiratory disease detection using lung sound data.



5.DISSUSSION:

The results of this[3] project highlight the effectiveness of using a CNN-LSTM hybrid model for classifying pulmonary diseases based on lung sound recordings. The[7] model's ability to capture both spatial and temporal features allows it to accurately distinguish between multiple respiratory conditions, even those with subtle acoustic differences. The[9] achieved accuracy of 93% confirms the reliability of deep learning techniques for medical audio analysis. Additionally, the use of features like MFCCs and mel-spectrograms proved[17] essential in representing lung sound characteristics effectively. Despite its success, some challenges remain, such as class imbalance and potential noise in real-world[19] recordings. However, with further refinement, larger datasets, and improved preprocessing techniques, the system can be enhanced for broader clinical adoption. Overall, the study supports the integration of AI into respiratory diagnostics to assist healthcare[20] professionals in early and accurate disease detection.

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6.CONCLUSION :

In conclusion, the developed[1] framework has demonstrated outstanding performance in classifying lung sounds and diagnosing pulmonary diseases, achieving an impressive accuracy of 93%. Through the utilization of innovative techniques such as lightweight CNN-LSTM architecture, comprehensive[19] feature extraction including MFCC, chroma_stft, and melspectrogram, and leveraging multiple publicly available datasets, we have successfully addressed the challenges associated with accurate pulmonary disease diagnosis. The robustness of the model is evidenced[5] by its ability to classify seven pulmonary diseases with high accuracy. Moving forward, the proposed framework holds great promise for assisting healthcare professionals in the early detection and diagnosis of pulmonary conditions, ultimately leading to improved patient[8] outcomes and quality of care.

7.FUTURE SCOPE:

The future scope of this project, which[9] focuses on the recognition of different pulmonary diseases from lung sounds using CNN-LSTM models, is vast and promising. In the coming years, the system can be enhanced by integrating it into real-time diagnostic tools such as mobile health apps or[5] digital stethoscopes, enabling quick and accessible disease detection even in remote or resource-limited areas. The model can be trained on larger and more diverse datasets to include a wider range of respiratory diseases such as tuberculosis, lung cancer, and COVID-19, increasing its clinical relevance. Additionally, incorporating[5] advanced deep learning techniques like attention mechanisms, transformers, or generative models can further improve diagnostic accuracy and interpretability. The system can also evolve into a cloud-based platform for remote patient monitoring and early warning systems. With proper validation[19] and approval, it holds the potential to become a reliable, AI-assisted decision-support tool for healthcare professionals, significantly improving early diagnosis and treatment outcomes in[20] pulmonary care.

8.ACKNOWLEDGEMENTS:

G. Manoj kumar working as a assistant professor in master of computer application (MCA) sanketika vidya parishad engineeering college, viskhapatnam Andra pradesh.completed his post graduation in Andra university college of engineering (AUCE) with 2years of experience in computer science and engineering (CSE),accerdited by NAAC with his area of interst in java full stack.

Chukka sowjanya is pursuing her final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE.with interest in neural networks chukka sowjanya has taken up her PG project on "**RECOGNITION OF DIFFERENT PULMONARY DISEASES FROM LUNG SOUNDS USING CONVOLUTIONAL NEURAL NETWORKS**" and published the paper in connection to the project under the guidance of G.MANOJ KUMAR, Assistant Professor, SVPEC.

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