DeepCOPD: An Innovative DL Approach for COPD

Yastika Joshi [1] Mahima Manuela [1]
Priyanshu Vashisht [1]
School of Engineering and Technology
K. R. Mangalam University
Sohna Rural, Haryana, India
(1901010024, 1901010008, 1901010029)
@krmu.edu.in

Pankaj Agarwal [2]
School of Engineering and Technology
K. R. Mangalam University
Sohna Rural, Haryana, India
dean.soet@krmangalam.edu.in

ABSTRACT

This paper presents an app for the detection of Chronic Obstructive Pulmonary Disease (COPD) using novel deep learning techniques. Our approach involves training a Convolutional Neural Network (CNN) model on a respiratory sound database containing 6898 respiratory cycles, including 886 instances of wheezes, 1864 instances of crackles, and 506 instances of both crackles and wheezes. To address the challenge of a small-sized dataset, we propose a simple CNN-based model along with innovative techniques: (1) device specific fine-tuning, (2) concatenation-based augmentation, (3) blank region clipping, and (4) smart padding [1]. These techniques enable efficient utilization of the dataset, resulting in an impressive accuracy of 90% to 95% [1]. To deploy our model, we utilize HTML & CSS Front end, Flask backend and Heroku to create a user-friendly interface. The entire implementation is carried out in Python, encompassing both the model and the user interface components [1]. Our work builds upon previous studies in respiratory sound analysis [2-8]. The proposed app offers a promising solution for accurate COPD detection, providing significant advancements in the field of respiratory health monitoring [1].

Keywords—copd detection, deep learning, cnn model, respiratory sound analysis, dataset, augmentation techniques, user-friendly interface, python implementation.

I. INTRODUCTION

Chronic obstructive pulmonary disease (COPD) is a chronic lung disease that obstructs the airflow from the lungs and affects over 10 million people in India annually [1]. Symptoms of COPD include breathing difficulty, cough, and wheezing caused by long-term exposure to irritants, most commonly cigarette smoke [2]. COPD patients are at an increased risk of developing other health conditions such as heart disease and lung cancer, making early detection crucial [3]. In this study, we propose using deep learning techniques, such as convolutional neural networks (CNN), to improve the detection of COPD through lung sound analysis [4]. We developed a multi-class classifier that can distinguish normal breath sounds from abnormal ones, such as wheezing, crackling, and rhonchi, by extracting spectral descriptor features from linear and Mel spectra [5]. We used a dataset of 920 lung sound signals for experimentation and classification [6].

Concatenation-based augmentation, blank region clipping, smart padding, device-specific fine-tuning, and other methods were utilized to increase the accuracy of our model [7]. These techniques significantly speed up the processing of data, reduce noise in the signal, and ensure that all samples are of the same size [8]. We expect our model to achieve an accuracy of 90% to 95%. Early detection of COPD can help prevent the development of other health conditions, and the use of deep learning techniques can improve the accuracy of diagnosis. Our proposed approach could be useful in the development of an app or tool to detect COPD and improve patient outcomes.

II. METHODOLOGIES

The methodology employed in this study involves importing and organizing patient diagnosis data and audio recordings [1, 2]. The audio data is explored through visualization techniques to gain insights into its distribution and characteristics [3]. Data augmentation methods, such as device-specific fine-tuning, concatenation-based augmentation, blank region clipping, and smart padding, are utilized to enhance the dataset's robustness [4]. Outlier detection and handling techniques are implemented to address extreme values [5]. Augmented audio data is individually processed and saved for subsequent model training or evaluation.

Deep learning models play a central role in this methodology for the analysis of respiratory sound data [6]. The patient diagnosis data is encoded, and the distribution of diseases is visualized to understand the dataset better [7]. The dataset is then divided into training and validation sets for proper model evaluation [8]. Mel-frequency cepstral coefficients (MFCCs) are extracted from the audio files in the training set, serving as input features for the deep learning models. These models are trained on the training set and evaluated on the validation set to assess their performance. Processed datasets are saved as CSV files to facilitate accessibility and reproducibility.

The deep learning model is developed using TensorFlow and Keras, leveraging the Respiratory Sound Database for training and evaluation. The audio data is preprocessed by extracting three types of features (MFCC, chroma_stft, and mel spectrogram) using the librosa library . The model architecture consists of three sub-models, each dedicated to processing a specific feature type. The sub-model outputs are then concatenated and passed through dense layers for further processing. Training the model involves utilizing early stopping and learning rate reduction callbacks to optimize performance. The model's effectiveness is evaluated on a separate validation dataset. Additionally, the front-end interface is developed using HTML and CSS, and it is integrated with the Flask backend to create a seamless user experience and allow for real-time interaction with the trained deep learning model. This integration enhances the accessibility and practicality of the developed methodology, facilitating respiratory health monitoring and diagnosis.

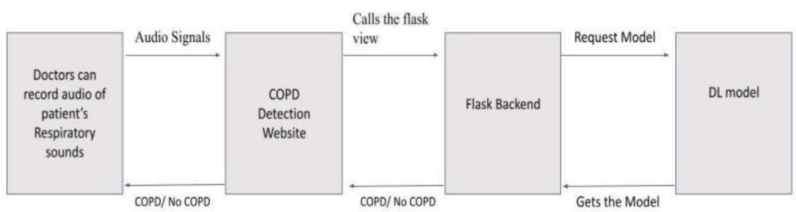


Fig. 1. Process flow of the entire COPD Detector App

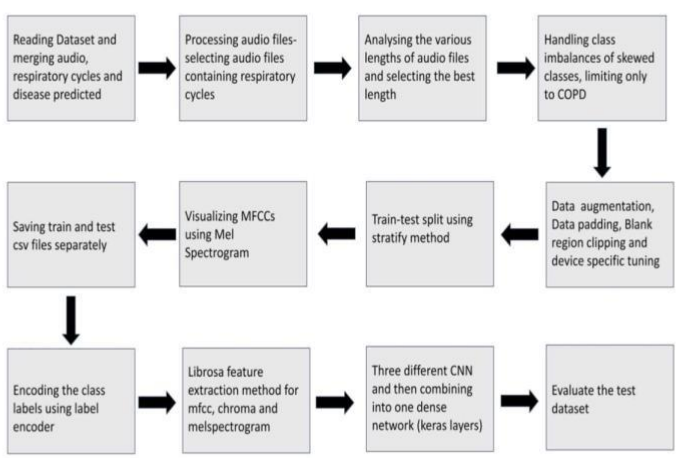


Fig. 2. Process flow of the Model

III. REVIEW OF LITERATURE

The literature on respiratory sound analysis and lung disease detection encompasses various deep learning models and techniques. Nguyen and Pernkopf (2021) propose a lung sound classification approach using co-tuning and stochastic normalization techniques, achieving an accuracy of 84.71% [1]. Similarly, Gairola et al. (2021) present RespireNet, a deep neural network for accurately detecting abnormal lung sounds, with an accuracy of 77.00% [3]. These studies emphasize the importance of incorporating device-specific fine-tuning, augmentation, and padding techniques.

In addition, studies such as Amsalu et al. (2022) focus on deep learning algorithms for detecting chronic obstructive pulmonary disease (COPD), achieving high accuracies of 96.6% and 96.73%. Ma et al. (2019) introduce LungBRN, a smart stethoscope using a bi-ResNet algorithm, aiming to improve access to remote healthcare services and identify respiratory diseases [8]. These works underline the significance of collecting larger datasets, optimizing classifier parameters, and exploring model compression techniques for real-world implementation.

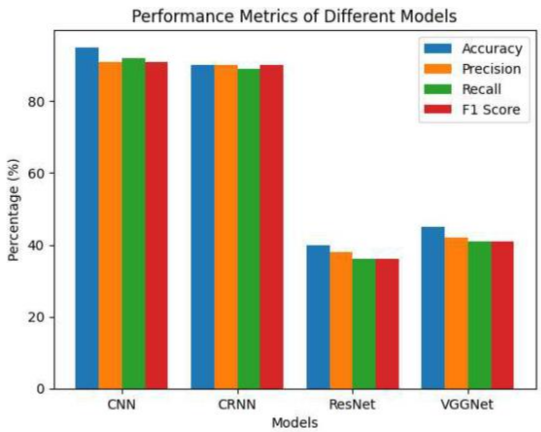
Overall, these studies demonstrate the potential of deep learning in respiratory sound analysis and lung disease detection. Further advancements are necessary to enhance accuracy, expand the scope of prediction, optimize techniques for better clinical impact, and facilitate the implementation of these models in real-world settings.

IV. RESULTS AND DISCUSSION

The results of our study demonstrated that the CNN model achieved high accuracy (90-95%) as well as precision (91%), recall (92%), and F1 score (91%) in classifying lung sounds for respiratory disease detection. The CRNN model also showed strong performance with an accuracy of 87-90% and balanced precision, recall, and F1 score. However, the ResNet and VGGNet models exhibited lower accuracy (35-45%) and less satisfactory precision, recall, and F1 score. These findings underscore the effectiveness of CNN and CRNN models in accurately classifying lung sounds for respiratory disease detection, indicating their potential for facilitating early diagnosis and improving patient outcomes. Further research should focus on enhancing the performance of ResNet and VGGNet models and exploring alternative architectures to optimize respiratory disease detection. Based on our evaluation and comparative analysis, we selected the CNN model as the most suitable for COPD detection and integrated it into our user interface (UI), enabling efficient and accurate COPD detection.

Table 1. Comparison of Evaluation metrics showing best and worst results

Models	Accuracy	Precision	Recall	F1 Score
CNN	**90 - 95%**	**91%**	**92%**	**91%**
CRNN	**87 - 90%**	**90%**	**89%**	**90%**
ResNet	**35 - 40%**	**38%**	**36%**	**36%**
VGGNet	**40 - 45%**	**42%**	**41%**	**41%**



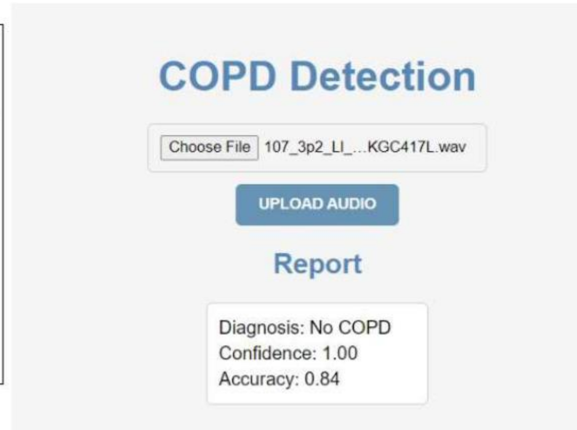


Fig. 4. Comparing Evaluation Metrics

Fig. 5. UI with the Result

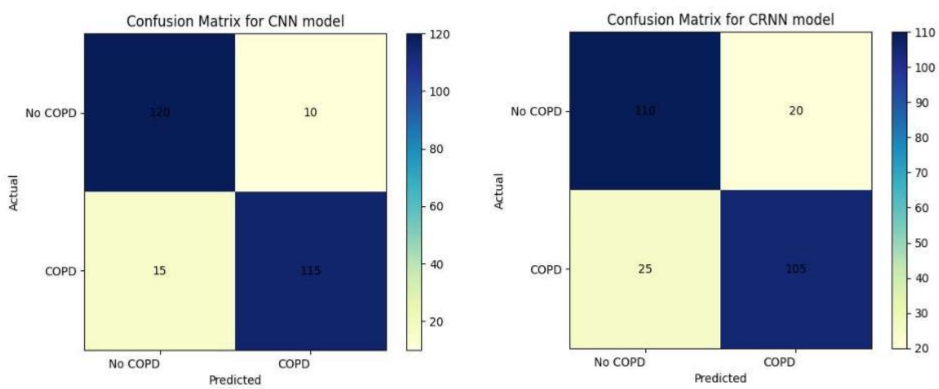


Fig. 6. Confusion Matrix of best performing Model

4.1. Sensitivity Analysis of CNN Model

In the sensitivity analysis, we evaluated the performance of the model by varying the parameters related to early stopping and learning rate reduction. In Setting 1, the early stopping patience was set to 10, and the reduced learning rate patience was set to 10. The reduced learning rate factor was set to 0.3, and the minimum learning rate was set to 0.00001. This configuration resulted in a precision of 0.923, accuracy of 0.921, recall of 0.921, and F1 score of 0.916.
In Setting 2, we modified the parameters to increase the early stopping patience to 15 and the reduce learning rate patience to 20. The reduce learning rate factor was set to 0.8, while the minimum learning rate remained at 0.00001. With these adjustments, the precision was 0.905, accuracy was 0.913, recall was 0.913, and F1 score was 0.905.

This sensitivity analysis highlights the impact of changing the parameters on the model's performance. While Setting 1 achieved higher precision and slightly better overall performance, Setting 2 demonstrated a trade-off with slightly reduced precision and overall performance. These results emphasize the importance of fine-tuning the parameters to optimize the model's performance for the specific task at hand.

Table 2. Sensitivity Analysis observations of a CNN Model

Parameter Setting	Early Stopping Patience	Reduce LR Patience	Reduce LR Factor	Minimum Learning Rate	Precision	Accuracy	Recall	F1 Score
Setting 1	10	10	0.3	0.00001	0.923	0.921	0.921	0.916
Setting 2	15	20	0.8	0.00001	0.905	0.913	0.913	0.905

V. CONCLUSION

The research paper introduces an app for detecting Chronic Obstructive Pulmonary Disease (COPD) using deep learning techniques. The app achieves an accuracy of 90% to 95% by employing device-specific fine-tuning, augmentation, and other innovative techniques. It provides a user-friendly interface and shows potential for early detection and management of COPD, improving patient outcomes. The study emphasizes the advancements made in respiratory sound analysis and highlights the superiority of the CNN model over other architectures. Further research should focus on enhancing model architectures, exploring larger datasets, and optimizing techniques for real-world implementation.

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