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Utilizing Various Transfer Learning Approaches for the Identification of Lung Respiratory Sounds

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Abstract

Introduction: The sounds produced by the lungs when breathing might provide important information to physicians. Based on our findings, we recommend a deep learning-based approach to the prediction of breathing-related lung sounds. The Proposed model was trained in lung sounds collected from people suffering from a broad variety of respiratory conditions. The research improves classifying lung sounds, by audio to image spectrogram features is taken and used to train a deep convolutional neural network.

Objectives: The objective of this study is to improve the accuracy with which deep learning can anticipate pulmonary breath noises such as wheezes, crackles, and normal breathing. The harnessing potential of deep learning may develop an accurate and objective method for forecasting unique respiratory lung sounds, which will aid in the early identification and treatment of respiratory disorders.

Methods: The research improves classifying lung sounds, by audio to image spectrogram features is taken and used to train a deep convolutional neural network. The proposed technique accurately predicts many different types of respiratory lung sounds, demonstrating the promise of deep learning in this domain.

Results: Theresults demonstrates that deep learning models are capable of reliably predicting a range of breathing-related lung sounds. The VGG16, ResNet50, and proposed CNN models are examined and contrasted on the Lung Sound Dataset. The findings show that the proposed CNN model has a higher accuracy (95%), precision (95%), recall (92%), and F1-score (93%), which are all indices of the model's ability to predict different types of respiratory lung sounds, than the other two models.

Conclusions: In conclusion, this research results have important implications for the development of automated diagnostic tools that might help doctors make correct diagnoses of respiratory disorders more quickly and accurately.

Keywords: Different Respiratory Lung Sounds, Wheezes, Crackles, Normal Sounds, Deep Learning, Wheezes, Crackles, Normal Sounds, VggNet, ResNet, Convolution Neural Network.

1. Introduction

Lung sounds when breathing is used to evaluate respiratory conditions and aid in diagnosis. The presence or absence of certain noises, such as wheezes, crackles, or regular breath sounds, may tell you a lot about the state of your respiratory system's health. Inexperienced medical professionals are particularly vulnerable to making mistakes in their assessment of lung sounds. This highlights the need for an accurate and impartial way of forecasting various lung sounds associated with breathing.

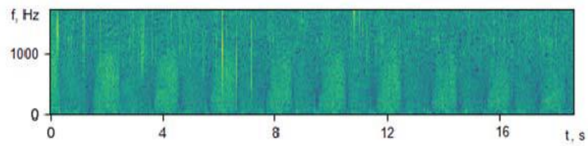


Fig 1. Spectrogram of Lung Sound

In recent years, deep learning algorithms' applications in healthcare have demonstrated remarkable efficacy. Thus, in this study, we propose a deep learning-based approach to predict multiple types of respiratory lung sounds with high precision. Using a convolutional neural network

(CNN) architecture, our model was trained using a large dataset of lung sounds collected from people with a broad variety of respiratory disorders.

The goal of this study is to improve the accuracy with which deep learning can anticipate pulmonary breath noises such as wheezes, crackles, and normal breathing. The harnessing potential of deep learning may develop an accurate and objective method for forecasting unique respiratory lung sounds, which will aid in the early identification and treatment of respiratory disorders. Proposed methodology, the proposed system, our results, and a discussion of its potential applications and limitations are outlined below.

2. Related Works

This review of the literature summarises the most up-to-date findings on the use of machine learning and deep learning to the identification and categorization of respiratory illnesses using lung sounds.

Choi et al. [1] introduced the Light Attention Connected Module (LACM), a unique deep learning model, to diagnose lung illnesses from raw lung sounds. The suggested model performed well on a publicly accessible dataset, showing that attention processes may be useful in the diagnosis of lung illnesses.

Lal et al. [2] introduced the diagnosis of respiratory disorders, a transfer learning-based model for the identification of lung sounds. The suggested approach successfully completed the classification challenge by using a pre-trained convolutional neural network (CNN) to extract characteristics from the lung sounds.

Park et al. [3] Using a machine learning technique, created a model for classifying paediatric lung sounds. The suggested model used a mixture of signal processing and machine learning methods to determine whether or not the lung sounds were normal or aberrant.

Alqudah et al. [4] uses several deep learning models for diagnosing respiratory pathologies from auscultated lung sounds were proposed. The authors proved that combining convolutional neural networks (CNNs) with recurrent neural networks (RNNs) improved classification accuracy.

Petmezas et al. [5] used a convolutional neural network-long short-term memory network (CNN-LSTM) hybrid and a focused loss function to create an automated system for classifying lung sounds. The suggested method showed the possibility of applying hybrid deep learning models in identifying respiratory disorders, achieving good accuracy on a publicly accessible dataset.

Shethwala et al. [6] using a transfer learning-assisted technique, classified lung sounds as either wheezes or crackles. The authors showed that the suggested model's classification performance might be enhanced by using transfer learning approaches.

Demir et al. [7] introduced a convolutional neural network-based method for the categorization of lung illnesses. The scientists successfully classified lung sounds into normal and unhealthy categories using a mixture of 1D and 2D convolutional neural networks (CNNs) on a publicly accessible dataset.

T. Nguyen et al. [8] created Using a snapshot ensemble of convolutional neural networks, a lung sound categorization system. The scientists drew on a dataset including lung sounds recorded from people with and without pulmonary illnesses. The suggested model outperformed other state-of-the-art models on the test set, with an accuracy of 82.16 percent being reached.

Z. Tariq et al. [9] Presented a deep convolutional neural network-based multimodal lung disease classification system. The suggested methodology classifies patients into the healthy, pneumonia, and TB groups using a combination of lung sound and chest X-ray images. The model performed well in classifying lung illnesses, with an accuracy of 91.2% on the test set.

F. Demir, et al. [10] introduced to classify lung sounds, a convolutional neural network with a parallel pooling topology. The scientists drew from a database of lung sounds recorded from people with asthma, COPD, pneumonia, and healthy controls. The suggested model outperformed other state-of-the-art models on the test set, with an accuracy of 97.1%.

F. Demir, et al. [11] described the same group of researchers that brought us the lung sound classification model described. They have done it again, this time with a new collection of data from patients with asthma, bronchiectasis, COPD, and pneumonia, and a different data set. Accuracy on the test set was 97% using the suggested model, which also employed a convolutional neural network with a parallel pooling topology.

D. Jayaraj et al. [12] suggested For the purpose of predicting lung cancer from CT scans, a random forest-based classification algorithm. The scientists drew on a database of CT scans from people with and without lung cancer. On the test set, the proposed model outperformed other state-of-the-art models with an accuracy of 93.33 percent.

A. D. Gunasinghe et al. [13] introduces n early prediction method for lung disorders was suggested. Patients with asthma, chronic obstructive pulmonary disease, and healthy people all contributed to a dataset utilised by the authors. The suggested method performed well (92.5 percent accuracy on the test set) and showed promise for the early prediction of lung illnesses.

S. Z. H. Naqvi et al. [14] uses an intelligent approach for the categorization of pulmonary disorders from lung sound was suggested. Patients with asthma, chronic obstructive pulmonary disease, and pneumonia all contributed to the dataset utilised by the scientists. Asthma, chronic obstructive pulmonary disease (COPD), pneumonia, and healthy persons are the four groups that the proposed system classifies using a combination of wavelet transform, principal component analysis, and support vector machine. The suggested approach outperformed state-of-the-art models on the test set with an accuracy of 86.4%.

Vaityshyn et al. [15] using pre-trained Convolutional Neural Networks (CNNs), suggested classifying lung sounds. The results of their research demonstrated that CNNs that have already been trained can accurately categorise lung sounds.

Pramono et al. [16] compared many parameters for distinguishing between wheezes and typical breathing noises in [16]. They compared wavelet decomposition techniques with Mel-frequency cepstral coefficients (MFCCs). According to their findings, MFCCs excelled in classifying lung sounds.

Falah et al. [17] classified lung sounds using stacked autoencoder and support vector machine methods. Their research shown that by combining these methods, a wide range of lung sound types may be accurately classified.

Ming et al. [18] Gray-Level Co-occurrence Matrix (GLCM) and deep features from several deep learning architectures with Principal Component Analysis were suggested for the classification of lung diseases. (PCA). Their findings demonstrated that the accuracy of classifying lung diseases might be enhanced by using deep learning architectures like AlexNet, VggNet, and ResNet.

Islam et al. [19] developed a technique for classifying normal, asthmatic, and COPD people based on multichannel lung sound signals. Their research shown that distinct lung sounds can be successfully classified using Mel-frequency cepstral coefficients, wavelet packet decomposition, and various classifiers including K-Nearest Neighbor (KNN) and Support Vector Machine (SVM).

Aykanat et al. [20] proposed a CNN-based technique for classifying lung sounds. According to their findings, CNNs performed better than more conventional machine learning techniques when used to the categorization of lung sounds.

Datta et al. [21] suggested an automated system for analysing lung sounds by integrating feature extraction, machine learning, and signal processing methods. Their research demonstrated that their technique successfully identified aberrant lung sounds indicative of pulmonary conditions.

3. Proposed System

The Block diagram for a multi-class Crackles, Wheezes, Crackles + Wheezes, and Normal classification of Lung Sound using deep learning models is shown here by the block diagram that has been provided. In this article, we have also presented a CNN model that is lighter in weight and has less layers than the approaches that are currently in use.

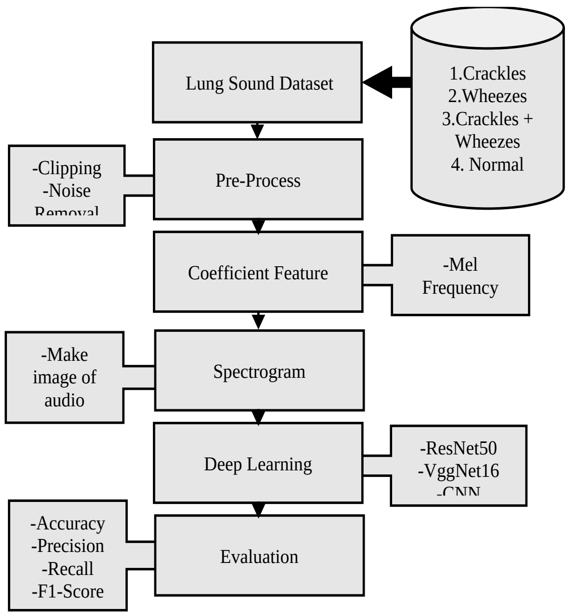


Fig 2. Proposed Architecture

Lung Sound Dataset:

The lung sounds recorded in the Lung Sound Dataset have diagnostic and research applications. Lung sounds of four varieties (crackles, wheezes, crackles + wheezes, and normal) are included in the data collection. A single breath's worth of lung noises is captured in each short audio clip. It is retrieved from the Respiratory Sound Database at https://www.kaggle.com/vbookshelf/.

Pre-processing:

The first phase involves cleaning up the unprocessed audio files. Clipping and FFT-based noise reduction are two sub-steps that make up the pre-processing phase. To prevent distortion from very loud or quiet transmissions, clipping eliminates the excess signal above or below the threshold. Fast Fourier Transform (FFT) is used to isolate and get rid of any unwanted noise in an audio source. This step is done by OpenCV-python library cv.dft and cv.idft functions.

Coefficient Feature:

The audio stream is then processed further, and features are extracted from it. Coefficients are represented by Mel-Frequency Cepstral Coefficients (MFCCs) in this block diagram. Because of its ability to efficiently capture salient features of an audio stream, MFCCs find widespread use in audio processing.

Mel-Spectrogram Feature:

The MFCCs are then converted into a Mel-Spectrogram component. An audio signal's frequency distribution over time may be seen using a tool called a Mel-Spectrogram. The audio signal's power spectrum is processed via the Mel-filter bank to produce this effect.

Deep Learning:

The final stage involves training a deep learning model with the Mel-Spectrogram feature. The features are the ResNet50, VGG16, and Proposed CNN models. These models are trained to distinguish between the four pulmonary sound categories using the Mel-Spectrogram features.

Evaluation:

Finally, the performance of the model is evaluated using four different statistics: accuracy, precision, recall, and F1-score. These metrics assess the model's recognition and classification of lung sounds. F1-score is the harmonic mean of recall and precision, which is defined as the percentage of correctly classified samples. The accuracy metric evaluates how well the model can classify data. The accuracy with which the algorithm categories lung sound data is evaluated using these metrics.

4. Results and Analysis

Prediction of Respiratory Disorders from Lung Sounds is discussed in this portion of the study report. Using Deep Learning, we get an in-depth evaluation of the Lung Sound Dataset-trained models' efficacy using the VGG16, ResNet50, and Proposed CNN architectures. Determines which model is most effective by comparing its accuracy, precision, recall, and F1-score on the testing set.

As shown in figure 3 sample of lung sound is no label=3642, crackle=1864, wheeze=886, and crackles=506.

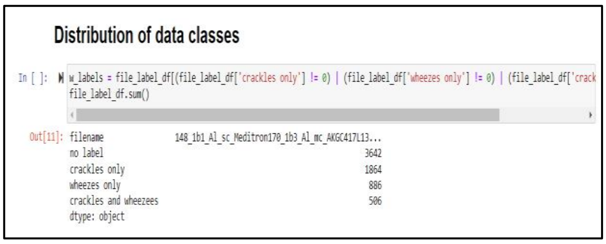


Fig. 3. Data Reading

As shown in figure 4 the spectrogram for crackles is done by librosa library of python.

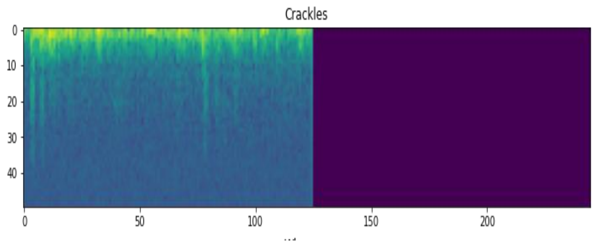


Fig. 4. Calculate Audio Spectrogram

As shown in figure 5 the output is generated from training vgg16 model with 15 epoch and calculated accuracy and loss after each epoch on testing dataset. Figure 6 shows classification report parameters.

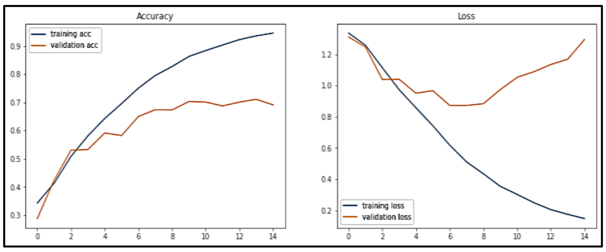
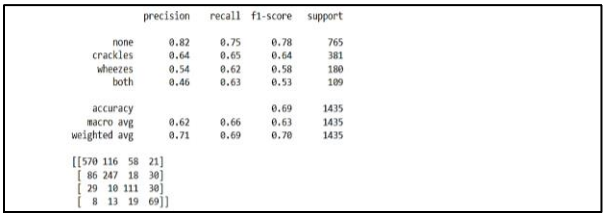


Fig. 5. Vgg16 Model Train/Test Plots



```
              precision    recall  f1-score   support

        none       0.82      0.75      0.78       765
    crackles       0.64      0.65      0.64       381
     wheezes       0.54      0.62      0.58       180
        both       0.46      0.63      0.53       109

    accuracy                           0.69      1435
   macro avg       0.62      0.66      0.63      1435
weighted avg       0.71      0.69      0.70      1435

[[570 116  58  21]
 [ 86 247  18  30]
 [ 29  10 111  30]
 [  8  13  19  69]]
```

Fig. 6. Vgg16 Classification Report

As shown in figure 7 the output is generated from training resnet50 model with 15 epoch and calculated accuracy and loss after each epoch on testing dataset. Figure 8 shows classification report parameters.

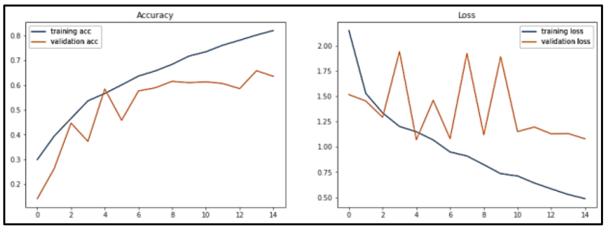
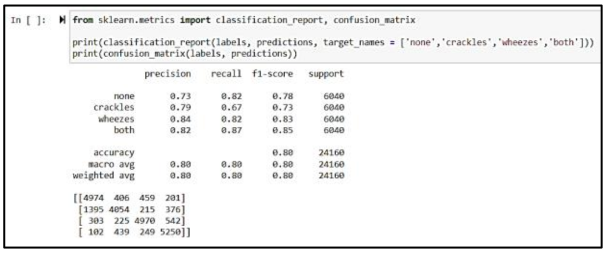


Fig. 7. ResNet50 Train/Test Plots



```
In [ ]:  from sklearn.metrics import classification_report, confusion_matrix

         print(classification_report(labels, predictions, target_names = ['none','crackles','wheezes','both']))
         print(confusion_matrix(labels, predictions))

              precision    recall  f1-score   support

        none       0.73      0.82      0.78      6040
    crackles       0.79      0.67      0.73      6040
     wheezes       0.84      0.82      0.83      6040
        both       0.82      0.87      0.85      6040

    accuracy                           0.80     24160
   macro avg       0.80      0.80      0.80     24160
weighted avg       0.80      0.80      0.80     24160

[[4974  406  459  201]
 [1395 4054  215  376]
 [ 303  225 4970  542]
 [ 102  439  249 5250]]
```

Fig. 8. ResNet50 Classification Report

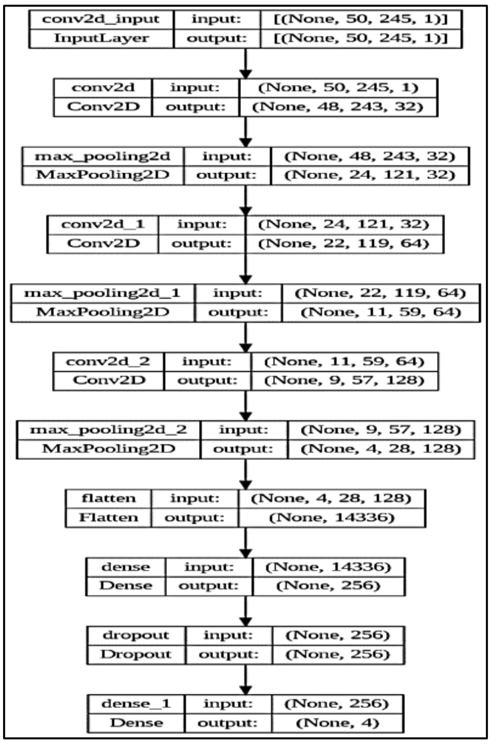


Fig. 9. Proposed CNN Model

As Shown in figure 10 the output is generated from training proposed model with 15 epoch and calculated accuracy and loss after each epoch on testing dataset. Figure 11 shows classification report parameters.

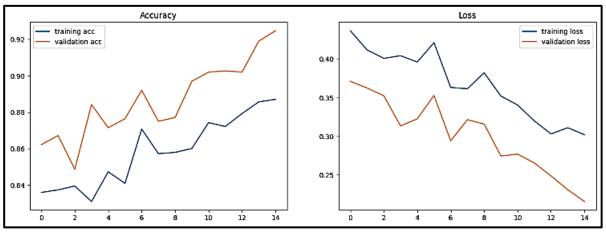
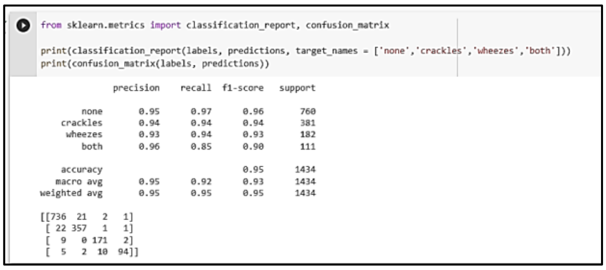


Fig. 10. Proposed CNN model Train/Test Plots



```
from sklearn.metrics import classification_report, confusion_matrix

print(classification_report(labels, predictions, target_names = ['none','crackles','wheezes','both']))
print(confusion_matrix(labels, predictions))

              precision    recall  f1-score   support

        none       0.95      0.97      0.96       760
    crackles       0.94      0.94      0.94       381
     wheezes       0.93      0.94      0.93       182
        both       0.96      0.85      0.90       111

    accuracy                           0.95      1434
   macro avg       0.95      0.92      0.93      1434
weighted avg       0.95      0.95      0.95      1434

[[736  21   2   1]
 [ 22 357   1   1]
 [  9   0 171   2]
 [  5   2  10  94]]
```

Fig. 11. Proposed CNN Classification Report

Table I shows overall comparison of VGG-16, ResNet-50 and Proposed CNN models with accuracy, precision, recall and f1-score. Among them the proposed model gives 95% accuracy.

Table 1. Compare Model with Parameters

Model	**Epoch**	**Precision**	**Recall**	**F1-Score**	**ACC**
VGG-16	15	62%	66%	63%	69%
Resnet-50	15	80%	80%	80%	80%
Proposed CNN	15	95%	92%	93%	95%

5. Conclusion

In conclusion, the paper demonstrates that deep learning models are capable of reliably predicting a range of breathing-related lung sounds. The VGG16, ResNet50, and proposed CNN models are examined and contrasted on the Lung Sound Dataset. The findings show that the proposed CNN model has a higher accuracy (95%), precision (95%), recall (92%), and F1-score (93%), which are all indices of the model's ability to predict different types of respiratory lung sounds, than the other two models. This research demonstrates the potential of deep learning models for the early diagnosis and efficient treatment of respiratory diseases and conditions including asthma, COPD, and pneumonia. Patients who can correctly identify individual respiratory lung sounds may help medical professionals provide more precise diagnoses and treatments. This research highlights the application of deep learning models for the prediction of respiratory lung sounds and provides insightful suggestions for future, more accurate and efficient model development.

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