RESPIRATORY SYSTEM RELATED SEVERAL DISEASES DETECTION SYSTEM USING LUNG SOUND ANALYSIS

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INTRODUCTION

Listening of sounds of lungs is a main diagnosis method related to diseases with the ***respiratory system***. Several diseases related to the respiratory system can be identified by analysing these sounds. Inaccurate treatment of diseases related to the respiratory system is a generic issue with ambiguous identification and misinterpretations of lung sounds [1].
Therefore, an automatic lung sound detection and analysis system to identify COPD and asthma is proposed in this research.

Aim

Analyse the acoustic parameters from respiratory signals in COPD and Asthma patients and develop a system with enhanced accuracy.

Objectives

1. Develop a classification model using lung sound analysis
2. Develop Electronic device to classify COPD and Asthma patients

Respiratory sounds of lungs are analysed to identify diseases related to the respiratory system. Usually, a stethoscope is used to listen to respiratory sounds. Both heart sounds and lung sounds can be listened to when using a stethoscope. Using a stethoscope to hear sound is called ***auscultation***. Lung auscultation is an essential part of the respiratory examination and is helpful in diagnosing various disorders, such as anomalies that may occur in the form of ***abnormal sounds*** (e.g., crackles and wheezes) in the respiratory cycle.
Most common respiratory diseases are ***COPD*** (Chronic obstructive pulmonary disease) and ***asthma***. COPD is a progressive inflammatory lung disease characterised by increasing breathing difficulty. It develops as a result of long-term exposure to irritants such as smoke, chemical fumes or dust, and may go unnoticed for years. Most people show symptoms after the age of 40 when the disease is already in its advanced stage. Symptoms of ***COPD*** are difficulty breathing and coughing. These problems occur due to the limitation of air flow in the respiratory system. COPD is not fully reversible, and it develops gradually.
Abnormal respiratory sounds occur mainly due to crackles, wheeze, and rhonchi. **Wheeze** and **rhonchi** are mainly lungs related abnormal sounds to identify COPD and asthma [2].

Differences of pneumonia or pleural effusion (water in lungs) versus health can be identified by analysing dynamic breath sound images in a digital screen [3].
Pneumonia and asthma can be separated by analysing cough sounds using MFCC (Mel-Frequency Cepstral Coefficients), formant frequency, zero crossing rate (ZCR), Shannon entropy, Non-Gaussianity score (NGS) and ANN (Artificial Neural Network) [4].
Time domain vs frequency domain 2D array can be obtained by applying MFCC to the sound wave clip. According to the paper, there are 6 steps to complete ***MFCC***. They are Frame signal, Window frame, FFT, Mel filter bank, log of the Mel filter bank and Discrete Cosine Transform (DCT) [5].

METHODOLOGY

Proposed detecting system detects sounds in the chest, analyses them to divide the condition of the lung status of the patient to COPD, Asthma or Healthy. When the stethoscope touches the chest, both blood pressure sounds, and lung sounds can be heard. Sounds of lungs with asthma and COPD have wheezing, Crackles, Rhonchi sounds than a healthier person.

The system detects lung sound by an electret microphone and extracts the MFCC features. Then classifies the sound by using CNN trained model. Finally, classified output is sent to a display.

Fig. 1 shows the functional block diagram of the proposed system. There are 9 functional blocks in the proposed system to classify lung sounds into 3 classes- COPD, Asthma and healthy. They are (1) Audio input, (2) recording,(3) Filter, (4) Feature extraction,(5) Client app,(6) Server app,(7) Inference,(8) Display classified output,(9) Display.

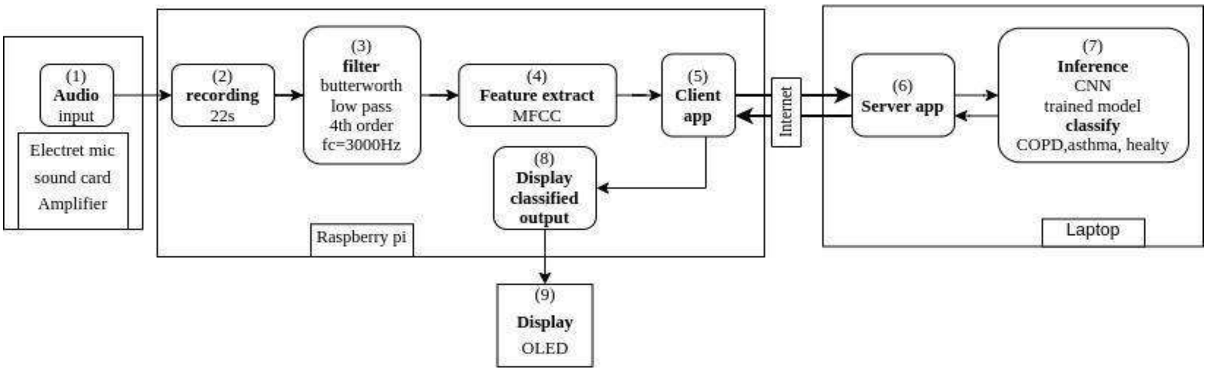

fig. 1 Functional block diagram of the proposed system

(1) Audio input-Electret microphone, preamplifier and sound card (portable HIFI Magic Voice 7.1CH) are used for detecting lung sounds from the chest. Sampling rate of the sound card is 48,000 Hz.

(2) Recording-Length of a recorded lung sound slot is 22s. Sampling rate of the recording is 22050 Hz because sound samples in training modules use the 22,050 Hz sample rate. Recording file format is ".wav".

(3) Filter-Butterworth low pass filter with 3000 Hz cut off frequency is used because lung sounds related to COPD and asthma are lower than 3000Hz.

(4) **Feature extraction-**22s recorded sound clip is sent through MFCC block for extract features. Vertical columns include MFCC coefficients 1 to 13 and horizontal rows include time. Feature extracting parameters-Sample rate = 22050, Hope length (number of samples between successive frames) = 512. **(5) Client app-**Client app is used to get MFCC 2D array and send it to the server and receive server output and send it to display classified output.

(6) Server app-Server app is used to receive MFCC 2D array data sent by client app and send data to the inference block.

(7) Inference-MFCC 2D array is used to input to the inference. Inference system classifies sound to either COPD or asthma or health. CNN model is used to infer. Graphical presentation of CNN is shown in fig. 2. CNN has 13 layers. Following list describes the 13 layers of CNN [6].

(1) Convolutional Neural Network- No of filters=64, Size of the filter 3x3, Activation function=ReLU, Regularisation=l2(0.001), (2) Batch normalisation, (3) Maxpool-filter=3x3, stride=2,2, padding=same

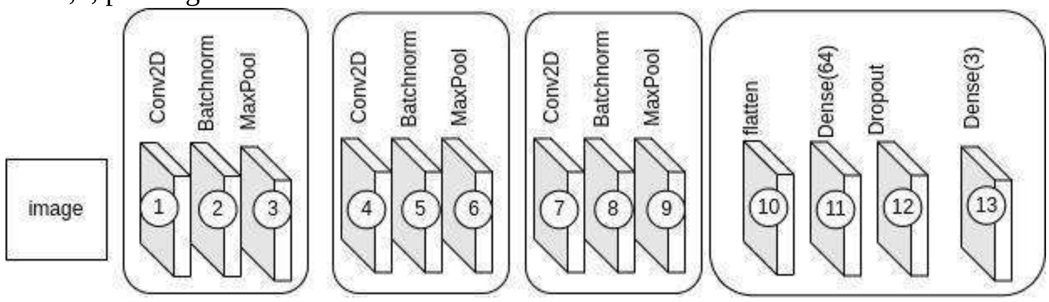

Figure 2 : Convolutional neural network used for the project

(4) Convolutional Neural Network- No of filters=32, Size of the filter 3x3., Activation function=ReLU, Regularisation=l2(0.001), (5) Batch normalisation,(6) Maxpool-filter=3x3, stride=2,2, padding=same
(7) Convolutional Neural Network- No of filters=32, Size of the filter 3x3., Activation function=ReLU, Regularisation=l2(0.001), (8) Batch normalisation,(9) Maxpool-filter=3x3, stride=2,2, padding=same
(10) Flattern, (11) Neural network (Dense)- No of neurons=64, Activation function=ReLU, (12) Dropout, (13) Output neural network-No of neurons=3, Activation function=softmax.
Hardware used for the proposed system to perform above functions are diaphragm of a stethoscope, electret microphone, sound card, raspberry pi microcontroller, and display unit.

CNN model Training

CNN are trained to set necessary weights of the neural network in CNN. Fig. 3 shows the training block diagram of the proposed system.

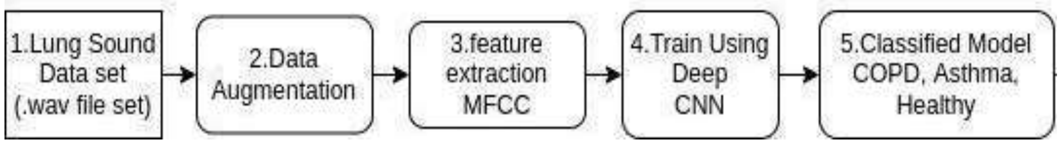

Figure 3 : Method of training

Lung sound data set

For training the system, a 2267 lung sound data set is selected from Kaggle Respiratory Sound Database and by performing Augmentation methods. This audio wave file data set includes lung sound taken from patients with respiratory problems and healthy persons. Duration of these files is an average of 22 seconds. Noise injection, shifting time and changing pitch augmentation techniques were used to reduce data imbalance which will cause machine learning models to perform poorly [7].

Audio input method

Lung sounds are normally low-pitched sounds. So, it is not possible to collect sound from lungs using only a microphone. Therefore, a condenser microphone with a stethoscope chest-piece was made for the detection process. This design is sensitive to lung sound but also ambient noises. Further, a preamplifier is used to gain the pitch.

RESULTS AND DISCUSSION

Figure 4 shows the last 2 epochs in CNN model training. It finished with 93.8% test accuracy. Number of epochs is 80.

Figure 5 (a) shows the training and validation accuracy. Accuracy increases rapidly within the first 10 epochs indicating that the network is learning fast. Afterwards, the curve flattens indicating that not too many epochs are required to train the model further. Less difference test accuracy against validation accuracy indicates balanced data.

Figure 5 (b) shows loss of the training and validation. Loss does not decrease at the same rate as the training set but remains almost flat for multiple epochs. This means our model is generalising well to unseen data.

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918/918 [==============================] - 4s 4ms/step - loss: 0.0676 - accuracy: 0.9946 - val_loss: 0.3344 - val_accuracy: 0.9412
Epoch 79/80
918/918 [==============================] - 4s 4ms/step - loss: 0.0805 - accuracy: 0.9886 - val_loss: 0.2635 - val_accuracy: 0.9657
Epoch 80/80
918/918 [==============================] - 4s 4ms/step - loss: 0.0729 - accuracy: 0.9935 - val_loss: 0.2810 - val_accuracy: 0.9510
8/8 [==============================] - 0s 9ms/step - loss: 0.6120 - accuracy: 0.9383
Test error: 0.6120044089842664, test accuracy: 0.9383260011672974

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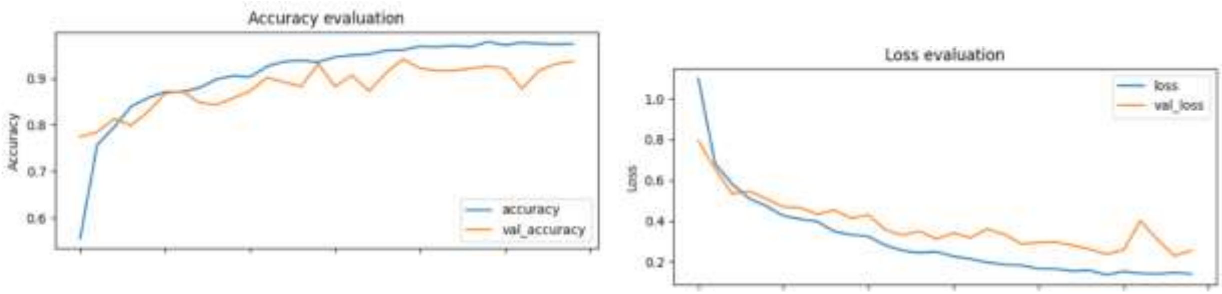

figure 4: CNN model training result

(a) (b)

figure 5: Accuracy and loss evaluation graph

CONCLUSION

In this study, a detection system of COPD, Asthma and healthy subjects in real time with classification of lung sounds using CNN is presented. For this purpose, at first MFCC features were extracted then these features were used for classification. The model training results show that the MFCC feature extraction method with CNN has better accuracy. Electret mic with Stethoscope diaphragm was a better low cost method for sensitive lung sound recording, but electronic stethoscope will do a better job also it will be expensive.

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