Cough sound analysis and objective correlation with spirometry and clinical diagnosis

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Y. Padma Sai
VNR Vignana Jyothi Institute of Engineering & Technology

V.Naveen Kumar
VNR Vignana Jyothi Institute of Engineering & Technology

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Cough sound analysis and objective correlation with spirometry and clinical diagnosis

Gowrisree Rudraraju [a,*], ShubhaDeepti Palreddy [a], Baswaraj Mamidgi [a], Narayana Rao Sripada [a], Y. Padma Sai [b], Naveen Kumar Vodnala [b], Sai Praveen Haranath [c]

[a] Salcit Technologies, VJHUB, India
[b] VNR VJIET, India
[c] Apollo Hospitals, India

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ABSTRACT

In India, there are 100 million people who suffer from various respiratory problems; globally it is about 1–1.2 billion. The main problem attributed to the prevalence of respiratory diseases is lack of cost-effective and lab-free methods for early diagnosis. Spirometry is the standard clinical test procedure for detection of respiratory problems, but it requires repetition, and is also expensive and not available in rural areas.

Cough sounds carry vital information about the respiratory system and the pathologies involved. Through this study, we detail how a combination of standard signal processing features and domain-specific features play a key role in distinguishing cough patterns. We could establish a relationship between cough pattern and respiratory conditions including widened airway, narrowed airway, fluid filled air sacs, and stiff lungs. Further, cough sound characteristics are correlated to the airflow parameters of spirometry.

Our results show strong correlation of cough sound characteristics with airflow characteristics including FEV1, FVC and their ratios, which are important in identifying the type of lung diseases as either obstructive (obstruction in airway) or restrictive (restricts lung expansion). We have constructed a machine learning model to predict obstructive versus restrictive pattern, and validated it using K-fold cross-validation based on ground truth data. With a pattern prediction accuracy of 91.97%, sensitivity of 87.2%, and specificity of 93.69%, our results are encouraging.

1. Introduction

The lungs are important organs in the respiratory system and used for gas exchange (oxygen and carbon dioxide). When we breathe. Our lungs transfer oxygen from the air into the blood, and carbon dioxide from the blood into the air. Lungs have two major components for gas exchange - airways and alveoli (air sacs) [1]. Airways are pipe-like passages which allow movement of airflow in and out of the lungs. Airways include the trachea and the two bronchi; bronchi are further divided into the smaller segments called bronchioles. Bronchioles end with a cluster of air sacs called alveoli. The walls of the alveoli contain small blood capillaries. The gas exchange mechanism takes place across the walls of the alveoli.

Respiratory disease includes any problem in the respiratory system that prevents the lungs from working in normal condition. Respiratory diseases are classified based on patterns as 'Obstructive', 'Restrictive', and 'Combined' (both obstructive and restrictive) [2]. The term obstructive lung disease includes conditions that decrease a person's ability to exhale all the air from their lungs. Some conditions of the lung, like widening and narrowing of the airway, leads to obstruction [11,14]. Those with restrictive lung disease have trouble in fully expanding their lungs. Conditions like scarring of the lung (stiff lungs) and fluid-filled lungs leads to restriction [11,14]. Sometimes, these two processes (obstruction and restriction) combine – where the total amount of air breathed in and how fast the air is breathed out are reduced.

Obstructive, Restrictive, and Combined lung diseases share some common symptoms like cough, shortness of breath, pain in the chest, etc. [2]. The knowledge about lung volumes and capacities will help in interpreting various lung diseases [24]. Spirometry is used to identify the presence of a respiratory disease, to differentiate obstructive and restrictive diseases, and to monitor disease severity [25]. Typically, in clinical practice, spirometry is used to perform an overall assessment of pulmonary function. A clinical test like spirometry measures the volume

* Corresponding author. VNR Vignana Jyothi Institute of Engineering and Technology, Nizampet Road, Pragathi Nagar, India.
E-mail address: info@salcit.in (G. Rudraraju).

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of air inspired and expired and provides ample information about the physiological derangement of the lung. Though spirometry is a simple and straightforward test, however, it requires the patient's cooperation, and some people may feel dizzy, shaky or even faint for a short period after the test. However, the spirometry test is to be repeated several times until there are two or three good efforts. In many rural and remote areas, the spirometry set-up may not be readily available. There is a need for an alternative mechanism, which is simple, non-invasive, lab-free and cost effective in addressing all of the gaps with spirometry.

Cough is the most common symptom of several respiratory diseases [2]. Cough is a defense mechanism of the body which prevents the respiratory tract from inhaling foreign materials accidentally or those produced internally by infection [20]. Based on the perception of presence of sounds related to secretions (fluids like mucus, pus) in the airways, cough is classified into two categories - 'wet cough' and 'dry cough.' By considering the acoustic quality of cough, it is characterized as wet when the sounds carry features indicative of mucus; in the absence of perceivable wetness it is called dry [37]. Changes in the character of the cough sound can reflect pathological situations in the lungs [7,9,13,17–19,21,29]. Pathological situations arise due to some conditions like obstruction, restriction, and combined patterns.

To the best of our knowledge, only two prior works exist in this area of using cough sounds to differentiate pattern/type of respiratory disease. 1) Achuth et al. [3], proposed a method for automatically predicting spirometry readings from cough and wheeze audio signals for asthma severity monitoring. The study reported root mean square error (RMSE) of 0.48L, 0.57L, and 0.08L in estimating FEV1, FVC, and FEV1/FVC respectively. The study dataset, however, was small with only 28 subjects: 16 healthy and 12 asthmatics. It is primarily focused on asthma. In addition, other obstructive, restrictive, and mixed diseases were not explored, and the cough signals were manually segmented. 2) In the latest research work, Roneel et al. [32], proposed that the mechanism of cough generation and the forced expiratory maneuver of spirometry share many similarities enabling the prediction of spirometry readings. These studies led to new research in respiratory sound analysis using cough. However, the work has been limited to a study of some characteristic features of coughs mainly based on standard signal processing techniques. There was no focus on understanding the cough sound characteristics like duration, number of bouts, type, number of occurrences in its predefined duration, etc. Cough characteristics will have a direct relation to different conditions in a respiratory system [15,38].

Researchers have made many attempts to develop methods for the automated, objective classification of cough to differentiate respiratory diseases. By various researchers, cough sound signal classification has been shown to be useful in detecting respiratory diseases such as pneumonia [16,26], asthma [10,23], croup [33], and COPD [26,27].

After analyzing literature surveys and acquiring knowledge on respiratory system by working closely with pulmonologists/physicians, and clinical investigation processes, we understand the need is more on providing indicative predictions based on which the next course of action can be taken, very similar to what a spirometry test does today. We were able to identify a few conditions of importance like widened airway, narrowed airway, airway narrowing due to loss of elastic support, inflammation of lining of the bronchial tubes, air sacs filled with fluid, lung compliance, and the interstitium becoming scarred and thickened. We collected cough sequences and annotated them based on these identified conditions, extracted features, and did a thorough analysis in relating the feature characteristics to these different conditions. Using standard correlation methods, we studied the relation between important cough sound characteristics (audiometric data) and air flow data (spirometry data). We further related audiometric data to different diseases and their respective conditions. We have built a machine learning model to predict normal, obstructive (obstruction in airway) or restrictive (restricts lung expansion) pattern and validated using K-fold cross-validation based on ground truth data including clinical diagnosis. This approach of ours is completely different from the previous and existing research methods based on cough sounds for early diagnosis of respiratory diseases.

The rest of this paper is organized as follows. The methods and materials are described in section 2 and it is detailed with sub sections such as data acquisition, feature extraction, different conditions of the lung related to disorders, pattern classifier and relation to spirometry. Results are presented in section 3, which explains independent cough analysis and relation to lung conditions of different disorders, relation between audiometric data and spirometry data, relating important features to disease and anatomy and performance of the classifier. Results are followed by discussion.

2. Methods

2.1. Data acquisition

As part of the study, we recruited and collected data from subjects suffering with various respiratory problems. The ethical committee at Apollo Research and Innovation, part of Apollo Hospitals approved our study. From 110 subjects we collected about 640 records, each of them with 1–2 min of duration. From these records we extracted about 1700 cough sequences. Cough in which one single inspiration is followed by successive expiratory flow spikes of cough, not separated by inspiratory phases, is called a cough sequence. Data distribution is shown in Fig. 1. We used the Zoom H1n Handy Recorder to record the sounds. The recorder is connected to a mobile phone through which sounds are transmitted and stored on a private cloud. We also have spirometry data for 40 of these subjects. We also collected normal coughs from 40 healthy subjects. All of the collected data is annotated with the labels as shown in Table 1.

The annotation here helped us in knowing exactly how the cough sound characteristics relate to the anatomical structure of the respiratory system, which in turn helped us to map the sound characteristics to various respiratory disease conditions and their corresponding pattern as shown in Table 2.

2.2. Feature extraction

The collected audio signals are analyzed to extract events, using the moving windowed signal standard deviation, as a function of time. The moving window works along the entire length of the audio signal, taking

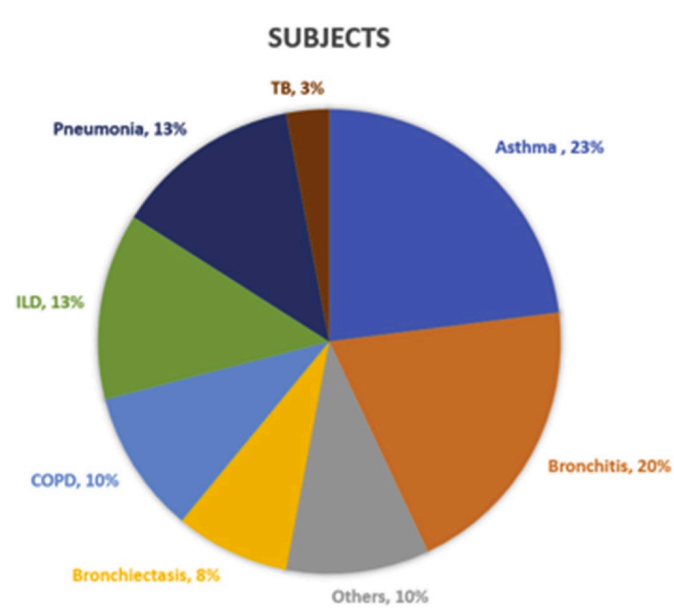

Fig. 1. Data distribution.

Table 1
Each cough sequence is labelled as detailed below.

Sound sequence	Type	Disease	Pattern and Conditions	Severity of inflammation	Respiratory track
Cough Sequence	Dry/ Wet	Asthma, COPD, ILD, Bronchitis, Pneumonia, Normal etc.	Obstructive: widened airway, narrowed airway. Restrictive: air sacs filled with fluid, interstitium becoming scarred and thickened.	No, Low, Medium, High.	Pleura, Parenchyma, Small airway, Large airway.

Table 2
Respiratory disease pattern and their corresponding conditions.

S. No	Pattern	Related conditions
1	Obstructive	widened airway, narrowed airway
2	Restrictive	air sacs filled with fluid, interstitium becoming scarred and thickened
3	Combined	any combination of obstructive and restrictive conditions

each frame as the center of a new window. This windowed standard deviation is similar to the more commonly used root mean square signal, however, it corrects for deviations of the mean from zero, thus removing noise in the signal [34]. The extracted events are classified using cough/non-cough classifier. From cough events features are extracted.

As part of the feature extraction we have two types of features. The first one is called primary features which are extracted using standard signal processing techniques in both time and frequency domain. The primary features include Energy, Zero-crossing rate (ZCR), Mel Frequency Cepstral Coefficients and Spectral features (spectral centroid, spectral bandwidth, spectral roll-off) [30]. The second set of features is called secondary/domain features. These include the type of cough sequence, number of bouts in a sequence, number of occurrences of cough sequence in a 2-min interval, duration of cough sequences and also important chest symptoms. We arrived at these features by analysing the data and further validated the same by discussing with specialists [39]. Some of these secondary features are derived from primary features and others are directly measured.

The primary features are explained in detail as follows:

Energy: Time average of squared amplitudes within a window of calculation (frame).

Mel Frequency Cepstral Coefficient (mfcc): A Mel scale is used to tone the obtained pitch and frequency to the actual measured frequency. To match our features with the sound that humans hear we employ the Mel scale. Converting from frequency to Mel scale is as follows:

$$M(f) = 1125 \ln (1 + f/700), \text{ where } f = \text{frequency}$$

Zero-crossing rate (ZCR): It is used to determine the number of times a signal crosses zero amplitude line i.e. changes from positive to negative sign and vice-versa. Zero-crossing rate helps us to understand the frequency of the audio signal. If the zero-crossing rate is high it implies that the audio signal is of high frequency, else, it is of low frequency.

Spectral Centroid: It is used as one of the important measures in the domain of digital audio processing. To characterize a spectrum, the Spectral centroid is used.

Spectral Bandwidth: It provides the information about the extent of the spectrum.

Spectral Roll-off: This feature is used to differentiate voiced sounds and sounds which do not involve any voice. Initially, we define a percentage of spectrum. Roll-off is used to obtain the frequency below the predefined percentage of the entire spectrum.

Table 3 shows the complete list of features.

Table 3
Features list.

No	Type of features	Number of features	Feature details
1	Primary features	45	1 to 40. MFCC coefficients 41. ZCR 42. Energy 43. Spectral Centroid 44. Spectral Bandwidth 45. Spectral Roll-off
2	Secondary features	8	1. Cough Type (dry/wet) 2. Cough sequence duration 3. Cough bout duration 4. Dry Frequency 5. Wet Frequency 6. Total Frequency 7. Kurtosis 8. Skewness
3	Symptoms	6	1. Frequent Cough 2. Cough at Night 3. Sputum 4. Wheezing 5. Shortness of Breath 6. Pain in Chest
4	Patient details	2	1. Gender 2. Age

2.3. Different conditions of the lung related to lung disorders

We collected cough sequences and annotated them based on these identified conditions, extracted features, and did a thorough analysis in relating the feature characteristics to these different conditions. Fig. 2 illustrates the various lung conditions and their airflow mechanism.

Normal airways: There is no problem in the process of exchanging gases CO_2 and O_2. The flow of air is normal without any interruption. Normal coughs arrive for clearing of airways, irritants such as smoke and gas, tobacco use or improperly swallowing food and liquids.

Narrowed airways: Narrowing of airways is due to accumulation of mucus along the lining of the walls of airways and inflammation of the muscle in the airways. Airway narrowing obstructs the flow of air in and out of the lungs. In this case we see that, the person does more than one expiration within a single inspiration.

Widened airways: Damage in the airway walls leads to widening of the airways. As a result, extra mucus tends to form and pool in the widened airways and can be seen in Bronchiectasis. A persistent cough and excess phlegm, or sputum is observed in this condition.

Stiff lungs: Thickened, stiff tissue makes it difficult for the lungs to work properly by not allowing the lungs to expand. Scarring makes it difficult for the lungs to transfer oxygen into the bloodstream. This means the brain and other organs may not receive the oxygen they need.

Fluid filled lungs: Alveoli are filled with excess fluid instead of air restricting the exchange of gases. This leads to difficulty in breathing and poor oxygenation of blood.

An obstruction may partially or totally prevent air from getting into the lungs. An airway obstruction is a blockage in any part of the airway. Conditions like narrowing and widening of airways results in obstruction. Because of damage to the lungs or narrowing of the airways inside the lungs, exhaled air comes out more slowly than normal. At the end of a full exhalation, an abnormally high amount of air may still linger in the lungs. Conditions like stiffness in the lungs or fluids in the lungs may lead to restriction in lung expansion. People with restrictive lung disease cannot fully fill their lungs with air.

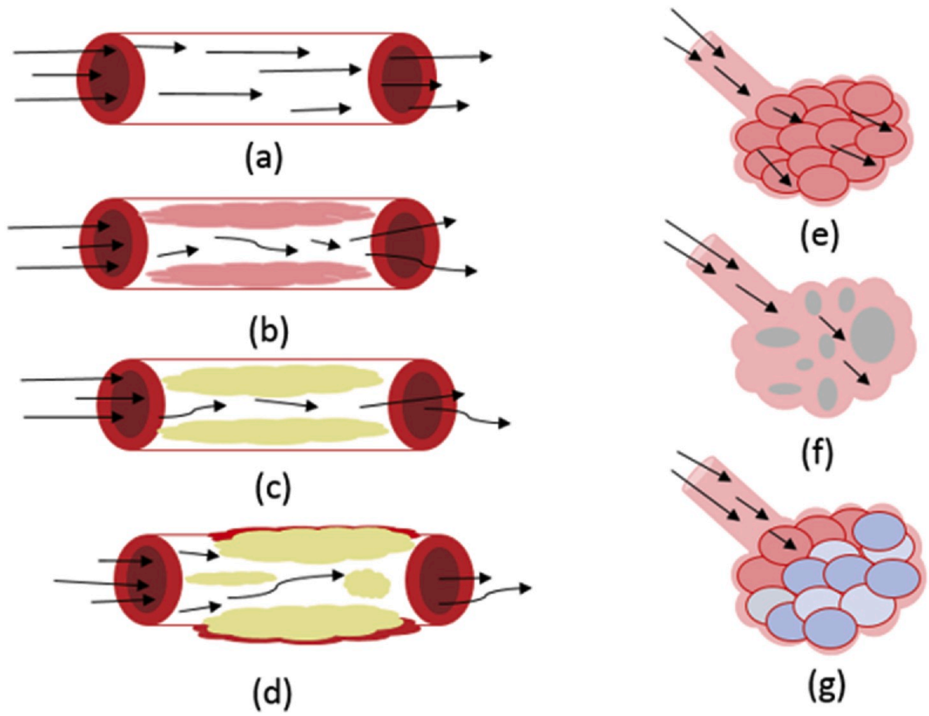

Fig. 2. (a) Normal condition of airways, (b) Narrowing of airways is due to inflammation of the muscle, (c) Narrowing of airways is due to mucus accumulation, (d) Widening of airways due to destruction of the lining which leads to excess mucus accumulation, (e) Normal alveoli where exchange of gas takes place, (f) Thickened and scared walls of alveoli which restricts gas exchange, (g) Fluid filled lungs - here the fluid which accumulated restricts gas exchange.

2.4. Spirometry test

Spirometry is designed to identify and quantify functional disorders of the respiratory system [31,35]. Spirometry measures the total amount of air you can breathe in and how fast you can exhale out. The volume of air which can be inhaled is based on height, weight, and gender of a person. Spirometry parameters differentiate normal values with obstruction and restriction values. Some important parameters of spirometry are FVC, FEV1, FEV1/FVC, FEV (25%–75%) and the definitions of these parameters are as follows [36]:

FVC - The Forced Vital Capacity is the maximum volume of air that can be breathed out as forcefully and rapidly as possible following a maximum inspiration. It indirectly reflects flow resistance property of airways.

FEV1 - Forced expiratory volume in 1 s (FEV1), the volume exhaled during the first second of the FVC maneuver. Measures the general severity of airway obstruction.

FEV1/FVC - Forced Expiration Value after 1 s as a Percentage of FVC – indicates what percentage of the total FVC was expelled from the lungs during the first second of forced exhalation.

FEV (25%–75%) - Reflects the independent expiration and status of small airways.

The key clinical differences between obstructive and restrictive pattern are as follows:

Obstruction: In this pattern FEV1 reduces, FEV1/FVC reduces, FVC is either normal or reduces, and flow volume loop is concave.

Restriction: In this pattern FVC reduces, FEV1/FVC is either normal or high, and a normal-looking shape on spirometry trace.

We have considered spirometry airflow parameters of 40 subjects along with corresponding audiometric data and performed a correlation study.

2.5. Pattern classifier

Annotated data is used for training the pattern classifier. Data is labelled by medical experts of the pulmonology department. For every record collected from a subject, there are multiple episodes of the cough sounds along with other sound events. Initially, in event extraction, all sound events are extracted using event extraction logic, with a moving window based standard deviation technique [37]. These events are classified into cough and non-cough events. Non-cough events include speech, fan sound, tap sound, cell phone rings, etc. From cough sounds primary and secondary features are extracted. Extracted features, symptoms, and patient details form a feature vector. The feature vector is given to an ensemble classifier to predict the pattern of the disease. The block diagram of the proposed method for predicting disease pattern is shown in Fig. 3.

The process of predicting the outcome of a new data sample is done in two levels as follows:

Level-1: In the first level, the data is parsed through Decision Trees, Random Forests, and XG_BOOST (extreme Gradient Boosting) models and the probabilities of each pattern are determined. These Probabilities are concatenated and sent to Level-2.

Decision trees perform classification with minimal computation. These handle both continuous and categorical variables. Decision trees provide a clear indication of which fields are most important for classification.

Random forest classifier will handle any missing values, and maintain the accuracy of a large proportion of data.

XG_BOOST is a scalable and accurate implementation of gradient boosting machines, and it is proven to push the limits of computing power for boosted trees algorithms, as it was built and developed for model performance and computational speed.

Level-2: In the second level the probabilities received from Level-1 is presented to the Multi-Layer Perceptron (MLP) Model. The MLP model outputs the pattern to which the given data belongs to.

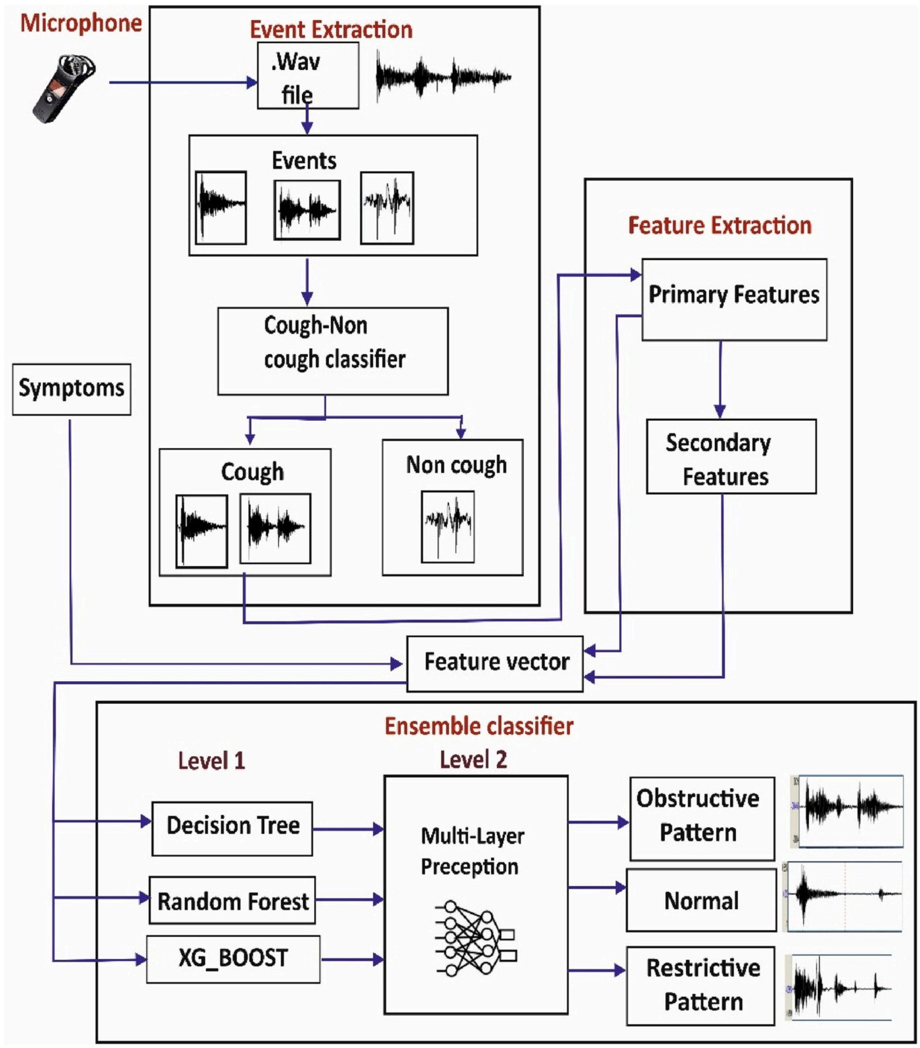

Fig. 3. The block diagram for predicting disease pattern.

3. Results

3.1. *Independent cough analysis and relation to lung conditions of different disorders*

Normal airways and lung expansion: In this condition the cough generated is a normal cough, which typically has two sounds. During the expulsive phase of the cough, in the moment of glottal opening the first burst emerges. The first sound is more extended and more folded in pathological cases. The glottis narrows at the end of expulsive phase and generates a second sound. The average duration of a cough sequence is low in normal cough when compared with coughs generated due to disorders.

Narrowed airways: Cough of some diseases like Asthma and Bronchitis relate to this condition. In this condition we noticed two or three strong cough bouts i.e., multiple expulsions within a single inspiration. Blockage of the airway occurs when the upper breathing passages become narrowed or blocked, making it hard to breath. Here, a deep inspiration is followed by 2–3 bouts of strong cough. The energy within a bout is constant, with maximum normalized energy relative to all other conditions.

Widened airways: Destruction of airway lining results in excess mucus accumulation. In this scenario, a strong cough bout is followed by 1–2 weak bouts. Initially the first bout is strong to clear the airway and allow the flow of air. Energy distribution is constant in the first bout.

Stiff lungs: Lung tissue becomes damaged and scarred like in ILD in this condition. This type of cough will not have a deep inhalation, and the cough is repeated with multiple bouts of weak cough with longer duration and has minimum of normalized energy relative to other conditions.

Fluid-filled lungs: In this condition, we observed cough with multiple bouts and with high energy in the first bout. Energy gradually decreases in the next bouts and is least in the last bout. Usually, Pneumonia patients have fluid-filled lungs; here cough originates from the lower portion of the lungs and results in multiples of weak cough.

Cough patterns related to different conditions can be seen in Fig. 4. Fig. 5 illustrates the energy distribution for one obstructive disease (asthma) and one restrictive disease (ILD). For obstructive disease the energy is sustained in each bout and for restrictive disease the energy is decreasing from bout to bout. In the figure the x-axis corresponds to time and the y-axis corresponds to energy.

3.2. *Relation between audiometric data and spirometry data*

In spirometry graphs, for the obstructive pattern, the time taken to exhale air is more than 6 s. When spirometry parameters FEV1, FVC, and FEV1/FVC are decreasing we notice audiometric data such as energy, zero-crossing rate and spectral parameters of the cough sequences are reduced. But among FEV1, FVC, and FEV1/FVC the rate of decrease is higher for FEV1. Here, FEV1 influence is more for obstructive diseases.

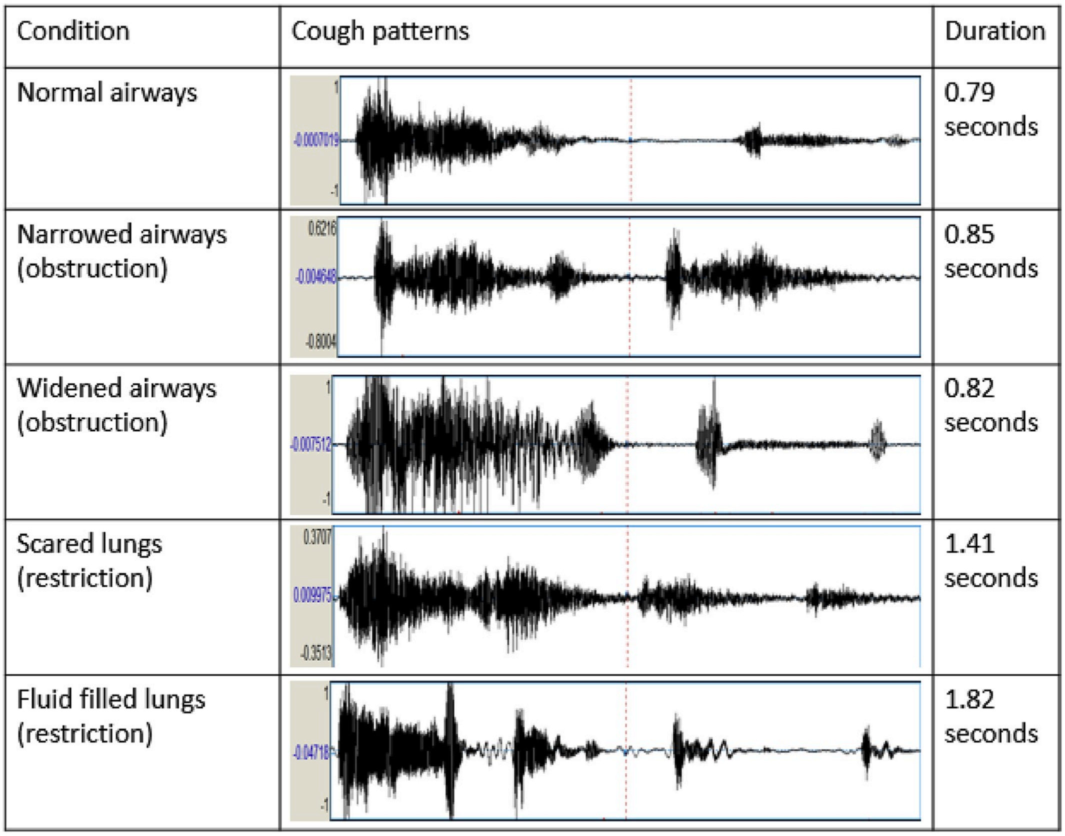

Fig. 4. Cough patterns related to different conditions of the lung.

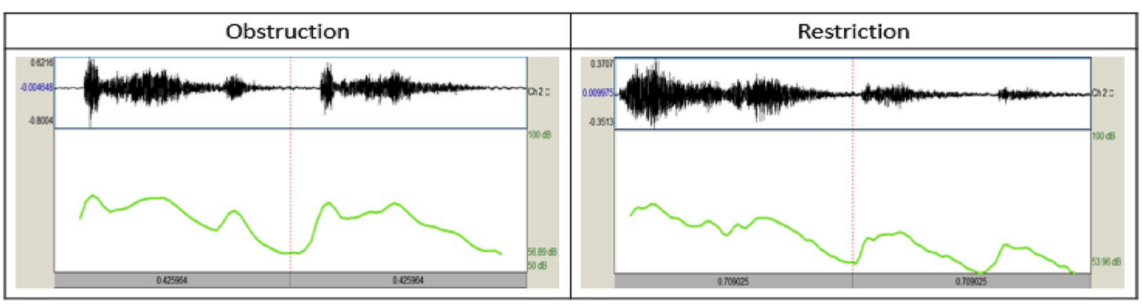

Fig. 5. Energy distribution in obstruction and restriction disease.

In spirometry graphs, for the restrictive pattern, when FEV1 and FVC are decreasing and FEV1/FVC is either normal or increasing, we notice energy, zero-crossing rate and spectral parameters getting reduced. But the rate of decrease is higher for FVC when compared with FEV1 and FEV1/FVC. Here, FVC influence is more for restrictive diseases.

In Fig. 6 from volume time curve of obstructive pattern, it is clear that more time is taken for exhalation. Both FVC and FEV1 are severely decreased. FEV1/FVC is moderately decreased. We can notice the number of bouts in a sequence ranging from 2 to 3. Within, the bout energy is sustained for longer duration.

From the volume time curve of the restrictive pattern, it is clear that exhalation was done quickly. We can notice the number of bouts in a sequence ranging from 3 to 5. The duration of cough sequences is also much higher when compared to a normal cough. Energy is diminished from bout to bout.

In audiometric data for the obstructive pattern, we noticed average cough sequence duration increasing with spirometry values decreasing, and total frequency of events is also increased. For the restrictive pattern, we observed weak coughs with a greater number of bouts within a sequence.

3.3. Relating important features to disease

From Fig. 6, we notice ZCR is greater for diseases like ILD and Pneumonia. These diseases are categorized with the restrictive pattern. When compared with the obstructive pattern, restrictive pattern related diseases have high ZCR values. In restrictive patterns, because of incomplete lung expansion or increased lung stiffness, we noticed high frequency components.

Entropy tells how different the distribution of energy is. Entropy is much less for COPD cough sequences, it is less for highly variant cough sequences, and more for less variant cough sequences like Asthma and Bronchiectasis.

The duration of normal cough sequences is low when compared to cough sequences related to diseases.

When there is obstruction in small airways as in asthma, bronchitis, and bronchiectasis, the cough sequences have more energy, less duration, and low ZCR values, which is evident in Fig. 7. When there is

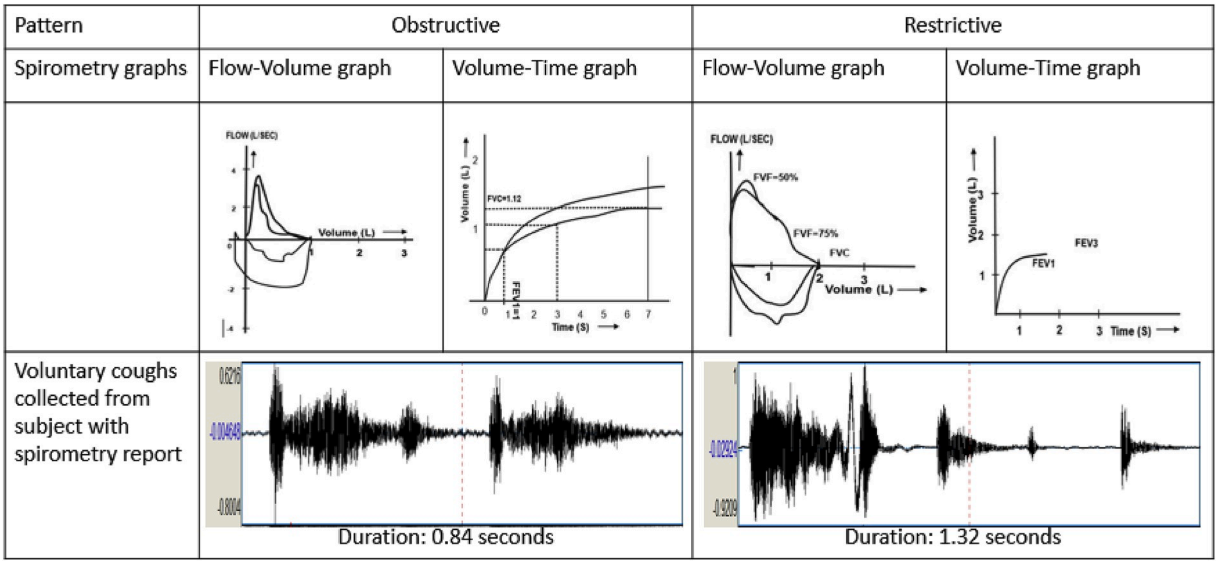

Fig. 6. Spirometry graphs and corresponding cough sequences for obstructive and restrictive patterns.

restriction of air because of scarring in the parenchyma, and fluids in alveoli like in ILD, Pneumonia cough sequences have less energy, more duration, and high ZCR values.

In Fig. 8, Correlation matrices are generated using Pandas in Python. Pearson correlation generates coefficients which reveal the relationship between variables. A coefficient close to 1 means that there is a strong positive correlation between the two variables. The diagonal line is the correlation of the variables to themselves, with unity values. A coefficient approaching −1 means that there is a strong negative correlation between the two variables.

From a closer look at the matrices in Fig. 8, one can notice how cough characteristics are correlated differently to spirometry values for obstructive and restrictive cases. The same was also discussed in the previous section III (Relation between audiometric data and spirometry data).

3.4. Performance of the pattern classifier

The pattern classifier performance is as per the data in Table 4. The pattern classifier is evaluated with the help of performance metrics like accuracy, sensitivity, and specificity.

Accuracy - It is the ratio of number of correct predictions by number of predictions made.

Sensitivity – Sensitivity means true positive rate. Specificity – Specificity means false positive rate.

For example, in the case of the obstructive pattern, **sensitivity** is the ability of a test to correctly identify those with the obstructive pattern as obstructive (true positive rate), whereas **specificity** is the ability of the test to correctly identify those with other patterns as non-obstructive (true negative rate).

In total from 110 subjects we obtained 1700 cough sequences. After proper training and testing, K-fold cross-validation is used to validate the model.

The accuracy of predicting normal data is greater when compared to obstruction and restriction. The overall accuracy in predicting the pattern of the disease is 91.97%, sensitivity is 87.2%, and specificity is 93.69%.

4. Discussion

Table 5 details how our approach is different when compared with the existing literature. This approach helped us in achieving a better result.

5. Conclusion

Through this research work we identified an opportunity in building a non-invasive device for screening respiratory problems in remote and rural health centres based on cough sounds. We started with a lab prototype of cough analyzer. Subsequently we received a grant from DBT-BIRAC in building Minimum Viable Product for developing a respiratory wellness monitoring device (ReWell-MD) using Cough sounds. Using these models, we completed one clinical validation of the device at Apollo Research and Innovation. The validations have helped us not only in collecting annotated data, but also to make our machine learning algorithm more robust. Using the device our objective is to provide indicative information including (a) Presence of Respiratory problem (yes/no) (b) Obstructive (obstruction in airway)/Restrictive (restricts lung expansion) pattern. (c) Severity of inflammation (Low, Medium, and High) and (d) the Anatomy (Small/Large Airway, Parenchyma/Pleura) involved. Clinical utility of the device seems highly relevant based on the various discussions we had with subject matter experts.

As our next steps we are planning to do (a) Correlation of audio metric data with CT images (b) study in depth for exceptional cases likely to be more meaningful, such as ILD pattern for early detection.

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Author contribution

Gowrisree Rudraraju: Data Analysis and writing, ShubhaDeepti Palreddy: Data collection and programming, Baswaraj Mamidgi: Building classifiers, Narayana Rao Sripada: Study design, Dr.Y. Padma Sai: Signal Processing, Naveen Kumar Vodnala: Data Analysis, Dr. Sai Praveen Haranath: Domain expertise/Advisor.

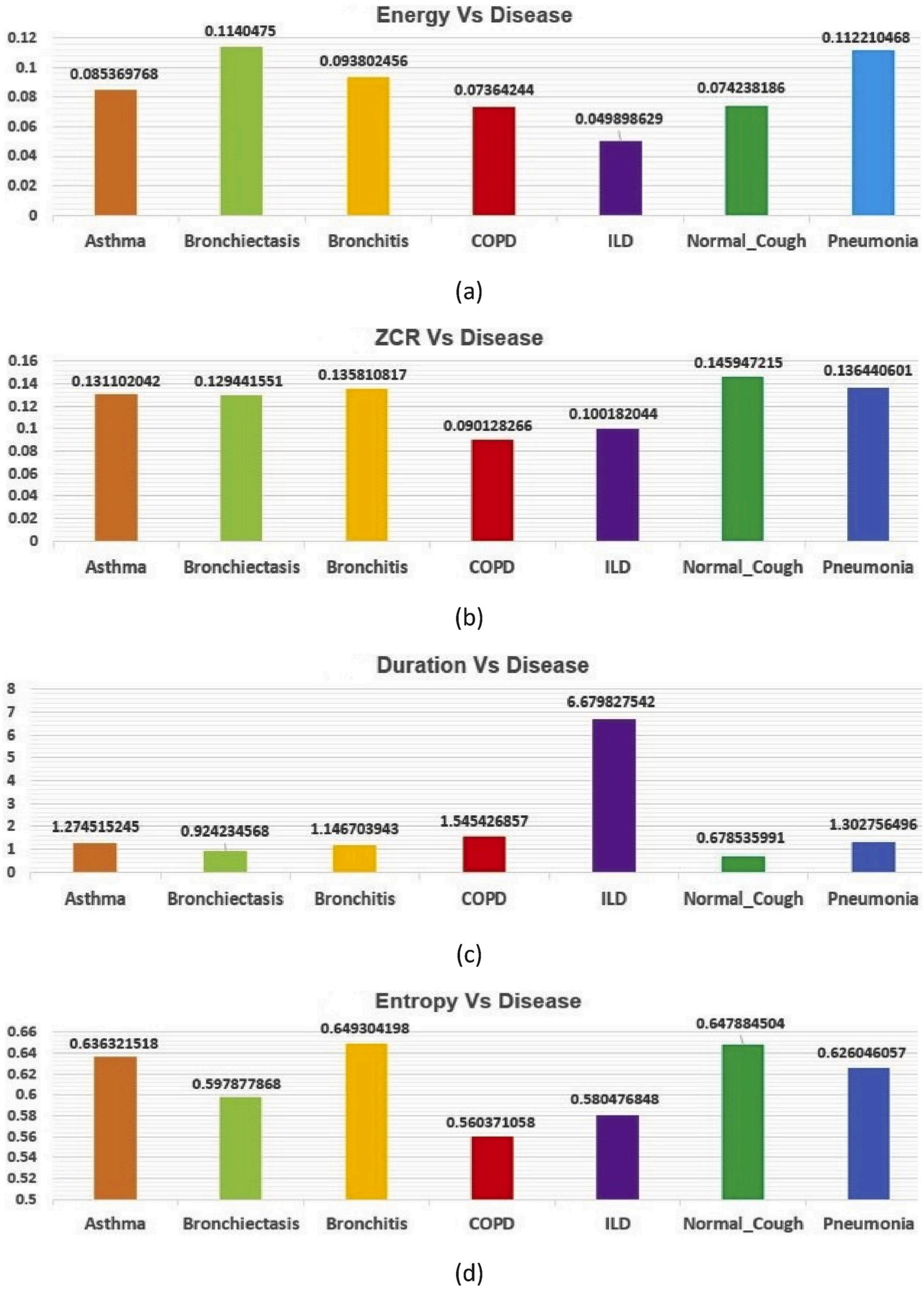
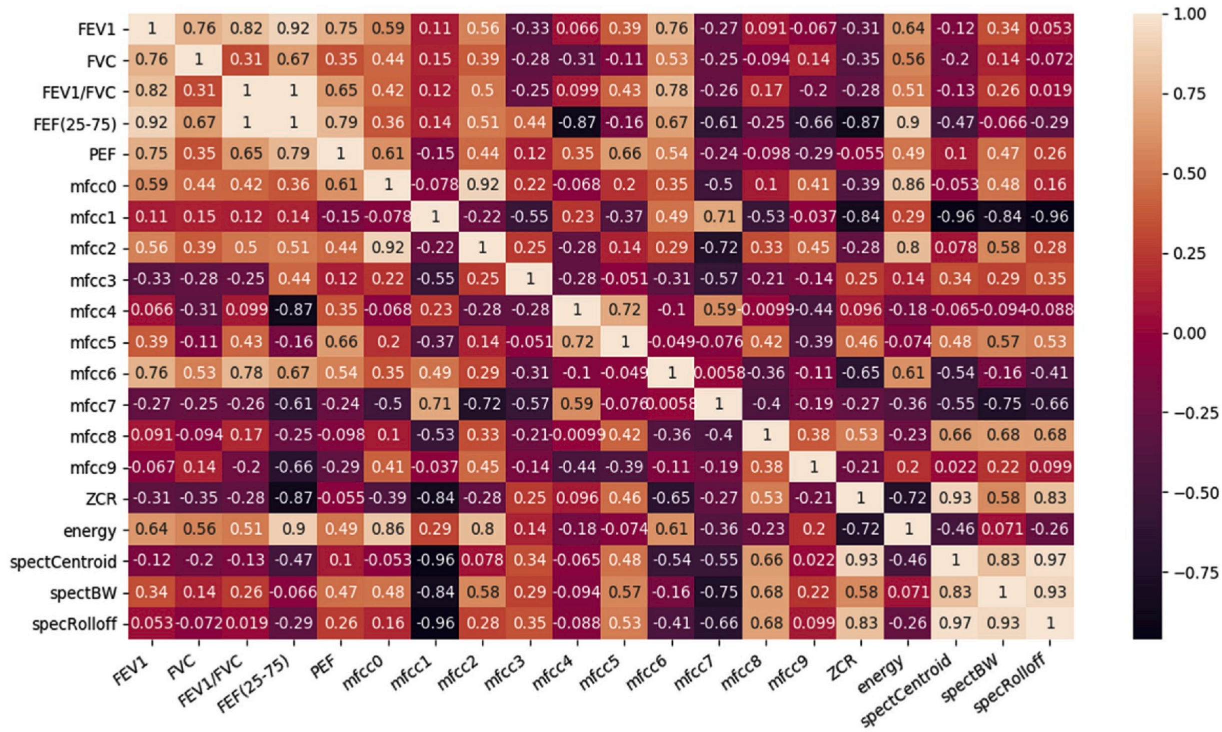
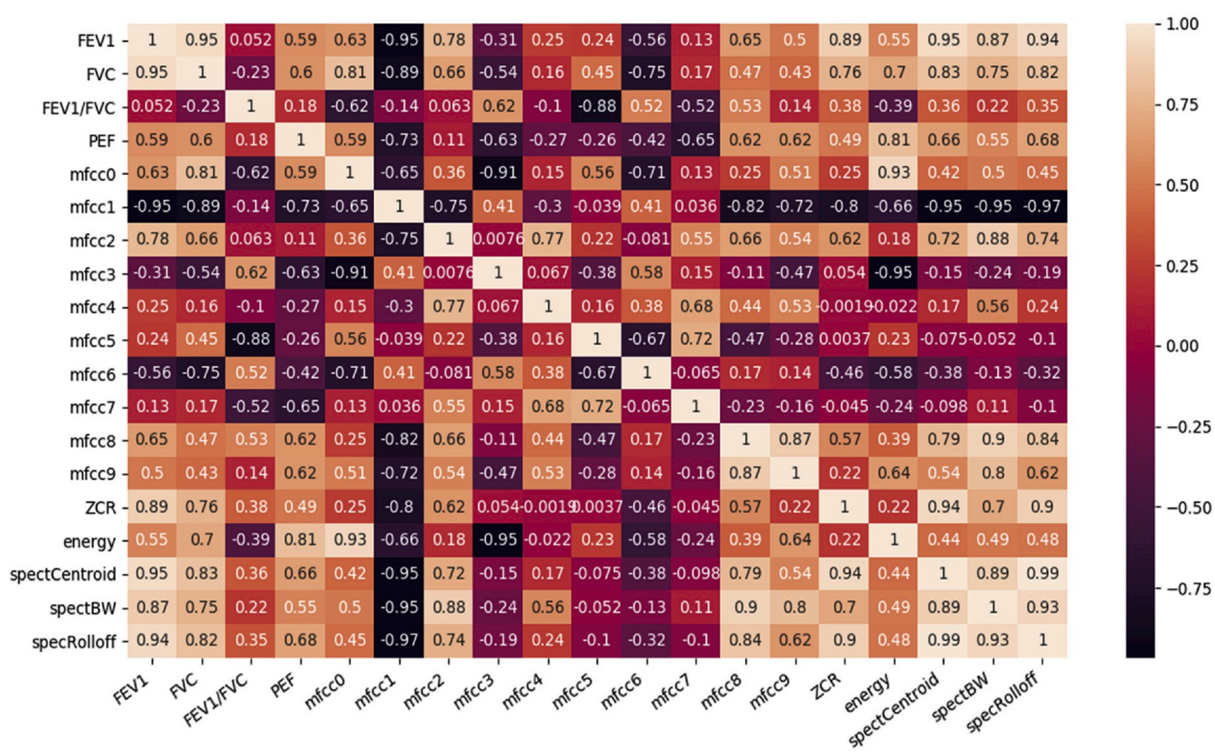


Fig. 7. Relating features like energy, ZCR, duration, and entropy to disease.



(a)



(b)

Fig. 8. (a) Correlation matrix of audiometric and spirometric data of obstructive pattern, (b) Correlation matrix of audiometric and spirometric data of restrictive pattern. In the above matrices, dark color indicates negative correlation and light color indicates positive correlation. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 4
Performance parameters of pattern classifier.

Pattern type	Accuracy	Sensitivity	Specificity
Obstruction	90.17%	83.4%	90.3%
Restriction	89.12%	85.3%	91.5%
Normal	96.64%	92.9%	99.29%

Table 5
Comparison with previous published works.

Paper	Objective	Methods used	Result
Achuth et al. [3]	To predict spirometry readings using cough sound data.	Used statistical spectrum description (SSD) as the cue from cough and wheeze signal to predict the spirometry readings using support vector regression (SVR).	Predicted FEV1% and obtained an accuracy of 77.77%.
Roneel et al. [32]	To predict spirometry readings using cough sound data.	The regression model is trained and validated using cough sound descriptors based on standard signal processing techniques. The trained model is then used to estimate the spirometry readings using sequential backward feature selection (SBFS).	Achieved sensitivity, specificity, and accuracy of 70% or higher by applying the GOLD standard for COPD diagnosis on the estimated spirometry test results.
Other existing works [4–6,8] [10,12, 16] [20,22, 27] [28,33]	Confirmative disease prediction	Use of models like Multi-layer neural networks, SVM.	Accuracies ranging between 75% and 85%
Our work	To predict the pattern (obstructive/ restrictive) of respiratory diseases as a functional equivalent to spirometry.	By understanding the relation between audiometric data and different respiratory conditions, studying the correlation of audiometric data with air flow characteristics. Pattern prediction using an ensemble classifier with a combination of signal processing and domain specific features.	Obtained accuracy of 91.79%, sensitivity of 90.26%, and specificity of 94.31%.

Consent

We have ethics committee approval from Apollo Research and Innovation, part of Apollo Hospitals, Hyderabad.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.imu.2020.100319.

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