Use of Cough Sounds for Diagnosis and Screening of Pulmonary Disease

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***Abstract*— Cough sound analysis has attracted interest as a potential low-cost diagnostic tool for low-resource settings, where the burden of pulmonary disease is quite high. However, published results on cough sound analysis are generally limited to specific pulmonary diseases (e.g. detection of Whooping cough -- Pertussis) and the study sizes are small. In this paper, we present a general framework for cough sound analysis, which includes automatic cough segmentation, feature extraction and a general classification design that can be applied to a wide range of pulmonary diseases. For our analysis, three evidence-based features were selected (variance, kurtosis, and zero crossing irregularity) as well as an additional feature that we developed (rate of decay). Our cough sound analysis framework was tested using voluntary cough data collected from 54 patients presenting a combination of pulmonary conditions (COPD, asthma, and allergic rhinitis) equally sampled from all patients arriving at a pulmonary clinic, as well as 33 healthy individuals. All study subjects were examined with a stethoscope auscultation, clinical questionnaire, and peak flow meter, and were given a full pulmonary function test (spirometer, body plethysmograph, DLCO), which was the gold standard used to determine each patient's diagnosis. When the classifiers were trained using cough sounds alone, the accuracy (as determined by the AUC of the ROC curve) was 74% for Healthy vs Unhealthy, 80% for Obstructive vs non-Obstructive, and 81% for Asthma vs COPD. We also compared the performance of our cough sound analysis against other low-cost diagnostic tools and observed that cough sounds surprisingly had better performance than lung sound auscultation alone, but had significantly lower performance compared to our clinical questionnaire or peak flow meter test. From these data, we conclude that cough sounds have value as a rapid and simple screening tool, but are of less diagnostic value compared to a clinical questionnaire or peak flow meter.**

Keywords—pulmonary, lung, cough, sounds, auscultation, mobile, phone, diagnostics, machine learning, intelligence, algorithms

I. Introduction

A. The Human Cough

Coughs are a natural physiological response used by the body to expel material from the airway. A cough can be an allergic response to environmental factors, or can be a symptom of disease [1]. Coughs are often characterized in several ways, such as whether or not the cough produces mucus (wet or dry cough). Certain coughs are characterized by their sound, such as a croup cough that contains stridor (barking/quacking sound). Other coughs are characterized by the style of coughing, such as in a whooping cough (pertussis), where a person exhibits a long series of coughs separated by vocal gasps for air [2].

Figure 1. Photo of mobile data collection tool used to record cough sounds as well as lung sounds.

B. The Cough as a Potential Diagnostic Tool

Over the past decade, interest in cough sounds has expanded as a result of new technologies that enable continuous monitoring of human sounds. Mobile phones, with connection to voice services in the digital "cloud," and voice recognition products for the home, such as the Amazon Echo or Google Home, now provide the opportunity for consumer devices that can monitor human signals and detect adverse health events.

In the context of low-resource settings and developing countries, cough sounds are of particular interest as biomarkers for pulmonary disease, which is a leading cause of mortality and disability worldwide. Furthermore, the burden

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of pulmonary disease is disproportionately high in developing countries, due to a higher prevalence of indoor and outdoor air pollution, accompanied by poor access to pulmonologists and trained doctors [3, 4, 5].

While many pulmonary diseases can exhibit cough sounds, lower respiratory infections, chronic obstructive pulmonary disease (COPD), lung cancer, and tuberculosis accounted for 14% of deaths worldwide in 2012, and Asthma and COPD accounted for 11% of disability-adjusted-life-years (DALYs) lost worldwide in 2008 [6, 7].

In these communities, health workers are now increasingly using mobile phones as job aids, such as India's Mobile Health Program for maternal and child care [8]. Phone-based diagnostic tools would provide an automated means to screen for disease and refer these patients to a clinic.

II. Prior and Related Work

A. *Applications for Cough Analysis*

General research in cough sound analysis has been focused on two primary application areas: 1) smart homes and consumer devices (e.g. Amazon Echo) which can continuously listen for sounds in the home; and 2) point of care diagnostic indicators for low resource areas.

The research in smart homes and consumer appliances is generally designed to detect and analyze *involuntary* (naturally occurring) coughs. However, for point of care applications, and for the purpose of this paper, we focus on *voluntary* coughs, which are prompted by the doctor or health worker, and can be readily recorded using a mobile phone platform.

B. *Cough Sound Analysis Research*

Creating a system to automatically analyze coughs requires several different system components. Prior technical research on cough sound analysis has generally been divided into three main categories:

i. *Cough recognition*: identifying recordings which contain involuntary (unprompted) cough sounds and distinguishing from other sounds and noises, such as speech. For example, simply knowing how often a person coughs is a can be a useful health indicator. This work has been led by the smart home, geriatrics, and telemedicine research communities [9].

ii. Cough segmentation: Given a recording containing multiple cough sounds, additional software is required to extract and isolate individual cough segments. Recent approaches have utilized neural networks [10].

iii. Sound analysis and association with illness: Once a single cough sound has been isolated, a variety of mathematical features can be computed for use in machine learning algorithms which can be applied to diagnostic prediction. Our group has previously demonstrated simple Wet/Dry classification of voluntary coughs [11], and other research groups have demonstrated cough analysis for predicting pneumonia, asthma, and pertussis [12, 13].

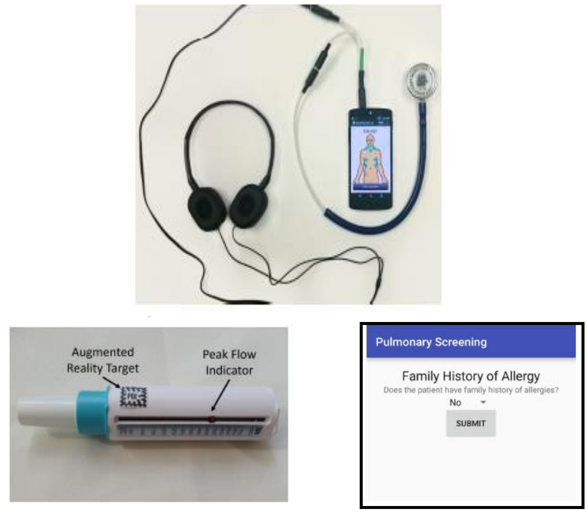

Figure 2. Our mobile health kit. (top) electronic stethoscope; (bottom left) augmented-reality peak flow meter; (bottom right) sample screen from questionnaire.

C. *Practical Challenges and Limitations*

While the diagnostic value of cough sounds has been successfully demonstrated as a diagnostic tool in specific cases where the disease has distinctive sounds (e.g. whooping cough pertussis), or as a means to discriminate between two disparate diseases (e.g. asthma vs pneumonia), the general use of cough sounds presents much greater challenges: there is great heterogeneity in cough sounds across patients; different respiratory illnesses can produce similar cough sounds; and more importantly, many patients have co-morbidities (e.g. simultaneous pneumonia and asthma, etc.). These practical challenges are important considerations when applying cough sound analysis in a real-world point of care setting.

D. *Focus and scope of this paper*

In this paper, we apply commonly used features of coughs sounds to assess their diagnostic value in a realistic cross sectional sample of 54 patients encountered in a clinic (plus 33 healthy control subjects), having a variety of respiratory illnesses, including comorbidities. We also present a framework which can be applied to the more general case of point of care diagnostics, and we propose how cough sounds may be used as part of a larger diagnostic kit.

III. Technical Implementation

A. *Cough Sound Recording*

In order to implement cough analysis, we added a cough recorder function to an existing mobile platform developed by our group to screen for pulmonary disease [14]. This platform consists of a digital questionnaire, a stethoscope, and a peak flow meter, as shown in Figure 2.

As shown in Figure 1, cough sounds are recorded from the patient trachea via a digital stethoscope with electret microphone, using the Lung Sound Recorder Android mobile application (freely available on the Google Play store). Sounds are recorded at a sampling rate of 8 KHz and saved as a .wav file.

B. *Cough Sound Segmentation*

The first step in cough analysis is to find the presence of a cough within the recorded sound file. While this task seems simple, typical recordings often contain multiple coughs as well as noise, which presents a challenge for sound segmentation. In order to extract the first complete cough in a recording the following algorithm was used:

- The original sound file (Figure 3) was first smoothed by applying local regression (weighted least squares with a 2^{nd} degree polynomial model) using a span of 2% of the data. The signal was then normalized to span 0 and 1. Figure 3 shows an example of a complete recording. Figure 4 shows the smoothed signal.
- A peak detection algorithm was then applied to the smoothed signal (Figure 4) to find all cough peaks present in the file.
- In order to select the first complete cough in the series, each peak was then analyzed individually in sequence. The zero-crossing of the first derivative was used to determine the starting point of the cough, and the slope of the trailing edge of the cough was used to determine the end point.
- The flatness of the slope was used as a criterion to determine if the cough segment was complete. If the algorithm encountered a new peak before the previous cough sound had settled, then the algorithm would discard the current cough segment and start a new search using the next available cough peak.

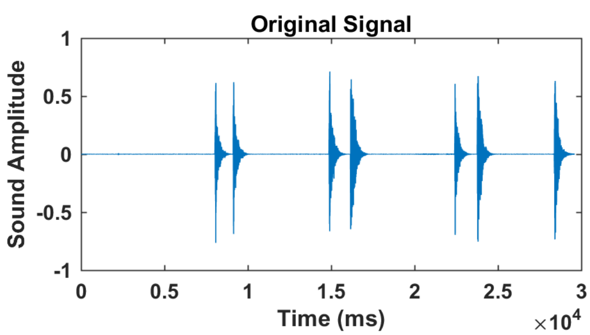

Figure 3. Sample sound file showing raw cough data.

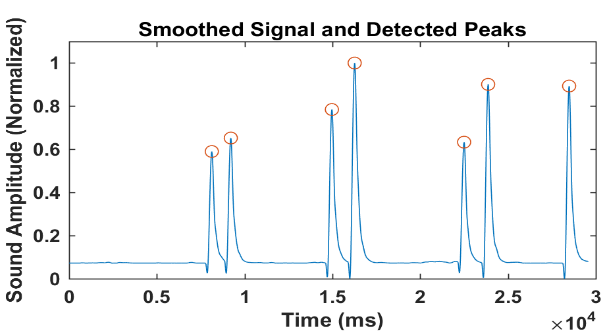

Figure 4. Smoothed cough signal magnitude and detected peaks (circled).

C. *Feature Extraction*

Once the leading cough segment was extracted from a recording, the next step is to analyze the sound and extract specific features. Starting from an initial set of approximately 30 features published in the literature, we selected the following four features, which have been previously used for diagnostic prediction:

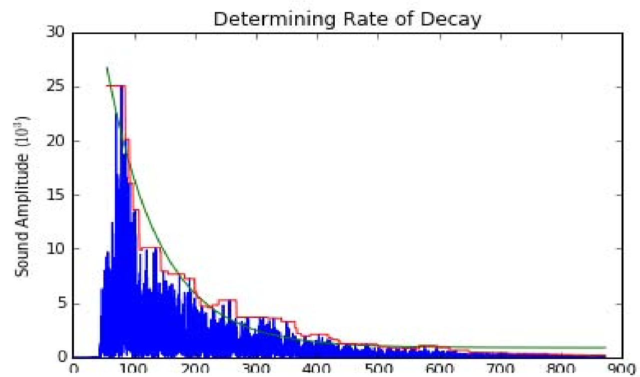

Figure 5. Plot of extracted cough segment (blue); computed upper envelope (red); exponential fit (green).

i. *Kurtosis:* the fourth-order moment of the signal, computed from the magnitude, |x(t)|, which is a measure of its "Gaussianity". This feature has been successfully used to automatically detect pertussis (whooping cough) [13].
ii. *Variance:* the variance of the signal's magnitude. This feature has been successfully used to detect abnormal pulmonary function [15].
iii. *Zero cross irregularity:* a measure of the deviation between time intervals in which the cough signal crossed the x-axis. This measure has been used in previous analyses to detect wheezes [16].
iv. *Rate of decay:* the exponent value (*B*) of an exponential curve ($A * e^{-B*t} + C$) fitted to the magnitude of the cough signal, |x(t)|, shown in Figure 5. We created this feature as an indication of the amount of mucus present in a cough, which affects the decay rate of the cough peak. We have used this successfully to classify wet vs dry coughs [11].

IV. Clinical Data Collection

For our clinical study, cough sounds were collected as part of an IRB-approved protocol at a pulmonary research hospital in Pune, India. Aside from the healthy controls, study subjects were recruited from an equal sample of all patients arriving at the clinic who exhibited pulmonary symptoms. Table I shows the distribution of diseases within the patient cohort. As shown in the Table, the most common pulmonary diseases exhibited by patients were respiratory infections, Asthma, and COPD; this distribution is typical of that found in many developing countries. Table II shows additional statistics for this group.

Cough recordings of 30-second duration were captured from each patient from the trachea, as mentioned previously, during which time patients were asked to cough multiple times. In addition to recording the cough sounds, all patients were tested using our mobile phone tools, which consisted of a clinical questionnaire, peak flow meter, and a stethoscope, which was used to collect lung sounds from 11 standard sites on the torso administered by a trained pulmonologist. The presence of any abnormal (adventitious) lung sound were also noted manually by the pulmonologist.

Following the use of the mobile phone tools, each patient also underwent a standard full pulmonary function test (PFT), which consisted of spirometry, body plethysmography, gas diffusion test (DLCO), and impulse oscillometry. Based on the data from the instrumentation and the clinical examination, the pulmonologist provided the final disease diagnosis, which was used as our "ground truth" for training our models.

The protocol for this study received ethics approval from the appropriate boards at the Chest Research Foundation (Pune, India) and the Massachusetts Institute of Technology (Cambridge, USA).

TABLE I. DISTRIBUTION OF DISEASE WITHIN THE DATASET

Pulmonologist Diagnosis	Count
No Pulmonary Disease	33
COPD Only	7
Asthma Only	15
Allergic Rhinitis Only	11
COPD + Allergic Rhinitis	4
Asthma + Allergic Rhinitis	17
Total	**87**

TABLE II. SUMMARY STATISTICS

Statistic	Value		Statistic	Value
Male (%)	52.05		Family History of COPD (%)	0.00
Age (years)	46.34		Family History of Allergies (%)	32.88
Weight (kg)	61.38		Personal History of Allergies (%)	15.07
Breathless (%)	58.90		Exposed to Biomass Cooking (%)	13.70
Coughing (%)	42.47		Smoke (%)	19.18
Chest Pain (%)	4.11		Chew Tobacco (%)	26.03
Fever (%)	1.37		Consume Alcohol (%)	9.59
Nasal Symptoms (%)	35.62		Max Peak Flow Meter Reading (L/min)	296.71

V. DATA ANALYSIS

A. Diagnostic Classification

For the purpose of exploring the value of coughs for general diagnosis, we developed a framework that could, in principle, be used to diagnose any pulmonary disease. Following the disease classification typically used in pulmonology, we defined our classification as follows:

- *Healthy vs unhealthy* – this differentiates subjects with pulmonary disease from those without pulmonary disease
- *Infective vs non-infective* – Within the "unhealthy" group, this differentiates patients with infectious diseases (e.g. tuberculosis, pneumonia, upper respiratory infectious) from patients with non-infectious diseases. In our study sample, we have few patients with infectious disease, so we did not use this classification.
- *Obstructive vs non-obstructive* – Within the "unhealthy" group, this differentiates between the obstructive diseases (asthma, COPD) from the non-obstructive diseases (allergic rhinitis, lung cancer, etc.) In our study sample, the non-obstructive diseases were entirely allergic rhinitis (AR), so this classifier essentially selected AR patients. Due to co-morbidities (e.g. asthma + AR), some patients belonged to both groups.
- *Asthma vs COPD* – Within the "obstructive" group, this classification differentiates between Asthma and COPD.

B. Unsupervised Learning – Cluster Analysis

In order to explore any potential hidden correlations between cough features and disease, we performed a standard k-means clustering analysis. The ideal number of clusters was determined to be three. This was computed by averaging the silhouette score over a range of cluster sizes from two to ten, over 100 trials.

The results of the cluster analysis are shown in Table III. Table IV show the average feature values (normalized) within each cluster.

TABLE III. RESULTS OF K-MEANS CLUSTER ANALYSIS

Diagnosis	*Cluster 1 (n=29)*	*Cluster 2 (n=11)*	*Cluster 3 (n=39)*
Asthma	7	0	5
Asthma + Allergic Rhinitis	4	4	7
Allergic Rhinitis	4	3	4
COPD	1	1	4
COPD + Allergic Rhinitis	0	2	2
Healthy	13	1	17

TABLE IV. SUMMARY OF NORMALIZED FEATURE VALUES FROM K-MEANS CLUSTER ANALYSIS

Feature	*Cluster 1 (n=29)*	*Cluster 2 (n=11)*	*Cluster 3 (n=39)*
Rate of Decay	1.01	-0.47	-1.01
Zero Crossing Irregularity	-0.06	0.08	-0.12
Variance	-0.33	-0.35	2.12
Kurtosis	1.00	-0.49	-0.91

While other types of clustering analysis are possible, the results from our simple k-means cluster analysis shown in Tables III and IV do not reveal any clear clusters in this set of features that map to disease diagnosis. The sample plots for different pairs of cough features are shown in Figure 6 and Figure 7, which demonstrate the range of heterogeneity in the cough sounds across all patients and diseases.

C. Classification Using Cough Sounds Alone

A second set of analysis was performed to explore how well cough features can be used to perform the diagnostic classification described previously. All of the cough features were treated as continuous variables and standardized to have zero-mean and unit-variance. Logistic regression models with L1-penalty were used to create the binary classifiers. 70 percent of the data were used for training, 30 percent for testing. During every trial, the data split for testing and training was done randomly. 100 training trials were run. To determine the ideal penalization parameter during each training trial, 100 trials of randomized cross validation were run over an exponential distribution—the parameter value

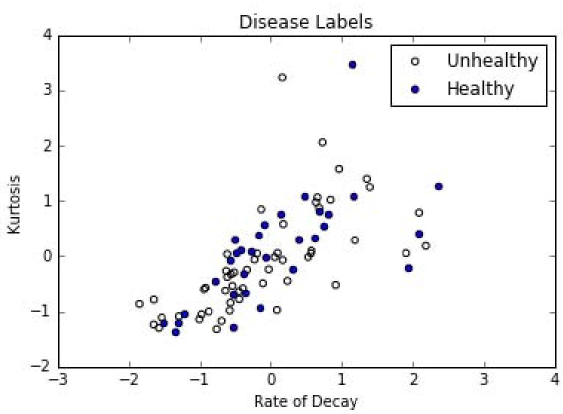

Figure 6. Plot of patients (Unhealthy vs. Healthy) using Kurtosis and Rate of Decay

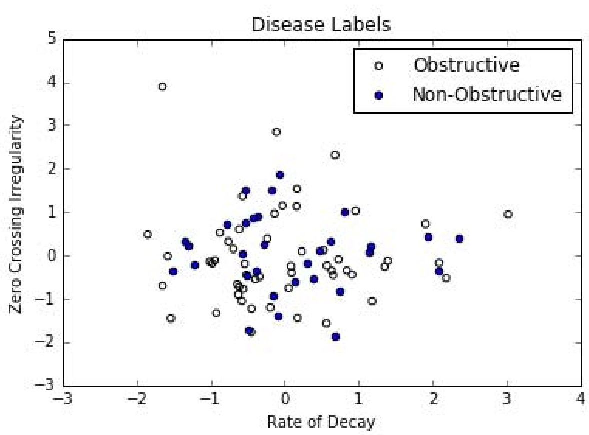

Figure 7. Plot of patients (Obstructive vs. Non-obstructive) using Zero Cross Irregularity and Rate of Decay

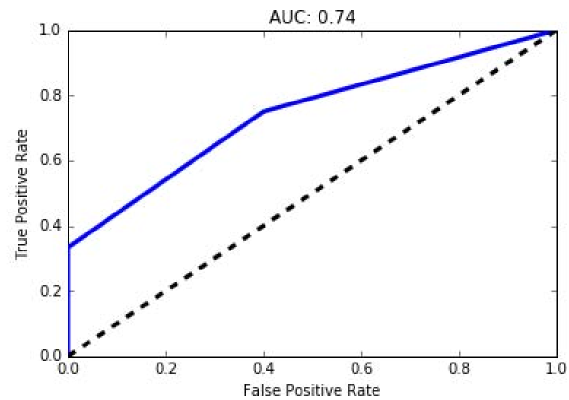

Figure 8. ROC curve for Healthy vs. Unhealthy classification.

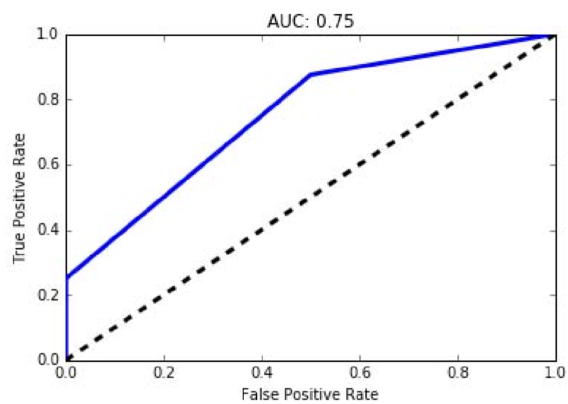

Figure 9. ROC curve for Obstructive vs. Non-obstructive

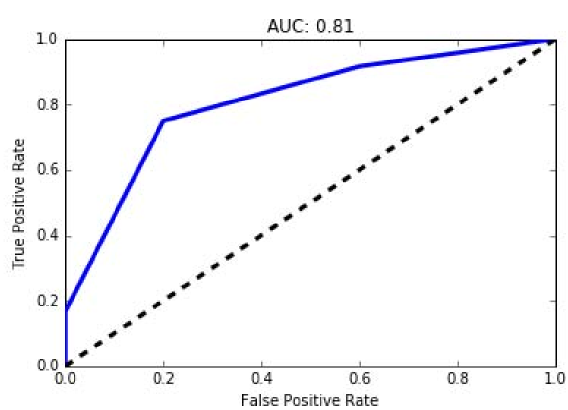

Figure 10. ROC curve for COPD vs. Asthma classification.

with the lowest validation error was chosen to create the final tested classifier.

The first classifier (Figure 8) determined pulmonary health, without specifying a disease (Healthy vs. Unhealthy). All of the data were used when creating this classifier.

The second classifier (Figure 9) determined whether patients had an obstructive pulmonary disease (COPD or asthma) or a non-obstructive pulmonary disease (allergic rhinitis). Healthy patients were omitted when creating this classifier.

The third classifier (Figure 10) determined whether patients had COPD or asthma. Healthy and allergic rhinitis patients were omitted when creating this classifier.

Table V summarizes the performance of the three classifiers using only the cough features.

TABLE V. PERFORMANCE OF CLASSIFIERS UTILIZING COUGH FEATURES IN ISOLATION

Classifier	Performance Metrics	
	Median AUC	***Average AUC***
Healthy/Unhealthy	0.74 (0.65, 0.80	0.72
Obstructive/Non-obstructive	0.75 (0.70, 0.74)	0.74
COPD/Asthma	0.81 (0.75, 0.83)	0.81

VI. COUGH SOUNDS AS PART OF DIAGNOSTIC KIT

A. Integrating Coughs Sounds with Diagnostic Kit

As a final analysis, we also explored the value of cough sounds when combined with other low-cost tools (stethoscope, peak flow meter, and questionnaire), which had been previously validated [17].

For this analysis, we combined the cough features with the questionnaire, the peak flow meter, and lung sounds. We retrained the same classifiers mentioned in Section V with different combinations of the features. Ultimately, we used each feature set in isolation, in pairs, and all together. Excluding the use of cough features in Section V, this resulted in each classifier being trained 14 times.

B. Additional Features

For the other tools (questionnaire, peak flow meter, and lung sounds), we added three new feature sets in this analysis.

The first set of features consisted of patient responses to a risk factor and symptom questionnaire. The questionnaire was created with the aid of a pulmonologist to determine the presence of breathlessness, coughing, chest pain, fever, and nasal symptoms in a patient. The questionnaire also captures basic demographic information (age, sex, weight, etc.). All binary responses were converted to Boolean variables for the purpose of analysis.

The second feature set consisted of five trials of a peak flow meter test. Each result can range from 0 to 800 L/min. Two features were extracted from these trials: 1) the maximum value, and 2) the ratio between the maximum value and the expected value given the patient's age, sex, and height, using the following equations:

$$\text{Male: } -1.807 * \text{Age (years)} + 3.206 * \text{Height (cm)} \quad (1)$$

$$\text{Female: } -1.454 * \text{Age (years)} + 2.368 * \text{Height (cm)} \quad (2)$$

The third feature source consisted of the lung sound labels noted by the pulmonologist during auscultation (wheeze or crackle). In total there were 10 features extracted, including abnormal sound heard at any site (Boolean), number of abnormal sounds heard, presence of wheezes, and presence of crackles.

All features (from the cough signal, questionnaire, lung sounds, and peak flow meter) were standardized to have zero-mean and unit-variance.

C. Model Training and Classification

The classifiers (Healthy vs. Unhealthy, Obstructive vs. Non-obstructive, COPD vs. Asthma) were retrained 14 times. The new trials used the peak flow meter, questionnaire, and lung sound features in isolation, all pairings between peak flow meter, questionnaire, lung sounds, and cough features, and all four sets combined. The same procedures described in the previous section were followed here.

TABLE VI. PERFORMANCE OF HEALTHY VS. UNHEALTHY CLASSIFIER UTILIZING DIFFERENT FEATURE SET COMBINATIONS

Feature Set(s)	***Median AUC (25^{th}, 75^{th} Percentiles)***	***Median AUC with Cough Features (25^{th}, 75^{th} Percentiles)***		***Mean AUC (without, with Cough Features)***
Lung Sounds (L)	0.61 (0.57, 0.64)	0.71 (0.66, 0.76)		(0.61, 0.70)
Questionnaire (Q)	0.98 (0.94, 0.99)	0.97 (0.95, 0.99)		(0.96, 0.86)
Peak Flow Meter (P)	0.89 (0.81, 0.94)	0.86 (0.80, 0.91)		(0.88, 0.85)
Q + P	0.96 (0.93, 0.99)	0.96 (0.92, 0.99)		(0.95, 0.95)
Q + L	0.97 (0.95, 1.00)	0.97 (0.95, 1.00)		(0.97, 0.96)
P + L	0.91 (0.86, 0.94)	0.88 (0.80, 0.95)		(0.90, 0.87)
Q + P + L	0.96 (0.94, 0.99)	0.97 (0.94, 0.99)		(0.96, 0.96)

TABLE VII. PERFORMANCE OF OBSTRUCTIVE VS. NON-OBSTRUCTIVE CLASSIFIER UTILIZING DIFFERENT FEATURE SET COMBINATIONS

Feature Set(s)	*Median AUC (25th, 75th Percentiles)*	*Median AUC with Cough Features (25th, 75th Percentiles)*		*Mean AUC (without, with Cough Features)*
Lung Sounds (L)	0.60 (0.56, 0.64)	0.73 (0.69, 0.80)		(0.61, 0.74)
Questionnaire (Q)	0.86 (0.76, 0.91)	0.79 (0.73, 0.88)		(0.84, 0.79)
Peak Flow Meter (P)	0.92 (0.88, 0.95)	0.87 (0.80, 0.92)		(0.91, 0.86)
Q + P	0.84 (0.78, 0.93)	0.86 (0.77, 0.93)		(0.85, 0.85)
Q + L	0.81 (0.75, 0.88)	0.77 (0.75, 0.88)		(0.81, 0.80)
P + L	0.91 (0.84, 0.96)	0.89 (0.79, 0.95)		(0.89, 0.87)
Q + P + L	0.88 (0.81, 0.94)	0.88 (0.79, 0.93)		(0.86, 0.85)

TABLE VIII. PERFORMANCE OF COPD VS. ASTHMA CLASSIFIER UTILIZING DIFFERENT FEATURE SET COMBINATIONS

Feature Set(s)	*Median AUC (25th, 75th Percentiles)*	*Median AUC with Cough Features (25th, 75th Percentiles)*		*Mean AUC (without, with Cough Features)*
Lung Sounds (L)	0.64 (0.57, 0.75)	0.83 (0.75, 0.92)		(0.67, 0.82)
Questionnaire (Q)	0.93 (0.86, 0.96)	0.90 (0.80, 0.95)		(0.90, 0.87)
Peak Flow Meter (P)	0.96 (0.83, 1.00)	0.85 (0.80, 0.95)		(0.91, 0.87)
Q + P	0.88 (0.79, 0.92)	0.82 (0.80, 0.95)		(0.87, 0.85)
Q + L	0.93 (0.89, 0.97)	0.90 (0.85, 0.95)		(0.93, 0.90)
P + L	0.92 (0.79, 0.96)	0.88 (0.80, 0.95)		(0.89, 0.86)
Q + P + L	0.92 (0.82, 1.00)	0.80 (0.75, 0.90)		(0.89, 0.83)

D. *Classifier Results*

Tables VI, VII, and VIII show the median and mean AUC for each classification (Healthy vs. Unhealthy, Obstructive vs. Non-obstructive, and COPD vs. Asthma, respectively) and for different combination of diagnostic tools (L=lung sounds; Q=questionnaire, P=peak flow meter). Results are shown with and without the addition of cough analysis features.

E. *Analysis with Co-morbidities*

A particular challenge of pulmonary disease diagnosis is that co-morbid conditions are very common. As shown in Table I, our patient sample is very typical, and demonstrates that many patients can have multiple pulmonary or respiratory problems simultaneously.

When performing a binary classification between two different diseases or disease categories, the presence of comorbidities adds additional variability to the results. In general, this problem can be addressed by increasing the number of subjects and the amount of data. However, even with our current study size, some improvements can be made with the way that the classification models are trained.

In order to improve our classification, we retrained our models using only patients without co-morbid conditions. The resulting classifiers were then applied to the entire data set, which included the patients with co-morbid conditions.

The results of running the comorbid analysis on the Healthy vs Unhealthy classifier are summarized in Table IX. The median AUC increased by an average of 2.13%, and the AUC's interquartile range decreased by 4.47%.

The results for the Obstructive vs Non-Obstructive classifier are summarized in Table X. The median AUC increased by an average of 3.4%, and the AUC's interquartile range decreased by 4.47%.

The results for the COPD vs Asthma classifier are summarized in Table XI. The median AUC increased by an average of 2.73%, and the AUC's interquartile range decreased by 8.67%.

TABLE IX. PERFORMANCE OF HEALTH VS. UNHEALTHY CLASSIFIER TRAINED ON PATIENTS WTHOUT CO-MORBIDITIES

Feature Set(s)	*Median AUC (trained on patients with co-morbidities)*	*Median AUC (trained on patients without co-morbidities)*
Lung Sounds (L)	0.61	0.61
Questionnaire (Q)	0.98	1.00
Peak Flow Meter (P)	0.89	0.92
Cough Sounds (C)	0.74	0.69
L + C	0.71	0.69
Q + C	0.97	1.00
P + C	0.86	0.90
Q + P	0.96	1.00
Q + L	0.97	1.00
P + L	0.91	0.94
Q + P + C	0.96	1.00
Q + L + C	0.97	1.00
P + L + C	0.88	0.91
Q + P + L	0.96	1.00
Q + P + L + C	0.97	1.00

TABLE X. PERFORMANCE OF OBSTRUCTIVE VS. NON-OBSTRUCTIVE CLASSIFIER TRAINED ON PATIENTS WTHOUT CO-MORBIDITIES

Feature Set(s)	***Median AUC (trained on patients with co-morbidities)***	***Median AUC (trained on patients without co-morbidities)***
Lung Sounds (L)	0.60	0.57
Questionnaire (Q)	0.86	0.86
Peak Flow Meter (P)	0.92	0.94
Cough Sounds (C)	0.75	0.80
L + C	0.73	0.81
Q + C	0.79	0.86
P + C	0.87	0.89
Q + P	0.84	0.94
Q + L	0.81	0.85
P + L	0.91	0.90
Q + P + C	0.86	0.91
Q + L + C	0.77	0.86
P + L + C	0.89	0.89
Q + P + L	0.88	0.90
Q + P + L + C	0.88	0.89

TABLE XI. PERFORMANCE OF COPD VS. ASTHMA CLASSIFIER TRAINED ON PATIENTS WTHOUT CO-MORBIDITIES

Feature Set(s)	***Median AUC (trained on patients with co-morbidities)***	***Median AUC (trained on patients without co-morbidities)***
Lung Sounds (L)	0.64	0.57
Questionnaire (Q)	0.93	0.95
Peak Flow Meter (P)	0.96	0.94
Cough Sounds (C)	0.81	0.76
L + C	0.83	0.74
Q + C	0.90	0.96
P + C	0.85	0.90
Q + P	0.88	0.96
Q + L	0.93	0.96
P + L	0.92	0.92
Q + P + C	0.82	0.95
Q + L + C	0.90	0.96
P + L + C	0.88	0.89
Q + P + L	0.92	0.97
Q + P + L + C	0.80	0.95

VII. DISCUSSION

A. Health vs Unhealthy

As shown in Table V, we see that cough sounds alone do have some value in determining the presence or absence of pulmonary disease, with a median AUC=74%. This is not surprising, because only certain pulmonary diseases exhibit abnormal coughs.

Comparing Table V to Table VI, we can see how cough sounds compare to other low cost diagnostic tools for the purpose of detecting any pulmonary disease (Asthma, COPD, Allergic Rhinitis). It is important to note that cough sound analysis performs better as a diagnostic tool than lung sound analysis alone, with a median AUC=61%. This result is significant because cough sounds can be recorded more quickly and easily than lung sounds.

Compared to the other diagnostic tools, however, we see that a clinical questionnaire (median AUC=100%) and peak flow meter (median AUC=92%) have significantly higher performance than cough sound analysis for detecting the presence of a pulmonary disease.

By combining cough sounds with other tools, as shown in the third and fourth column of Table VI, we see that the addition of cough sound analysis has negligible improvement to the performance of the other tools, with a minor improvement to lung sound analysis.

B. Obstructive vs Non-Obstructive

From Table V, we can see that cough sound analysis also has some utility in differentiating between obstructive and non-obstructive pulmonary diseases, with a median AUC=80%. This indicates that coughs from patients with allergic rhinitis have somewhat different characteristics from coughs from Asthma/COPD patients.

Comparing Table V to Table VII, we see that once again cough analysis performs better than lung sound analysis (median AUC=60%) but does not compare with the better performance of the questionnaire (median AUC=86%) and peak flow meter (median AUC=94%).

Looking at columns 3 and 4 of Table VII, we see that with the exception of lung sounds, adding cough sounds analysis to the other tools provides no improvement.

C. Asthma vs COPD

As shown in Table V, the cough sound analysis performs best (median AUC=81%) when distinguishing between two specific diseases – in this case Asthma and COPD, which are both obstructive pulmonary diseases. This result supports the clinical observation that Asthma patients tend to have dry coughs and COPD patients tend to have wet coughs.

As shown in Table VIII, the questionnaire (median AUC=95%) and peak flow meter (median AUC=96%) both outperform the cough sound analysis for distinguishing between Asthma and COPD.

As shown in columns 3 and 4 of Table VIII, cough sounds analysis can be combined with lung sound analysis to achieve a median AUC=83%. However, cough sounds provide no improvement to the performance of other tools.

D. Co-morbidities

The inclusion of co-morbid patients in the classifier training set can be considered noisy samples which decrease performance. While this added error is reduced as the training size increases, the relatively small size of our dataset is affected by the inclusion of these patients. As shown in Tables IX, X, and XI, higher classification accuracy was possible by removing the co-morbid patient data when training our models. While this may be a practical approach for our current data size, we expect that greater improvements in classification could be made by increasing the overall sample size and including co-morbid patients in the training as well. As the sample size increases, we expect the differences between the classifiers trained on co-morbid patients, and those not, to decrease significantly. Currently, we recommend that the classifiers be trained on patients without comorbidities to ensure maximum performance.

VIII. Conclusions

We have presented a general framework for assessing the value of cough sounds for diagnosing common pulmonary diseases, and we have demonstrated this analysis using data collected from a realistic sample of patients encountered in a pulmonary clinic in Pune, India.

To the best of our knowledge, this is the first study to attempt using cough sound analysis to classify a heterogenous group of pulmonary patients having several different pulmonary diseases, including comorbidities. In addition, the number of patients in our study (54 sick + 33 healthy) is slightly larger than most published cough sound studies and our diagnosis was rigorously supported by a complete pulmonary function testing (PFT) lab.

Based on our results, we have shown that cough sounds alone do have some utility as a screening tool for classifying between different groups of pulmonary diseases. Interestingly, the cough sound analysis seemed to perform just as good as lung sound analysis (wheeze, crackle) for diagnostic prediction. However overall, the performance was moderate.

When combined with other simple diagnostic tools (stethoscope, peak flow meter, questionnaire), we found that cough sounds provided little or no improvement, and the value of cough sounds alone does not compare well against the value of the other tools alone.

When the classifiers were trained on patients without comorbidities, we achieved better performance. However, we believe this is due to the small size of our dataset. While we recommend the training of classifiers on patients without comorbidities for sample sizes similar to our own, the performance of classifiers trained on patients with and without comorbidities will converge as the sample size increases.

Based on our results, we conclude that the primary value of cough sounds, may be as a simple and rapid pulmonary screening tool that can be administered by community health workers without the need for a questionnaire or other instruments. Our analysis here with voluntary coughs could also be applied to involuntary coughs as a means to automatically and continuously monitor a patient's health in the hospital or in the home.

Cough sounds are the simplest type of screening tool, and in its most primitive form, can be recorded with a mobile phone microphone without the need for any additional device. However, if more resources (money, time) are available, cough sounds provide little value over other low-cost tools, such as a stethoscope, peak flow meter, and questionnaire.

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