

Original Research Article

Spectral pattern of cough sounds as an aid to diagnosis in children with common respiratory diseases

Mohammed Shahnawaz Ansari^{1*}, Pradeep Singh², Raghav Awasthi²,
Tav Pritesh Sethi², Varinder Singh¹

¹Department of Pediatrics, Kalawati Saran Children's Hospital and Lady Hardinge Medical College, New Delhi, India

²Computational Biology, Indraprastha Institute of Information Technology, New Delhi, India

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*Correspondence:

Dr. Mohammed Shahnawaz Ansari,
E-mail: Shahnawaazansari@gmail.com

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ABSTRACT

Background: Objectives were to identify discriminatory spectral patterns of cough consistent with common respiratory sounds, through machine learning, to assist diagnosis.

Methods: Spectral analysis of cough recordings of 50 children each with crackles alone, wheezing alone and absence of crackles and wheezing. Identification of unique features through machine learning by dividing them into training (75%) and testing (25%) datasets. Feature extraction was done using R python and Librosa programming language. Two class classifications of the features extracted from the training dataset were done using classifier models like support vector machine, random forest, K nearest neighbor and classification and regression tree. Identification of the most suited classifier model that could accurately differentiate between the studied respiratory sounds in terms of sensitivity and specificity.

Results: Random forest classifier model using Mel-frequency cepstral coefficient (MFCC) gave the best results in differentiating crackles from wheezing with sensitivity and specificity of 66.67% and 66.67%. Classifier model performance improved when augmented with clinical features (Respiratory rate, history of recurrent nebulization and family history of atopy); providing sensitivity and specificity of 83.33% and 91.67%.

Conclusions: Cough features extracted and classified by machine learning can be used for non-auscultatory diagnosis of crackles and wheeze. This raises the possibility to develop smart applications for possible use by non-medical personnel to enhance their capability.

Keywords: Spectral pattern, Random forest, Mel-frequency cepstral coefficient

INTRODUCTION

World health organization (WHO) community case management algorithm for pediatric pneumonia relies solely on symptoms of cough with or without lower chest indrawing for case identification. Evaluation of this algorithm in the field showed relatively good sensitivity (69-94%) and poor to moderate specificity (16-67%) suggesting likely overdiagnosis of pneumonia and unnecessary use of antibiotics.¹ Wheezing disorders are

the major confounder which can be identified by auscultation but this skill is harder to transfer to the community health personnel. Keeping this issue in mind, digital auscultation of the respiratory sound has also been attempted with good results.² Cough is a common symptom that appears early to mid-stage of common respiratory disease such as pneumonia. Cough carries important information of the adventitious sounds such as crackles and wheeze originating from the lung. Researchers have found that the sound frequencies expressed in the cough vary between healthy subjects and

those with bronchitis, as the band width increases in the latter with frequencies at 500, 700 and 1200 Hz being accentuated.^{3,4} Spectral analysis of sound frequency using methods like wavelet frequency can allow objective analysis of cough sound.⁵ To assist the machine, the modification like MFCC is used to cut down on frequencies not well discriminated by human ear so as to identify the frequency patterns depicting specific adventitious sounds heard by a clinician. Machine learning (artificial intelligence) can be employed to identify the specific respiratory sounds as carried into the cough sound in a particular disease. The heterogeneity of the cough within the same individual during disease and between different individuals with same disease is taken care of by using a large training data set. However, the tools and settings required for recording the cough sounds for analysis have been rather sophisticated and non-portable.^{1,6,7}

With technological evolution and availability of recording apps on smartphones, a new vista has opened to explore and possibly harvest the benefits of this.^{8,14}

Proxy recognition of respiratory sounds from cough sounds by a handheld simple device like a smart phone can be a helpful tool for frontline health personnel to assist community diagnosis of common respiratory diseases. The present study was conducted to identify the unique features from cough sounds recorded in real life setting of OPD and IPD using a mid-range android smart phone, hoping that the results received would be more easily translatable to a point of care use.

METHODS

This cross-sectional study was conducted in the real life busy and noisy settings of OPD and IPD of department of pediatrics at Kalawati Saran children's hospital, New Delhi, India, between November 2018 and March 2020 after approval by the institutional ethics committee for human research. Written informed consent and assent was obtained. The patients included were assessed by the consultant or senior pediatrician and classified as pneumonia (based on rapid breathing with only crackles as the adventitious sound on chest auscultation), wheezy disorder (based on rapid breathing with only wheezing and no crackles as adventitious sound on chest auscultation) and upper respiratory tract infection (URTI) (cough without rapid breathing and normal chest auscultation). There were 50 patients in each category

with the age between 2 months to 18 years. It was a convenience sample of patients seeking care in a time period. Those patients who were not having coughs, seriously ill and irritable/fussy children were excluded.

Cough sounds were recorded by using an android smartphone (Xiaomi Redmi Note 7 pro). Recording was made long enough to have at least 3 cough epochs. Sampling rate of the recorder was set to 44.1 khz. The samples taken were both from spontaneous and non-spontaneous, voluntary cough as per the feasibility. Feature extraction from the recorded cough dataset was done by using programming language R open source and python having extraction packages like Librosa and Ts (Time series). Visual features such as MFCC, zero crossing rate, spectral roll-off and spectral centroid were extracted from the spectrogram. Statistical features extracted from each cough recording were seasonal period, trend, spike, entropy, linearity, curvature, E-ACF1, E-ACF10 mean, variance, lumpiness, Max_level Shift, Max_var_shift, Flat spots, Crossing points, Max kl Shift, Time Kl Shift. Cough datasets were randomized into testing (75%) and training dataset (25%). Classification of features extracted from the training dataset was done using classifier models such as support vector machine, random forest, K nearest neighbour and classification and regression trees. The performance of the classifier model was tested using relevant features of extraction from cough sounds alone, and, after augmentation with clinical features (Respiratory rate, history of recurrent nebulization and personal or family history of atopy like skin allergy or asthma) on the cough recordings from testing dataset.

RESULTS

Baseline characteristics of enrolled children is shown in Table 1.

The mean duration of cough recording was 15±5.86 seconds with each recording having at least three cough epochs. Out of one hundred and fifty cough sounds recorded, seventy-six were spontaneous and the rest of them were non spontaneous.

By applying feature extraction packages like Librosa and Ts (Time series) on cough recordings statistical and visual features were extracted from each cough recordings. Visual features were in the form of spectrograms (Figure 1).

Table 1: Demographic data.

Age (in years)	Total	URTI	Wheezing disorder	Pneumonia
<5	59	9	26	24
5-10	81	36	20	25
>10	10	5	4	1
Mean±SD: 5.62±2.84				
Male: female: 100:50				

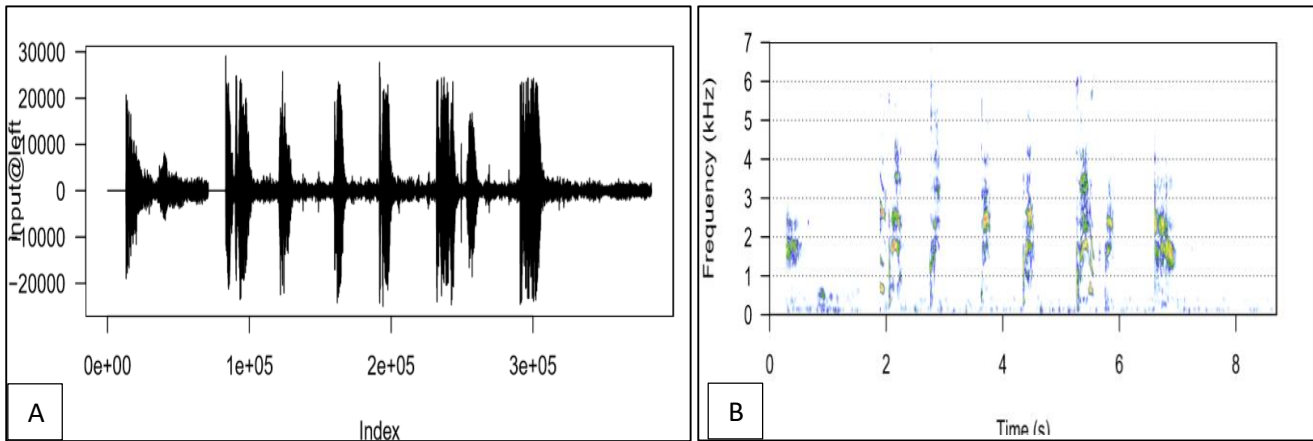


Figure 1 (A and B): Depicting spectrogram of a child with crackle.

Spectrogram of cough in a study case-First graph shows the event of cough recorded in wave form, second graph shows spectrogram in which X-Axis represent time in sec and Y-axis represent frequency in hertz, -spikes of spectrograms can be seen with each cough event.

Likewise, the statistical features were also collected and rated in terms of their performance. Without clinical data Max_level_shift and with clinical data MFCC20 stands out to be the most important among all the visual and statistical features that have been extracted for classification of cough datasets.

On extracted features, we performed 2 class classification on support vector machine, random forest, K nearest neighbour and classification and regression trees models. Random forest model stood out as the best model in differentiating cough sounds of URTI, wheezing disorder

and crackles. When augmented with clinical features sensitivity (sens), specificity (spec), positive predictive value (PPV), negative predictive value (NPV), accuracy, AUC (area under curve), precision, Recall and F1 score were increased as shown in Table 2.

Receiver operating characteristic curve (ROC) for most suited feature extracted from cough plotted using various classification models of machine learning are depicted in Figure 2. AUC improved significantly from 65-86% in RF models when respiratory rate, past h/o recurrent nebulization and h/o atopy were used to augment result.

Table 2: Statistical feature + visual feature + clinical features (respiratory rate, past history of recurrent nebulization /history of atopy).

Model	Two class classification	Sens	Spec	PPV	NPV	Accuracy	Positive class	AUC	Precision	Recall	F1 score
Random forest	URI vs crackle	1.00	1.00	1.00	1.00	1.00	Crackle	1.00	1.00	1.00	1.00
	URI vs wheezing	1.00	1.00	1.00	1.00	1.00	URI	1.00	1.00	1.00	1.00
	Crackle vs wheezing	0.91	0.75	0.78	0.90	0.83	Crackle	0.86	0.83	0.83	0.83

URI-upper respiratory tract infection, sens-sensitivity, spec-specificity, PPV-positive predictive value, NPV-negative predictive value, AUC-area under curve. All the data are in (%).

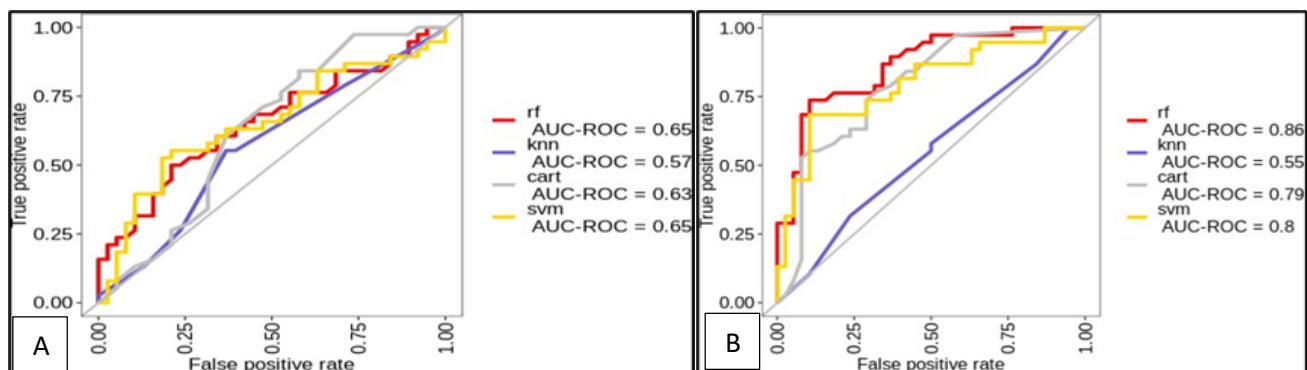


Figure 2 (A and B): AUC and ROC curve for differentiating crackles and wheeze using cough features shows cough features alone and cough feature augmented with clinical features.

DISCUSSION

One of the major problems in WHO community case management algorithm for pediatric pneumonia is the wrong diagnosis of wheezing disorders like bronchiolitis, virus associated episodic wheezing and asthma as pneumonia. This leads to poor treatment of such cases as the specific therapy is delayed and there is overuse of antibiotics with an attendant risk of augmenting antibiotics resistance.

To address this issue, WHO rationalized the diagnostic algorithm by doing bronchodilator test for the children having wheezing and fast breathing before they are classified as pneumonia.⁹ The children having audible wheeze are given a trial of bronchodilators (3 doses of salbutamol given 20min apart) and reassessed after 1 hour of bronchodilator therapy. Antibiotics are prescribed only to those who continue to have fast breathing and/or lower chest indrawing even after bronchodilator therapy. However, this well-intentioned change still does not take care of the larger group of wheezing children (over 90%) who do not have audible wheeze. The community health workers are not skilled enough to auscultate and identify less severe but more common auscultable wheezing and problem of inadequate therapy persists. Thus, tool is needed at peripheral health care level for objective registration of chest sounds which can be utilized by peripheral health care worker at ground level for

diagnosis of common respiratory diseases as pneumonia.

There were various devices used for recording cough sounds like bedside microphone, personal computer, low noise microphone with pre amplifier and A/D (analog to digital) converter and I phone.^{6-8,10} In the current study, recording of the cough sounds was made using a commonly available mid-range android smart phone so that the results could be translated to the clinical settings without need for any special equipment.

Studies on subject have used a variety of features extracted from the cough, such as, Bispectrum score, the Non-Gaussianity score, first 4 formant frequencies, log energy, zero crossing, kurtosis and twelve MFCC.^{6,8,10-13} In our study of all the visual and statistical features that were extracted, MFCC 20 and Max_level_shift came out as best features for classifier modelling.

We employed a variety of classifier models and found that random forest model best differentiated crackles from wheeze with relatively good sensitivity and specificity. The accuracy of the model was augmented further when clinical features were used along with statistical and visual features. The results of our study done in a busy hospital setting, mimicking real life scenario, are comparable with the other studies done on this subject, albeit with more sophisticated equipment or in studio settings (Table 3).

Table 3: Comparison of the current study results with the published data.

Variables	Abeyratne et al 2013 ⁶		Amrulloh et al 2015 ¹⁰	Amrulloh et al 2017 ⁹	Kosasih et al 2015 ¹²	Sharan et al 2017 ⁸	Current study, 2020	
Type of model classifier	Logistic Regression Model		A form of artificial neural network known as Time delay Neural network and Linear Discriminant analysis	Hidden Markov Model	Morlet, Mexican, Paul, Daubecheis, Du	Support vector machine	Random forest SVM CART KNN	
Classes compared	Pneumonia vs other respiratory diseases		Cough and non cough event in pediatric population	Pneumonic cough vs asthmatic cough	Pneumonia and non pneumonia patients	Croupy cough from non croupy cough	Crackle vs wheezing disorder	
Dataset	Only cough features	Cough+ clinical features	Only cough dataset	Only cough dataset	Only cough dataset	Only cough dataset	Only cough features	Cough+ clinical features
Sensitivity	80%	85.5%	92.8%	100%	94%	88.37%	66.67%	83.33%
Specificity	63%	88%	97.5%	80%	63%	91.59%	66.67%	91.67%
accuracy	75%	86.4%	97.3%	90%	-		66.67%	87.50%
PPV	82%	94%	-	-	-		66.67%	90.91%
NPV	60%	74%	-	-	-		66.67%	84.62%

SVM-Support vector Machine, RF-Random Forest, KNN-K nearest neighbour, CART-Classification and regression trees.

Limitations

We have used cough from cases with a single auscultatory finding; either rhonchi/ crackles for machine

learning and modelling. In real case scenario, the patients may have overlapping symptoms, which may affect the performance of the model. Further, it is also possible that the samples collected from non-spontaneous cough may

have also affected the performance in an unknown fashion. Further, we have fewer cases with first time wheezing disorders like bronchiolitis and thus the prediction and identification of such cases may suffer for lack of some of the clinical features utilized to augment the outcomes. Larger studies with wider representation from the individual diseases within the spectrum of wheezy disorders and pneumonia need to be tested to establish the utility of our findings.

CONCLUSION

The present study provides insight that machine learning and artificial intelligence can be applied to distinguish wheeze and crackles in a non-auscultatory manner from the cough sounds using feature extraction and classification. It may thus make it possible to create simple apps to be used on the phone device by peripheral health care workers for a more accurate diagnosis and rational therapy even in community settings.

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Conflict of interest: None declared

Ethical approval: The study was approved by the Institutional Ethics Committee

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