Article

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Identification of Elderly Patients with Lower Respiratory Tract Infection by Artificial Intelligence Analysis of Cough Pattern Sounds

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Background: Automatic recognition of cough sounds shows promise in the diagnosis of respiratory conditions. This study investigated the diagnostic value of cough sounds in elderly patients with lower respiratory tract infection (LRTI).

Methods: We selected 83 elderly patients with suspected LRTI who sought medical advice at our hospital from January 2022 to September 2022, and grouped them into the infected and uninfected categories, according to their clinical traits. The cough sound of each subject was recorded and features were extracted using the Mel Frequency Cepstrum Coefficient. Four cough sound indexes, including the length of light or heavy cough time (T1), frequency of sound, decibels full scale (dBFs) and total length of cough time (T0) were compared between the two groups. The diagnostic efficacy of each index was analyzed using the receiver operating characteristic (ROC) curve.

Results: 22 patients were diagnosed with LRTI in the infected group including 15 males and 7 females, 13 were in the LRTI-free uninfected group, including 7 males and 6 females. Cough sound indexes were higher in the infected group compared with the uninfected group at T1 (p = 0.127), frequency of sound (p = 0.894), dBFs (p = 0.532) and T0 (p = 0.854). ROC curve analysis showed that the area under the curve (AUC) values of the above four indexes and the combined indexes for LRTI diagnosis were 0.680, 0.503, 0.577, 0.486 and 0.696, respectively.

Conclusions: Cough sounds are correlated with LRTI. However, due to the small sample size of this study, the current results do not find that automatic recognition of cough has obvious diagnostic value, but its diagnostic potential in elderly patients with LRTI cannot be denied.

Keywords: cough sound; lower respiratory tract infection; artificial intelligence; diagnostic value

Introduction

The respiratory tract infection is a condition frequently diagnosed in inpatient and outpatient settings. It can be divided into upper respiratory tract infection (URTI) and lower respiratory tract infection (LRTI), of which the LRTI is more serious than the former [1]. LRTI is mainly caused by viral pathogens, such as the respiratory syncytial, influenza and parainfluenza viruses, the coronavirus and human metapneumovirus. It disproportionately affects adults aged ≥70 years and children <5 years [2,3]. In the background of COVID-19 epidemic, it was shown that pneumonia and other LRTI contribute to the fourth most important cause of death worldwide [4]. Auscultation, blood tests, chest X-ray, computed tomography (CT), sputum test, and pleural fluid culture are commonly used to differentially diagnose LRTI. However, patients in the out-of-hospital community lack reliable tools to assess their conditions for the need of medical advice and attention.

Elders, pregnant women and children are limited by their mobility and availability for examinations during their hospital visits. In addition, the differences in experience and diagnosis level of physicians impose a bias in the outcomes for physiological sound auscultation. Therefore, the assessment of LRTI by artificial intelligence has the potential to improve the timeliness, feasibility and efficacy of the diagnosis, resulting in a more effective treatment.

Cough is the result of a physiological reflex mechanism to protect the respiratory tract and one of the main symptoms of respiratory disorders. Cough sound can reflect the presence and amount of mucus on the surface of the lungs and airways, as well as the ability of pulmonary inflation, as influenced by factors of tissue characteristics and acoustic properties [5]. Available evidence has shown that cough sound varies in common respiratory conditions including pneumonia, bronchitis and asthma, due to differences in the lesion's location, its physicochemical properties and its surface characteristics [6,7]. Due to the availability of the smartphones and wearable sensors, there is a growing interest in developing artificial intelligence (AI) techniques to automatically assess cough sounds for the identification of respiratory diseases. For instance, Kosasih *et al*. [8] used a regression classifier to distinguish pneumonia from 815 cough sounds collected from 91 patients with pneumonia, asthma and bronchitis, with a sensitivity and specificity of 94% and 88%, respectively. Rao *et al*. [9] automatically predicted lung function based on acoustic signals from coughing and wheezing, helping patients monitor asthma severity non-invasively without spirometry. Also, Liu *et al*. [10] achieved an 80% detection rate of patients with COVID-19 by analyzing cough sound features using the Mel Frequency Cepstrum Coefficient (MFCC), among other specific statistics. Although cough sound has been reported to show good accuracy in screening for common respiratory disorders among children [7], its role in clinical diagnosis and out-of-hospital assessment of LRTI in elderly patients needs to be further explored.

In this study, we used an artificial intelligent algorithm to analyze the cough sound data collected from suspected LRTI patients who were admitted to our hospital. We also investigated the clinical value of four cough sound indexes in the diagnosis of LRTI elderly patients.

Materials and Methods

Study Design

This study enclosed elderly patients with LRTI and it was completed by a research team from the Department of Respiratory Medicine at Lishui People's Hospital. It was approved by the Ethics Committee of Lishui People's Hospital (Ethics Approval Number: 2023-075). A flowchart describing its design is provided in Fig. 1.

Selection of Study Subjects

Individuals ≥60 years of age were defined as elderly patients. A total of 83 were diagnosed after chest CT scan and biochemical tests at Lishui People's Hospital between January 2022 and September 2022 with pneumonia, chronic obstructive pulmonary disease and bronchiectasis that are prone to LRTI. The inclusion criteria comprehended: (1) patients with no recent history of systemic anti-infective therapy, and (2) willingness to enroll. The exclusion criteria included: (1) subjects with cardiovascular diseases, (2) liver and kidney malfunction, (3) coagulation and hematopoietic impairment, (4) immune dysfunction, and (5) oncological diseases except for lung tumor. The dropout criteria enclosed: (1) individuals who died during the test period or (2) disagreed to provide complete information. In accordance with the Declaration of Helsinki, all patients signed a written informed consent before enrollment.

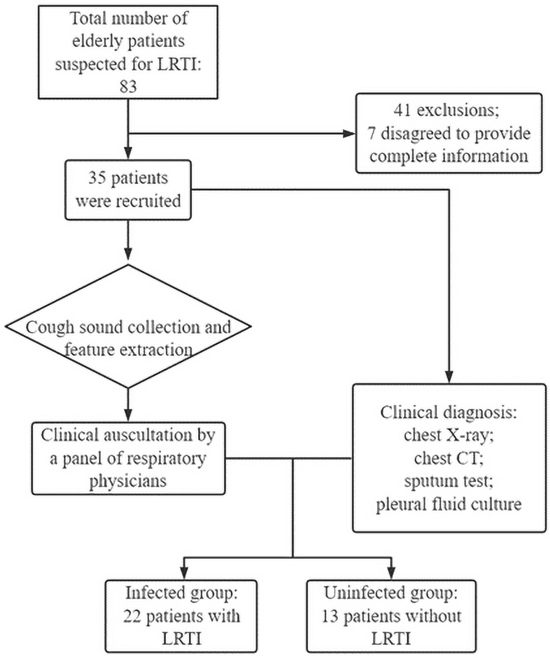


Fig. 1. Flowchart describing the study design. LRTI, lower respiratory tract infection; CT, computed tomography.

Cough Recording

Using a vocal distance from 25 to 50 cm, the cough audio streams were recorded in an iPhone 11 (iOS 13.1.1, Apple, Los Altos, CA, USA) at a sampling frequency of 44.1 kHz. The files were saved in 16-bit WAV format [7]. Each sound sample lasted less than 5 minutes. Recordings were performed by a respiratory nurse in a hospital environment where background noises included talking, crying, footsteps and door sounds, and excluded others' coughing, loud conversation and television sounds. During the entire process, it was required to record three voluntary or spontaneous cough sounds from each subject.

Cough Sound Processing and Feature Extraction

The audio data was normalized and preprocessed, including noise reduction and fast Fourier transformation. To extract the feature vector of acoustic signals, MFCC was obtained by taking the logarithm of the output value from the mel-filter banks and performing a discrete cosine transformation. Conversion between the Mel frequency and the actual frequency included the following equation:

$$f_{Mel} = 2595 \times \lg(1 + f/700)$$

After that, an automatic cough detector was employed to identify LRTI where the pattern recognition of Support Vector Machine (SVM) was operated, to analyze MFCC feature vector with characteristic parameters of 32 orders. The implementation of SVM model was based on the LIBSVM software package (www.csie.ntu.edu.tw/~cjlin/libsvm/) (National Taiwan University, Taiwan, China) [11]. The entire process was automated. The short-time energy threshold segmentation method was used to normalize the time series. The frame number of the cough sound time series was 12; multiplied by the number of orders, this amount renders a total of 384-dimensional speech feature vector sequences for each cough sound. This value could be obtained as the input of SVM. The Radial Basic Function Kernel was used to find the optimal penalty parameter C with a value of 1, and the kernel function parameter γ with a value of 0.8. The grid optimization method was employed.

Clinical Diagnosis

Cough sound files from each subject were assessed by a panel conformed from three to five respiratory physicians, holding by average 15 years of specialized practice experience. The clinical information of the patients was excluded to avoid bias. Auscultatory results were classified as positive for patients with LRTI and negative for those without LRTI. The medical data of chest X-ray, chest CT, sputum test or pleural fluid culture were compared with the auscultatory results. The identification of patients with LRTI met the diagnostic criteria stated in the 2011 Guidelines for the Diagnosis and Treatment of Adult Lower Respiratory Tract Infections [12].

Outcomes

Regarding the diagnostic indexes, LRTI was defined as acute if the condition remained for 21 days or less. The symptoms considered included coughing, accompanied by at least one other lower respiratory tract symptoms like expectoration, dyspnea, wheezing, chest discomfort and pain, and sinusitis and asthma were excluded [12].

Concerning the cough sound indexes, the length of light or heavy cough time (T1), the frequency of sound, referring to the frequency with the most power present in the cough sound pressure wave, the decibels full scale (dBFs) and the total length of cough time (T0) were analyzed. The sensitivity and specificity of the combined diagnosis of the above four indexes served enclosed the diagnosis [13].

Covariates

For the analysis of baseline data, we selected clinically meaningful factors from a previous study, including gender, age, body mass index (BMI) (kg/m^2), smoking history (never, ex-smoker or current smoker), and visual analogue scale of cough. Cough severity was measured on a visual analogue scale of 0 to 10 (highest) [14].

Statistical Analysis

All statistical analysis was performed using SPSS (version 20.0, IBM, Chicago, IL, USA). Data was presented as mean $\pm$ standard deviation. Counting data was compared using a χ^2 test. The age, BMI, visual analogue scale of cough and the cough sound indexes (T1, Frequency of sound (Hz), dBFs, T0) were in accordance with Shapiro-Wilk (S-W) normal distribution test. The difference comparison between the two groups were analyzed by independent t-test for the age, BMI, visual analogue scale of cough and cough sound indexes or χ^2 test for gender and smoking variables. The clinical diagnostic value of cough sound indexes for LRTI in elderly patients was analyzed by receiver operating characteristic (ROC) curves, followed by the area under the curve (AUC) value calculation. The threshold of statistical significance for comparing differences was set at $p < 0.05$.

In order to determine the sample size, the diagnostic sensitivity of cough sound frequency was considered as the main indicator, according to the previous literature [13]. The probability of occurrence of LRTI was 25.42%; and the minimum sensitivity and minimum specificity of the diagnostic indicator were 8% and 53%, respectively. In the PASS software (Version 11.0.7, NCSS, Kaysville, UT, USA), using a setting power of 0.9, an alpha of 0.05, and an expected sensitivity of 90%, we calculated that the minimum of LRTI samples required for the analysis was 20. Therefore, it was reasonable to enroll 22 cases in the infection group of this study.

Results

Analysis of Baseline Data

Of the enrolled 83 patients, 35 were ultimately included in the study. According to the clinical diagnosis, there were 22 patients with LRTI in the infected group, 15 males and 7 females. In the uninfected group without LRTI, there were 13 patients, 7 males and 6 females (Table 1). As to other baseline characteristics of age, BMI, smoking history and visual analogue scale of cough, they were no significant differences between the infected and the uninfected group (all $p > 0.05$, Table 1).

Comparison of Cough Sound Indexes between Two Groups

As shown in Table 2, cough sound indexes were higher in the infected group than those in the uninfected group at T1 ($p = 0.127$), frequency of sound ($p = 0.894$), dBFs ($p = 0.532$) and T0 ($p = 0.854$).

Analysis of Diagnostic Efficacy

As shown in Table 3, we predicted the clinical efficacy of four cough sound indexes employed to diagnose elderly patients with LRTI using the ROC curve analysis. The results showed that the AUC value of T1 was 0.680, of the sound frequency was 0.503, of dBFs was 0.577 and of T0 was 0.486 (all $p > 0.05$, Table 3). Moreover, a combination of four cough sound indexes indicated a high diagnostic value for LRTI in elderly patients, with a sensitivity of 81.8% and a specificity of 61.5%, AUC = 0.696, $p = 0.056$ (Table 3, Fig. 2).

Table 1. The baseline data of the two groups were compared.

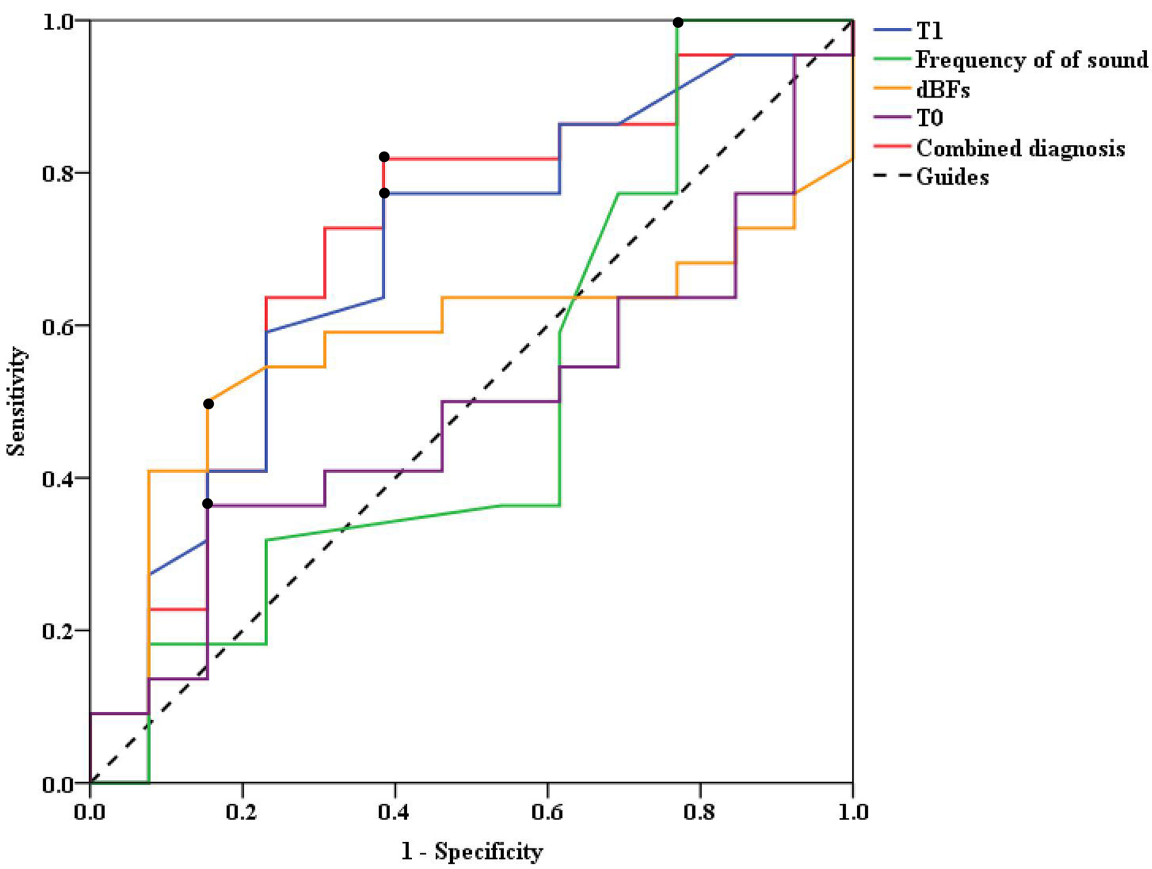
Group	N	Gender [n (%)]		Age (years)	BMI (kg/m^2)	Smoking [n (%)]			Visual analogue scale of cough
		Male	Female			Never	Ex-smoker	Current smoker	
Infected group	22	15 (68.18)	7 (31.82)	66.55 ± 12.91	25.46 ± 2.92	15 (68.18)	5 (22.73)	2 (9.09)	7.14 ± 2.21
Uninfected group	13	7 (53.85)	6 (46.15)	64.62 ± 15.30	25.69 ± 2.84	6 (46.15)	6 (46.15)	1 (7.70)	7.31 ± 2.25
χ^2/t		0.719		0.399	–0.229		2.106		–0.220
p		0.396		0.692	0.820		0.349		0.827

BMI, body mass index.

Table 2. The cough sound indexes were compared between the two groups ($\bar{x} \pm$ s).

Group	n	T1	Frequency of sound (Hz)	dBFs	T0
Infected group	22	0.21 ± 0.11	760.85 ± 370.97	–24.07 ± 6.29	11.09 ± 6.38
Uninfected group	13	0.15 ± 0.11	743.40 ± 375.30	–25.20 ± 1.72	10.73 ± 3.82
T		1.567	0.134	0.631	0.186
p		0.127	0.894	0.532	0.854

T1, length of light or heavy cough time; dBFs, decibels full scale; T0, total length of cough time.



	AUC	Cut-off point	*P*
T1	0.680	(0.385, 0.773)	0.079
Frequency of of sound	0.503	(0.769, 1)	0.973
dBFs	0.577	(0.154, 0.5)	0.453
T0	0.486	(0.154, 0.364)	0.891
Combined diagnosis	0.696	(0.385, 0.818)	0.056

Fig. 2. Receiver operating characteristic (ROC) curves for each index.

Table 3. The diagnostic efficacy of each index was compared.

	AUC	Sensitivity (%)	Specificity (%)	95% CI	*p*
T1	0.680	77.3	61.5	0.490~0.870	0.079
Frequency of sound	0.503	100	23.1	0.291~0.716	0.973
dBFs	0.577	50.0	84.6	0.383~0.770	0.453
T0	0.486	36.4	84.6	0.291~0.681	0.891
Combined diagnosis	0.696	81.8	61.5	0.504~0.888	0.056

AUC, the area under the curve; CI, confidence interval.

Discussion

The current study focused on investigating the feasibility of AI-supported cough sound analysis used as an auxiliary diagnostic tool for LRTI. Our current results did not find significant diagnostic value in automatic cough recognition, and follow-up studies with larger sample sizes are needed to demonstrate that it can be used to improve the accuracy of physician auscultation.

The efficient diagnosis of respiratory sounds during the initial auscultation phase of respiratory track diseases can be a challenge for both experienced and inexperienced physicians, even with access to multiple diagnostic tools [15,16]. Since the frequency range of breath sounds is about 50–3000 Hz and the sensitive frequency range of the human ear is 1000–2000 Hz, conventional auscultation often results in delayed and erroneous diagnosis, affecting the optimal treatment of the patients. Cough and counting cough events have been used for the management of asthma and chronic obstructive pulmonary disease [17]. Although coughing is shared as a common symptom of both URTI and LRTI, the sounds show their own unique acoustic signals which enable physicians to diagnose patients with LRTI from their spontaneous cough sounds.

Typically, infection-induced respiratory conditions like chronic bronchitis, pneumonia and lung abscess are frequently characterized by chronic wet cough or productive cough, as well as conditions like tracheitis, chronic laryngitis and intratracheal foreign body-caused dyspnea; those are featured by dry cough with zero or scarce sputum [18]. Therefore, automatic classification can potentially be achieved by comparing the difference of energy rate between the two types of cough sounds in the middle- and high-frequency bands, which has a high-level diagnostic value in the clinical practice.

In recent years, automatic analysis of cough sounds combined with personal medical data has shown great promise in the intelligent assessment of respiratory diseases [19]. Based on empirical-mode decomposition, which is a general-purpose signal processing method for acoustic and vibration data, Chung *et al*. [14] established a diagnostic algorithm through long and short-term memory to classify cough sounds caused by pneumonia or non-pneumonia, with a diagnostic accuracy of 84.9%. Based on the application of the SVM classifier, Reynolds *et al*. [20] underlined that the automatic recognition of cough airflow signals has the potential in assessing the mechanical properties of the pulmonary system by identifying abnormal spirometry. In addition, a study of asthma has shown that the analysis of cough signals using support vector regression to predict lung function indicators attains an accuracy of 77.77% for grading asthma severity [9].

At present, the development of cough sounds both domestically and internationally and its role in the assessment of LRTI remains to be explored. SVM is a novel type of machine learning method, widely used in pattern recognition because of its advantages of high adaptability, high training efficiency and good generalization performance for solving small-sample, nonlinear and high-dimensional pattern recognition problems [21,22]. In this study, the potential value of cough sounds in the clinical diagnosis of LRTI was predicted by using SVM to recognize the feature vector of cough sounds from patients with suspected LRTI. We found that cough sound indexes were higher in patients with LRTI than those in patients without LRTI at T1 ($p = 0.127$), frequency of sound ($p = 0.894$), dBFs ($p = 0.532$) and T0 ($p = 0.854$). Of note, the results of the ROC curve analysis revealed that AUC values of the combined indexes for the LRTI diagnosis were 0.696, indicating a relatively low predictive power of the model. Therefore, it showed that it's difficult to evaluate the combined diagnosis accurately. More influencing factors need to be added in order to improve the identification process. However, according to the diagnostic results of cough sound, the sensitivity and specificity of the combined diagnosis were shown as 81.8% and 61.5%, respectively. It is indicated that automatic recognition of cough sounds aids in the clinical diagnosis of elderly LRTI, but its accuracy needs to be further optimized.

However, the results of AUC did not meet the standard of *p* less than 0.05, but the *p* value was close to the critical value. The reason may be that the small sample size of this study affected the diagnostic results between LRTI patients and cough sound, therefore more samples need to be collected in the future to explore the correlation and diagnostic value between cough sound and LRTI.

Conclusions

This pioneering study provides compelling evidence for the correlation between cough sounds and LRTI. Because of small sample size, the automatic recognition of cough sounds did not have diagnostic value for elderly patients with LRTI in this study. However, the potential of cough in diagnosing LRTI should not be ignored.

Availability of Data and Materials

The analyzed data sets generated during the study are available from the corresponding author upon reasonable request.

Author Contributions

YLL and SYY designed the research study; ZTY and ZYY performed the research; XPC and JWP collected and analyzed the data. All the authors have been involved in drafting the manuscript and have been involved in revising it critically for important intellectual content. All the authors give final approval of the version to be published. All the authors have participated sufficiently in the work to take public responsibility for appropriate portions of the content and agreed to be accountable for all aspects of the work in ensuring that questions related to its accuracy or integrity.

Ethics Approval and Consent to Participate

This was a study on the direction of elderly patients with LRTI, co-completed by a research team from the Department of Respiratory Medicine at Lishui People's Hospital. The study was approved by the Ethics Committee of Lishui People's Hospital (Ethics Approval Number: 2023-075). In accordance with the Declaration of Helsinki, all patients signed a written informed consent before enrollment.

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Conflict of Interest

The authors declare no conflict of interest.

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