Review

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# Wheeze sound analysis using computer-based techniques: a systematic review

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**Abstract:** Wheezes are high pitched continuous respiratory acoustic sounds which are produced as a result of airway obstruction. Computer-based analyses of wheeze signals have been extensively used for parametric analysis, spectral analysis, identification of airway obstruction, feature extraction and diseases or pathology classification. While this area is currently an active field of research, the available literature has not yet been reviewed. This systematic review identified articles describing wheeze analyses using computer-based techniques on the SCOPUS, IEEE Xplore, ACM, PubMed and Springer and Elsevier electronic databases. After a set of selection criteria was applied, 41 articles were selected for detailed analysis. The findings reveal that 1) computerized wheeze analysis can be used for the identification of disease severity level or pathology, 2) further research is required to achieve acceptable rates of identification on the degree of airway obstruction with normal breathing, 3) analysis using combinations of features and on subgroups of the respiratory cycle has provided a pathway to classify various diseases or pathology that stem from airway obstruction.

**Keywords:** adventitious sound; airway obstruction; lung function; severity level; wheeze analysis; wheeze detection.

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## Introduction

Auscultation is a clinical procedure that involves listening to the sounds in the human body and was first developed in 1816 with the invention of the stethoscope [37]. Physicians in the field of pulmonary medicine use a stethoscope and listen to respiratory sounds with the goal of diagnosing respiratory disorders and abnormalities. Acoustic signals are generated in the lungs due to the oscillation of the bronchi walls, which produce turbulent air flow during breathing [32], and these respiratory sounds constitute a powerful source of information regarding lung conditions [37]. In the field of pulmonary medicine, respiratory sounds are closely related to pulmonary pathology. Accounts of computerized respiratory sound analysis has been appearing in the literature as early as 1980 [42].

Respiratory sounds are divided into normal and abnormal (adventitious) sounds depending on their acoustic properties [42]. Normal respiratory sounds are produced by healthy subjects with normal airway and tracheal pathologies, whereas adventitious sounds are produced as a result of airway obstruction and can be subdivided into continuous and discontinuous lung sounds. In addition, continuous sounds are further subdivided into rhonchi and wheezes, and discontinuous respiratory sounds are further subdivided into fine and coarse crackles [2, 42].

Wheezes are sounds that are produced due to airway obstruction. These sounds are most frequently heard in patients with asthma but are also detected in patients with several other diseases, such as chronic obstructive pulmonary disease (COPD), pneumonia, pulmonary edema and bronchomalacia [33]. These sounds have also been observed in healthy subjects during forced respiratory maneuvers [18, 33, 53].

Wheezes are continuous sounds that are superimposed on normal breath sounds. The American Thoracic Society (ATS) defines the duration of wheeze to be longer than 250 ms and indicates that the dominant frequency of wheeze as 400 Hz [2, 33]. However, according to the recently developed Computerized Respiratory Sound Analysis (CORSA) standards, the duration of wheeze is longer than 100 ms and their dominant frequency is greater than 100 Hz [55]. CORSA also reports that no wheeze has been found with a frequency greater than 1600 Hz [9]. Wheezes constitute melodic tones with a distinguishable high pitch, and their waveform has a sinusoidal shape [33]. Monophonic wheezes have a single pitch, whereas polyphonic wheezes have multiple frequencies [33]. It also has been observed that wheezes consist of at most four harmonics [58].

According to the World Health Organization (WHO), 235 million individuals are suffering from asthma [12], and 15% of children die due to pneumonia [46]. It has also been predicted that in 2030, COPD will become the third most common cause of death worldwide [11]. Thus, researchers are attempting to develop methods for computerized wheeze analysis to accommodate and facilitate the self-monitoring and self-management of related diseases by patients. Physician assisted devices that are currently used for the examination of airway obstruction are the peak flow meter and spirometer, which are expensive and not user-friendly. These devices are predominantly utilized during supervised forced respiratory maneuvers, as opposed to normal breathing, and hence cannot be used to monitor related diseases for long durations and during sleeping. In addition, the existing devices are not suitable for monitoring airway obstruction in children due to the suggested breathing maneuvers [32]. Further, diagnoses conducted by physicians from listening experiences could be subjective and inaccurate as the source of the signal is limited to the acoustic range. Taken together, these have stirred much interest in researchers to work on computer-based techniques of wheeze sound analysis.

The aim of this review was to identify studies in the literature describing computerized wheeze sound analysis and to determine open areas in this field of research. We intend to maximize the area of coverage on wheeze sound analysis as much as possible. This area is not isolated and some related review articles are already available in the literature. In 2017, Pramono et al. [47], reviewed the detection and classification of adventitious sounds. In 2016, Jácome and Marques [24] addressed the characteristics of respiratory sounds in COPD patients and Palaniappan et al. [42] addressed the machine learning techniques for lung sounds. In 2014, Palaniappan et al. [43] focused on works related to supervised and unsupervised techniques for lung sound classification. Palaniappan et al. [41] looked into computer-based techniques used for respiratory sound analysis in 2013. In 2011, Gurung et al. [22] summarized the detection and classification of abnormal sounds. To the best of our knowledge, none of these reviews have critically analyzed works specifically related to the findings from wheeze sound analysis using computer-based techniques.

## Methodology

A comprehensive literature search of findings related to computerized wheeze sound analysis on the SCOPUS, IEEE Xplore, ACM, PubMed, Springer and Elsevier electronic databases was performed until June 2017. The set of keywords applied in the article search was the following: wheeze, adventitious sound, wheeze detection, breath sounds, asthma severity and analysis of airway obstruction. Books, letters, journal articles, conferences and clinical reports were screened for potentially eligible studies. In addition some of the references' important articles that were retrieved in the search were also included. The selection (inclusion and exclusion) criteria were the following: (i) articles published between 1996 and mid 2017 were included; (ii) articles written in English were included; (iii) articles on completely other adventitious sounds (e.g. crackles, rhonchi, etc.) were excluded; (iv) only articles with findings related to wheeze sound analysis using computer-based techniques were included; (v) articles discussing only medical issues were discarded; (vi) duplicates and extended version articles were removed; (vii) articles with insufficient information were excluded; and (viii) some of the relevant articles published before year 1996, identified from the references of the selected articles, were also included. Figure 1 shows the process flow diagram to obtain the 41 articles finally shortlisted in this review.

The findings of the selected articles contribute to the following research areas – wheeze detection or classification, and wheeze characterization. Wheeze detection or classification was conducted using logic-base algorithms (11 articles [1, 16, 23, 31, 48, 53, 56, 58, 60, 64, 70]), topological methods (two articles [14, 15]) and machine learning algorithms (16 articles [2–8, 10, 25, 28, 29, 32, 35, 49, 52, 67]). Wheeze characterization focused on determining spectral parameters (six articles [18, 27, 30, 54, 57, 59]) and the correlation of airway obstruction and spectra (six articles [36–40, 50]). A summary of important details from each article and the key findings is provided in Table 1.

It should be noted that while wheeze phenomena is an active area of research, computerized wheeze sound analysis is still in its infancy stage. A study by Earis and Cheetham [13], indicated that from 1986 to 1996 (10 years span), out of 1672 studies, only 163 (12.6%) reliable "electronic-based" studies were available in the literature. Work from European research institutions, accounted for about 25% of the total identified papers. Of these, only three articles (3%) were identified to be wheeze related between 1991 and 1996 (5 years). These statistics reveal that on average, about two reliable articles on computerized wheeze analysis can be observed annually in the literature. Our systematic review concurs

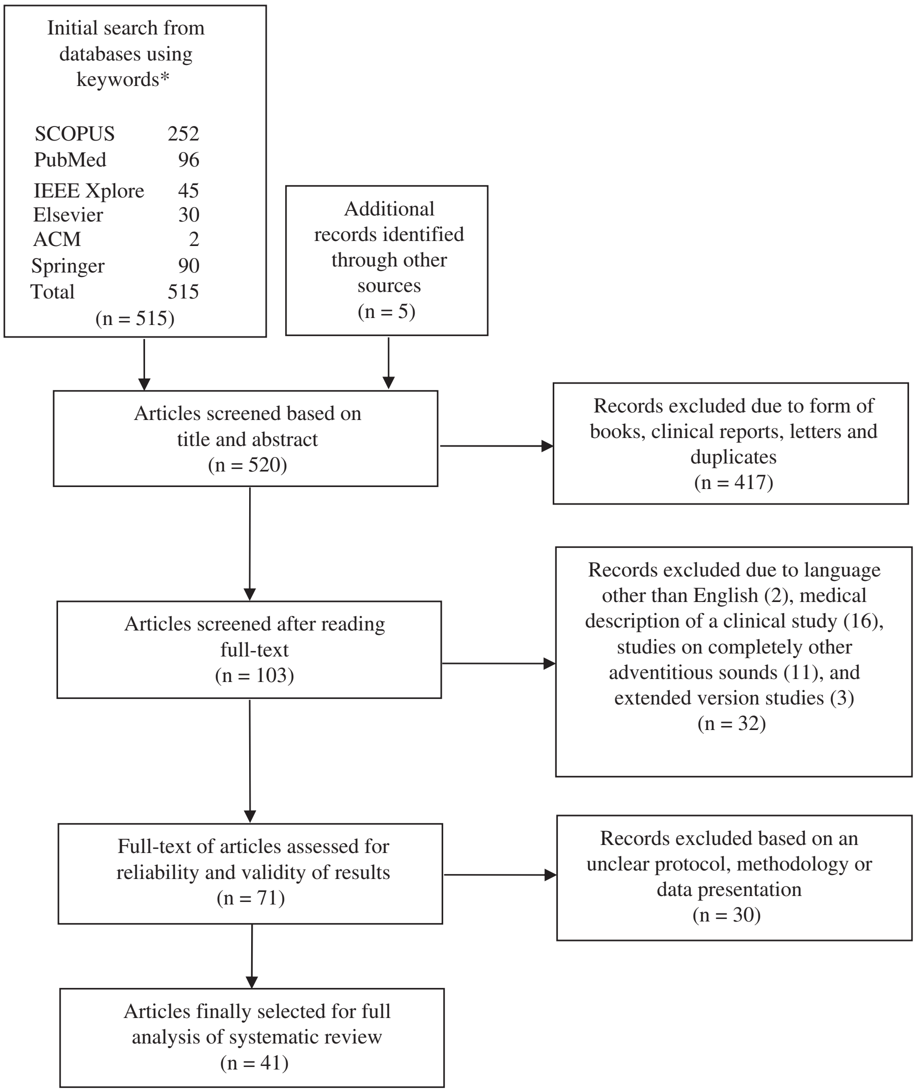


**Figure 1:** Flow chart for article selection.
*Keywords – Wheeze, adventitious sound, wheeze detection, breath sounds, asthma severity and analysis of airway obstruction.

with these statistics. Taking heed from Earis and Cheetham [13], beginning from 1996 to 2017 (approximately 20 years span), we have found 41 articles to be worthy of review.

## Wheeze sound acquisition

### Sensors and devices

Generally, the literature reveals that microphones are used for data acquisition of respiratory sounds. There are two major approaches when microphones are used – kinematic and acoustic. Irrespective of the approach, mechanical vibrations are converted into electric signals through a condenser or piezoelectric sensor. Condenser microphones are normally attached to the skin through couplers known as air couplers while piezoelectric microphones are directly attached to skin surface, for the collection of respiratory sounds [63]. Some studies have utilized piezoelectric contact-microphones [17, 18, 23, 53] while others have used air-coupled microphones [56, 60]. The RALE and MARS databases consist of data collected from an accelerometer (EMT-25C) and air-coupled microphone (ECM-77), respectively.

Some of the studies used custom-made devices to collect respiratory sounds. Two studies acquired respiratory sounds using a device that utilized an electret microphone (EK-3024) and an accelerometer (BU-3173) [31, 32]. Researchers in [27] introduced a device which consists of a condenser sensor (TS-6022A) embedded in a stethoscope

**Table 1:** Studies of wheeze sound analysis.

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| [16] | – 7 children (age 10–16)<br>– 5 with asthma<br>– 2 normal | – Data was self-recorded<br>– Tidal breathing<br>– Wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Trachea and right upper lung lobe | Peak detection by setting threshold within power spectrum obtained using FFT of recordings for wheeze identification | Asthma (4 severe, 1 moderate) | Yes + flow meter | – Validation of system not reported |
| Key findings: 1) The comparison of power spectrums indicate that the trachea is a superior location for wheeze sound recording while the chest wall filters some of the high frequencies. 2) Percentage of wheeze in expiratory and inspiratory phases provides valuable information on the dynamics of wheezing and follows change in lung function. 3) False positive rate <2% and false negative rate <2% between normal and asthmatic subjects | | | | | | | |
| [53] | – 5 male adults<br>– All normal | – Data was self-recorded<br>– Forced respiratory maneuvers<br>– Validation of wheeze segments not reported | Trachea | Peak detection by logic-based algorithm on the power spectrum obtained using FFT of recordings for wheeze identification | Not applicable | Yes + flow meter | – Validation of system not reported<br>– No inference was made to the inspiratory and expiratory phases |
| Key findings: 1) Wheeze frequency range and spectrogram did not change as a function of the gas density, experiment done with the mixture of air, He, $SF_6$ and $O_2$ | | | | | | | |
| [36] | – 1 female<br>– Asthma patient (age 18) | – Data was self-recorded<br>– Tidal breathing<br>– Continuous recording for about 6 h<br>– Breathing cycle segments were validated by physician using only audio inspection of recordings | Trachea | Comparison of systems between features of breathing cycles extracted from the power spectrum that is normalized by Box-Cox transformation coupled with either k-NN or ANN classifiers for wheeze identification in three classes – no wheeze, few wheeze and much wheeze | Mild to severe asthma episodes identified by physician | Not reported | – Data collected from only one subject<br>– Validation of system not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) Analysis of full breathing cycle which is normalized through Box-Cox transformation is useful for classification of severity levels. 2) Without normalization, ANN and k-NN shows overall error rate of 12 ± 4%, 20 ± 3% and 11%, 13% for two class (no wheeze, much wheeze) and three class (no wheeze, few wheeze, much wheeze), respectively. 3) After normalization, overall error rate of k-NN decreased by 6% for both two classes and three classes. 4) After normalization, ANN cannot perform three class classification and obtained accuracy of two class as 76 ± 11% (no wheeze, few wheeze) and 83 ± 10% (much wheeze), respectively | | | | | | | |
| [38] | – 2 adults<br>– 1 asthma male (age 18)<br>– 1 normal female (age 19) | – Data was self-recorded<br>– Forced respiratory maneuvers<br>– Asthma induced in three sessions with mite dust allergen<br>– Validation of breathing cycle segmentation not reported | Trachea | Features of breathing cycles extracted from the power spectrum that is normalized by Box-Cox transformation and interpolated using k-NN to identify relationship between sound spectra and different groups of lung function values | Mild to severe asthma episodes identified by $\Delta FEV_1\%$ | Not reported | – Data collected from only two persons<br>– Validation of system not reported |
| Key findings: 1) Overall rate of correctly interpolated $FEV_1$ values was 80% with 8% standard deviation | | | | | | | |
| [64] | – 8 subjects<br>– 4 asthma patients<br>– 4 normal subjects | – Data was self-recorded<br>– Wheeze segments were validated by physician using audio-visual inspection of recording and time-expanded sinusidal signal waveforms | Lower lung base | Pattern recognition using image processing conducted on spectrogram obtained from FFT of recordings for wheeze identification | Not reported | Yes + flow meter | – Age range of subjects not reported<br>– Breathing maneuver not reported<br>– Validation of system not reported<br>– No inference made to the inspiratory and expiratory phases |
| Key findings: 1) Accuracy of system in terms of false positive varies from 1% to 9% with respect to the duration of wheezes | | | | | | | |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| [39] | – 1 adult male<br>– Asthma patient | – Data was self-recorded<br>– Forced respiratory maneuvers<br>– Asthma induced in two sessions with mite dust allergen<br>– Validation of breathing cycle segmentation not reported | Trachea | Comparison of systems with features of breathing cycles like mean frequency, median frequency and those extracted from the power spectrum of various bin widths that is normalized by Box-Cox transformation and interpolated using k-NN to identify relationship between sound spectra and different groups of lung function values | Mild to severe asthma episodes identified by $\Delta FEV_1\%$ | Not reported | – Data collected from only one person<br>– Validation of system not reported |
| Key findings: 1) Interpolation score of system is 71% with 150 Hz power spectrum bin width and 32 ± 4% for each mean and median frequency. 2) Spectral information increases when spectral details are averaged over frequency bin widths greater than the spectral resolution | | | | | | | |
| [50] | – 60 children (age 7–18)<br>– 50 asthma<br>– 10 normal | – Data was self-recorded<br>– Tidal breathing<br>– Continuous recording for 10 h<br>– Breathing cycle segments were validated by author using only audio inspection of recordings | Trachea | Comparison of systems with features of breathing cycles obtained from bar-graph spectrogram between humans and ANN for classification according to level of obstruction | Mild to severe asthma identified by physician through $\Delta PEF\%$ | Not reported | – Classification accuracy of system is high only for training vectors<br>– Validation of system not reported |

Table 1 (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) Humans cannot classify a bar-graph spectrogram visually into more than two classes, whereas a neural network performs classification into three classes. 2) Degree of airway obstruction was correctly classified into three classes – 95% (training vectors) and 43% (test vectors) using neural network | | | | | | | |
| [40] | – 10 subjects<br>– All with asthma | – Data was self-recorded<br>– Forced respiratory maneuvers<br>– Asthma induced in two sessions with mite dust allergen<br>– Validation of breathing cycle segmentation not reported | Trachea | Comparison of systems with features of breathing cycles extracted from power spectrum and Welch spectra of various bin widths that is normalized by Box-Cox transformation and interpolated using k-NN to identify relationship between sound spectra and different groups of lung function values | Mild to severe asthma levels observed by $\Delta FEV_1\%$ | Not reported | – Age range of subjects not reported<br>– Validation of system not reported |
| Key findings: 1) Wheeze sound spectra contain sufficient information for determining the severity of airway obstruction in asthmatic patients. 2) Either Welch spectra or DFT with the resolution of 15–75 Hz is optimum for detailed spectral information. 3) About 60%–90% of sound data can be interpolated to $FEV_1$ values using one-nearest neighbor classifier. 3) Overall classification score of 61%–87% for all $FEV_1$ values | | | | | | | |
| [18] | – 37 subjects<br>– 16 with asthma (age 56.5 ± 15.2)<br>– 6 with COPD (age 58.8 ± 4.9)<br>– 15 normal (age 45.8 ± 12.5) | – Data was self-recorded<br>– Forced respiratory maneuvers<br>– Wheeze segments were validated by physician using only audio inspection of recordings | Trachea | Number of wheeze, duration and frequency related features obtained from power spectrum analysis of recordings within intervals 1.2–0.2 l/s exhalation and statistical test applied to observe significance levels between patients and normal persons | Moderate to severe airway obstruction with $FEV_{1(predicted)}$ =37.2%–67.8% | Yes + flow meter | – Analysis done only on expiratory phase<br>– Validation of results not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) The mean frequency of wheezes is higher in normal subjects than in patients. 2) Number of wheeze episodes increases with the increase in severity level | | | | | | | |
| [37] | – 10 subjects<br>– All with asthma | – Data was self-recorded<br>– Forced respiratory maneuvers<br>– Asthma induced in two sessions with mite dust allergen<br>– Validation of breathing cycle segmentation not reported | Trachea | Feature of breathing cycles extracted from Welch spectra that are normalized by Cox-Box transformation and PCA used to reduce number of components. Reduced features interpolated using feed-forward neural network classifier to identify relationship between sound spectra and different groups of lung function values | Mild to severe asthma levels observed by $\Delta FEV_1\%$ | Not reported | – Age range of subjects not reported<br>– Validation of system not reported |
| Key findings: 1) In asthmatic patients, a deterministic relationship exists between lung function ($FEV_1$) and sound spectra. 2) It has been concluded that acuteness of patients can be identified by computer-based wheeze analysis. 3) Interpolation yielded score between 26 ± 2% and 80.1 ± 0.8% for all $FEV_1$ values | | | | | | | |
| [31] | – 26 children<br>– 10 with asthma (age 3–7)<br>– 16 normal (age 1–7) | – Data was self-recorded<br>– Tidal breathing and force respiratory maneuvers<br>– Validation of wheeze identification done by physician using only audio inspection of recordings | Trachea and lower lung base | Power spectral analysis obtained using FFT of recordings for wheeze identification | Mild to severe asthma identified by physician | Not reported | – Analysis conducted on frequency >200 Hz which does not fulfil the suggested frequency range of wheeze as suggested by CORSA<br>– Validation of system not reported |
| Key findings: 1) Wheeze sound analysis with forced exhalation can be performed at home in asthmatic infants. 2) Accuracy of system reported as 70% | | | | | | | |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| [3] | – 24 subjects<br>– 12 wheezy<br>– 12 normal | – Validation of wheeze segments not reported | Trachea | Comparison of systems with MFCC feature extraction method and other features extraction methods like FFT, LPC, SBC or WPD, coupled with a GMM classifier for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Age range and pathology of subjects not reported<br>– Source of data collection not reported<br>– Breathing maneuver not reported<br>– Validation of system and not reported |
| Key findings: 1) Maximum performance of wheeze detection with MFCC and GMM is 77.5% | | | | | | | |
| [60] | – 14 subjects<br>– All with asthma | – Data was self-recorded<br>– Tidal breathing<br>– Wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Trachea, upper lung lobe, lower lung base | Peak detection by logic-based algorithm on the power spectrum obtained using DFT of recordings for wheeze identification | Not reported | Not reported | – Age range of subjects not reported<br>– Validation of system not reported |
| Key findings: 1) Wheeze-episode detection (WED) algorithm introduces frequency sub-bands and defines local maxima for each sub-band to detect wheezes. 2) Rate of detectability with WED algorithm 93.4 ± 11.9% | | | | | | | |
| [23] | – 31 adults<br>– 16 with asthma (age 53.6 ± 16.3)<br>– 15 normal (age 45.8 ± 12.5) | – Data was self-recorded<br>– Forced respiratory maneuvers<br>– Wheeze segments were validated by physician using only audio inspection of recordings | Trachea | LAWDA peak detection by logic-based algorithm on the power spectrum obtained using FFT of recordings within intervals 1.2–0.2 l/s exhalation for wheeze identification and statistical test applied to observe significance levels between patients and normal persons | Moderate to severe asthma with $FEV_{1(predicted)}$ = 36.7%–67.3% | Yes + flow meter | – No inference was made to the severity levels<br>– Analysis done only on expiratory phase<br>– System was validated using 60 breath sound samples (37 asthmatic patients and 23 normal subjects) |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) LAWDA introduces grouping of nearest peaks to enforce the wheeze duration criteria, which increases the accuracy of wheeze detection. 3) Sensitivity of the system for wheeze detection as a function of airflow was $71\%_{(0.2–0\ l/s)}$, $87\%_{(0.4–0.2\ l/s)}$ and $100\%_{(1.2–0.4\ l/s)}$, respectively. 4) Wheeze produced by patients and normal subjects using forced respiratory maneuvers shows statistical significant difference | | | | | | | |
| [5] | – 24 subjects<br>– 12 wheezy<br>– 12 normal | – Validation of wheeze segments not reported | Trachea | Comparison of systems with MFCC feature extraction method coupled with either VQ, GMM or ANN classifier for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Age range and pathology of subjects not reported<br>– Source of data collection not reported<br>– Breathing maneuver not reported<br>– Validation of system not reported |
| Key findings: 1) Post-processing of the score function i.e. smoothing the score function and taking into account wheeze duration increases the accuracy by 20%. 2) The MFCC-GMM combination yielded the best performance of all combinations | | | | | | | |
| [56] | – 24 subjects<br>– All wheezing patients (age 61 ± 18) | – Data was obtained from MARS database<br>– Tidal breathing with maximum airflow of 1.5 l/s<br>– Wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Trachea, upper lung lobe and lower lung base | Continuous wavelet transform of recordings by applying scale-dependent threshold for wheeze identification | Mild to severe airway obstruction $FEV_{1(predicted)}$ = 48.61%–87.1% | Yes + flow meter | – Pathology of patients not reported<br>– Validation and accuracy of system not reported<br>– No inference was made to the severity levels or the inspiratory and expiratory phases |
| Key findings: 1) Continuous wavelet transform introduced for wheeze detection | | | | | | | |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| [4] | – 24 subjects<br>– 12 wheezy<br>– 12 normal | – Validation of wheeze segments not reported | Trachea | Comparison of systems between the MFCC and SBC feature extraction methods coupled with either the GMM, VQ, or ANN classifier for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Age range and pathology of subjects not reported<br>– Source of data collection not reported<br>– Breathing maneuver not reported<br>– Validation of system and not reported |
| Key findings: 1) The MFCC-GMM combination gives the best results with specificity almost 92% | | | | | | | |
| [48] | – 36 subjects<br>– 11 with asthma<br>– 25 normal | – Data was self-recorded<br>– Tidal breathing<br>– Wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Trachea | Logic-based algorithm with frequency and duration-dependent threshold using STFT of recordings for wheeze identification | Not reported | Not reported | – Age range of subjects not reported<br>– Validation of system not reported |
| Key findings: 1) A frequency and time-based threshold is introduced in this study. 2) Ten out of 11 patients correctly identified by algorithm | | | | | | | |
| [58] | – 13 subjects (age 44–79)<br>– 7 with COPD<br>– 4 with asthma<br>– 2 with pneumonia | – Data was obtained from MARS database<br>– Tidal breathing with maximum airflow of 1.5 l/s<br>– Wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Trachea, axillae, lower lung base | TF-WD peak detection logic-based algorithm on the power spectrum obtained using FFT of recordings for wheeze identification | Asthma (1 severe, 2 moderate, 1 mild), COPD (6 severe, 1 very severe), pneumonia NA | Yes + flow meter | – No inference was made to the severity level<br>– Validation of system not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) The time-frequency wheeze detection (TF-WD) algorithm introduces peak coexistence, i.e. number of detected peaks should not be greater than 4 for wheeze identification. 2) Performance of system does not change between the expiratory and inspiratory phases. 3) Overall efficiency of system – rate of detectability 99.7 ± 1%, sensitivity 95.5 ± 4.8%, specificity 93.7 ± 9.3% | | | | | | | |
| [1] | – 26 children with asthma<br>– 7 subjects self-recorded<br>– 19 subjects other sources | – Data was self-recorded, obtained from RALE and other online databases<br>– Wheeze segments were validated by author using only audio inspection of recordings | Trachea and lower lung base | Pattern recognition of discrete stationary wavelet spectrogram using image processing of recordings for wheeze identification | Not reported | Not reported | – Uniform breathing maneuver in the combined sources of data could not be identified<br>– Validation of system not reported |
| Key findings: 1) Performance of the system for wheeze detection is given for recorded and online data separately – a) Recorded data: true positive 40/43, doubtful 5/7, false positive 5, b) Online Data: true positive 22/22, doubtful 3/3, false positive 4 | | | | | | | |
| [57] | – Adult asthma subjects | – Data was obtained from MARS database<br>– Tidal breathing with maintain airflow of 1.5 l/s | Trachea, axillae, and lower lung base | Wavelet bicoherence (WBC) and wavelet bispectrum (WBS) calculated from time-bi-frequency domain for analysis of wheeze spectral characteristics | Mild to severe asthma patients identified by $FEV_1$ values | Yes + flow meter | – Number of subjects not reported<br>– No inference made to severity levels<br>– Validation of results not reported |
| Key findings: 1) Inspiratory and expiratory phase of asthmatic patients shows different behavior when analyzed with third-order spectra/statistics | | | | | | | |
| [49] | – 28 subjects (total from all sources)<br>– Wheezing patients and normal subjects (age 1 day–76) | – Data obtained from the RALE database and other online sources<br>– Validation of wheeze segments not reported | Trachea | Image processing of the spectrogram to identify patterns (features) and then recognition using neural network classifiers for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Pathology of subjects not reported<br>– Wide range of age-group has been selected<br>– Uniform breathing maneuver in the combined sources of data could not be identified<br>– Validation of system not reported |

Table 1 (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) Results of system has been reported with total accuracy 84.82% | | | | | | | |
| [2] | – 24 subjects (total from all sources)<br>– 12 asthma<br>– 12 normal | – Data self-recorded and obtained from ASTRA and RALE databases<br>– Wheeze segments were validated by author using audio-visual inspection of recordings and spectrogram | Trachea | Comparison of 17 systems from combinations of either FFT, LPC, MFCC or CWT feature extraction methods coupled with either VQ, GMM or ANN classifiers for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Age range of subjects not reported<br>– Validation of system not reported |
| Key findings: 1) The comparison of various combinations of feature extraction methods and classifiers based on the ROC curve showed that the best result was obtained with the MFCC-GMM combination. 2) Sensitivity 94.6% and Specificity 91.9%. 3) Significant improvement can be achieved by smoothing the score function | | | | | | | |
| [59] | – 21 adults<br>– 10 patients with COPD<br>– 11 patients with asthma | – Data was obtained from MARS database<br>– Tidal breathing with maximum airflow of 1.5 l/s<br>– Monophonic and polyphonic wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Trachea, axillae, lower lung base | 23 features calculated from the time-bi-frequency domain. All features obtained from monophonic and polyphonic wheezes within inspiratory and expiratory phases. Statistical analysis conducted to determine strength of features to differentiate asthma and COPD pathology | Asthma (2 severe, 6 moderate, 1 mild, 2 NA), COPD (2 very severe, 3 severe, 4 moderate, 1 NA) | Yes + flow meter | – No inference made to severity levels<br>– Validation of results not reported |
| Key findings: 1) For, full breath cycle – 22/23, inspiratory phase – 18/23 and expiratory phase – 22/23 features, individually showed significant statistical difference between asthma and COPD pathology. 2) Features obtained from high-order analysis can be used to differentiate asthma and COPD | | | | | | | |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| [25] | – 36 subjects<br>– 21 subjects self-recorded (age 15 ± 9)<br>– 15 subjects obtained from other sources (age 17 ± 11)<br>– 26 wheezy patients with asthma, CORP and pneumonia, bronchiolitis<br>– 10 normal subjects | – Data was self-recorded and obtained from other sources (CD + Books)<br>– Monophonic and polyphonic wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Trachea (self-recording), upper lung and lower lung base (data obtained from other sources) | Spectral dominance energy (spectral derivative) based feature selection with k-NN classifier for wheeze identification in four classes – normal, polyphonic wheeze, monophonic wheeze and stridor | Not reported | Yes + Physician (audio inspection of recordings) | – No inference made to the inspiratory and expiratory phases<br>– Uniform breathing maneuver in the combined sources of data could not be identified<br>– Validation of system not reported |
| Key findings: 1) Temporal-spectral features (spectral derivative) selected based on peak dominance in spectrogram. 2) The overall average accuracy for all types of respiratory sounds (normal, monophonic wheeze, polyphonic wheeze and stridor) on trachea and chest is 92.4 ± 2.9%. 3) Maximum overall accuracy obtained with k-NN classifier with k = 3 | | | | | | | |
| [70] | – 8 children (age 2.5 ± 1.87)<br>– All asthma patients | – Data was self-recorded<br>– Wheeze segments were validated by physician<br>– Validation method not reported | Trachea | Thresholds and coefficients of correlation for each 5s segments in the recordings were calculated through power spectrum obtained from FFT for wheeze identification | Mild to moderate asthma identified by physician | Not reported | – Breathing maneuver not reported<br>– Validation of system not reported<br>– System was validated using 21 breath sound samples (12 wheeze subjects and 11 normal subjects) obtained from other online sources |
| Key findings: 1) Respiratory spectrum correlation coefficient (RSACC) algorithm introduced to obtain the coefficients of correlation and thresholds. 2) Overall efficiency of system with testing set – sensitivity 88% and specificity 94%. 3) In the validation set, 11 out of 12 wheezing sounds were correctly classified as true positive | | | | | | | |
| [14] | – 9 subjects (total from all sources)<br>– 6 wheezy patients<br>– 3 normal subjects | – Data obtained from other sources (CD + Books)<br>– Wheeze segments were validated by expert using only audio inspection of recordings | Chest | Topological method with time delay embedding to capture harmonic behavior. Subsampling of point clouds conducted using maxmin and random function to obtain barcodes for wheeze identification | Not reported | Not reported | – Age range and pathology of subjects not reported<br>– Uniform breathing maneuver in the combined sources of data could not be identified<br>– Validation of system not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) Topological method using time-delay embedding introduced for wheeze detection. 2) Maxmin and random based subsampling used. 3) Accuracy of the system is 98.39% | | | | | | | |
| [28] | – 46 adult<br>– 24 with asthma<br>– 12 normal | – Data was self-recorded<br>– Wheeze segments were validated by physician<br>– Validation method not reported | Trachea | Pattern recognition using image processing conducted on spectrogram obtained from FFT. Features fed into a SVM classifier for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Breathing maneuver not reported<br>– Validation of system not reported |
| Key findings: 1) Overall efficiency of system – sensitivity 90.78%, specificity 93.47% and overall accuracy 92.11% | | | | | | | |
| [54] | – 10 children<br>– 5 with asthma (age 10.9 ± 2.1)<br>– 5 normal (age 12 ± 2.2) | – Data was self-recorded<br>– Validation of wheeze segments not reported | Trachea, oral cavity and lower lung base | FFT spectrum of recordings were compared between normal and asthma subjects for identification of wheeze spectral characteristics | Not reported | Not reported | – Breathing maneuver not reported<br>– Data also has been collected from upper airways<br>– Validation of system not reported |
| Key findings: 1) In asthmatic children, the harmonic amplitude of breath sound spectrum at the trachea increases to a frequency near 400 Hz. 2) In asthmatic children, the wheezing period ranges from 80 to 250 ms | | | | | | | |
| [15] | – 67 breathing sounds (total from all sources)<br>– 37 wheezy sounds<br>– 30 normal sounds | – Data obtained from other sources (CD + Books)<br>– Wheeze segments were validated by author using only audio inspection of recordings | Chest | Topological method with time delay embedding to capture harmonic behavior. Subsampling of point clouds conducted using density based function to obtain barcodes for wheeze identification | Not reported | Not reported | – Age range, number of subjects and pathology not reported<br>– Uniform breathing maneuver in the combined sources of data could not be identified<br>– Validation of system not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) Topological method using time-delay embedding introduced for wheeze detection. 2) Density based subsampling used. 3) Sensitivity of the system is 98.39% | | | | | | | |
| [10] | – 20 male (age 24) | – Data was self-recorded<br>– Validation of breathing cycles or wheeze segments not reported | Right upper interior chest wall | MFCC and k-mean for feature extraction and clustering coupled with k-NN classifier for classification in four classes – normal, wheeze and two other adventitious sounds | Not reported | Not reported | – Pathology of subjects not reported<br>– Breathing maneuver not reported<br>– Validation of system not reported |
| Key findings: 1) k-mean clustering improves the rate of identification of wheeze sound by 19.5%. 2) Rate of identification of wheeze sounds with k-mean clustering and k-nn classifier is 90.5% | | | | | | | |
| [67] | – 260 breath sounds (30% self- recorded and 60% from other sources)<br>– 130 wheezy sounds<br>– 130 normal sounds | – Data was self-recorded and obtained from other online sources<br>– Wheeze segments were validated by author using audio-visual inspection of recordings and spectrogram | Lower lung base | Audio spectral envelope (ASE) and tonal index (TI) feature extraction methods coupled with SVM classifier for wheeze identification in two classes – wheeze and non-wheeze | Mild to severe asthma identified by physician | Not reported | – Age range and number of subjects not reported<br>– Uniform breathing maneuver in the combined sources of data could not be identified<br>– No inference made to the severity levels<br>– Validation of system not reported |
| Key findings: 1) Fluctuations of audio spectrum were calculated by ASE using MPEG-7 audio standards and value of TI from MPEG-2 audio standards, respectively. 2) Accuracy of system reported at 93% | | | | | | | |
| [52] | – 30 subjects (total from all sources)<br>– 24 wheezy cycles<br>– 24 normal cycles<br>– 24 other adventitious sound cycles | – Data was obtained from RALE database and other online sources<br>– Validation of all types of cycle segmentation not reported | Trachea | Comparison of five systems from either LPCC, PLPCC (Perceptual LPCC), MFCC, LFCC (Linear frequency cepstral coefficients) or IMFCC (Inverted MFCC) feature extraction methods coupled with ANN classifier for classification in three classes – normal, wheeze and one other adventitious sound | Not reported | Not reported | – Age range and pathology of subjects not reported<br>– Uniform breathing maneuver in the combined sources of data could not be identified<br>– Validation of system not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) For all type of classifications, IMFCC shows worst results and MFCC shows best results. 2) Overall accuracy of system with MFCC is 97.20%. 3) Results of system for wheeze class sound with MFCC is – accuracy 95.83%, sensitivity 97.91% and specificity 95.83% | | | | | | | |
| [35] | – 36 total respiratory cycles<br>– 8 normal cycles<br>– 4 monophonic wheezy cycle<br>– 4 polyphonic wheezy cycle<br>– 20 other adventitious sounds cycle | – Data obtained from other sources (CD + Book)<br>– Segments were validated by physician<br>– Validation method not reported | Chest | High-order statistics (second, third and fourth order cumulants) used for feature extraction. Feature reduction done with genetic algorithm (GA) with the Fisher discriminat ratio (FDR). Features fed into k-NN for three class classification of normal, wheeze and one other adventitious sounds, and then 2nd stage Naive-Bayes (NB) classifier used to classify wheeze and adventitious sounds into four subclasses –monophonic, polyphonic wheeze and two other adventitious sound | Not reported | Not reported | – Age range, number of subjects and pathology not reported<br>– Limited number of cycles selected for five class (deepest level) classification<br>– Breathing maneuver not reported<br>– Validation of system not reported |
| Key findings: 1) Accuracy of system for wheeze (5 class level) – monophonic wheezes 91.9 ± 2.3% and polyphonic wheezes 90.3 ± 3.3% | | | | | | | |
| [8] | – 58 adults<br>– 32 patients (age 49 ± 21) with asthma<br>– 26 normal (age 34 ± 24) subjects | – Data was self-recorded<br>– Wheeze segments were validated by physician<br>– Validation method not reported | Trachea | Pattern recognition using image processing conducted on spectrogram obtained from FFT. Features fed into a BPNN classifier for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Breathing maneuver not reported<br>– Validation of system not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) System performance is sensitivity 94.6% and specificity 100% | | | | | | | |
| [32] | – 16 children<br>– All patients (age 1–6) with asthma, pneumonia and obstructive bronchitis | – Data was self-recorded<br>– Tidal breathing<br>– Wheeze segments were validated by physician using audio-visual inspection of recordings and spectrogram | Lower lung base | MFCC with two-layer SVM coarse-to-fine classifier for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Yes + physician (audio-visual inspection of recordings and spectrogram) | – Validation of system not reported |
| Key findings: 1) Two-layer SVM cascade classifier structure introduced to eliminate inspiratory stridor (false positives). 2) Two-layer SVM improves the classification results compared with those obtained with an ordinary SVM classifier. 3) Overall mean reliability of system 97.68% | | | | | | | |
| [30] | – 30 subjects<br>– All with asthma | – Data was self-recorded<br>– Validation of wheeze segments not reported | Upper and lower lung base | Performance evaluation of Hilbert spectrum (HS) and power spectrum by comparing error of several wheeze time-frequency parameters between recorded and synthetic signals | Not reported | Yes + flow meter | – Age range of subjects not reported<br>– Breathing maneuver not reported<br>– Analysis done only on inspiratory phase |
| Key findings: 1) HS time-frequency representation introduced for wheeze detection. 2) HS and spectrogram applied to both recorded and synthetic signals, and results obtained as: Mean frequency calculated 5% less then actual in spectrogram, and duration show error of 13% and 23% in HS and spectrogram, respectively | | | | | | | |
| [7] | – 18 adults<br>– 9 patients with asthma<br>– 9 normal subjects | – Data was self-recorded<br>– Wheeze segments were validated by physician<br>– Validation method not reported | Trachea | MFCC feature extraction and GMM classifier for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Age range of subjects not reported<br>– Breathing maneuver not reported<br>– Validation of system not reported |

**Table 1** (continued)

| Authors | Subject details | Data collection environment + ground truth identification | Data collection position(s)/point(s) | Method used for analysis and its purpose | Indication of the severity of bronchial obstruction | Indication of Inspiratory and Expiratory phase (Yes/No) + source of determination | Limitations/ observations |
|---|---|---|---|---|---|---|---|
| Key findings: 1) 21 MFCC and GMM combination gives the system performance as sensitivity 88.1% and specificity 99.51% | | | | | | | |
| [29] | – 30 subjects<br>– All asthma patients (age 45 ± 14) | – Shallow breathing to deepest breathing, (patients divided into four groups according to airflow)<br>– Wheeze segments were validated by physician using audio-visual inspection | Trachea, upper lung and lower lung base | Hilbert spectrum (HS) used to extracted instantaneous frequency (IF) and instantaneous envelope (IE) features coupled with SVM classifier for wheeze identification in two classes – wheeze and non-wheeze | Moderate to mild asthma patients with $FEV_{1(predicted)} = 63\%–97\%$ | Yes + flow meter | – Analysis done only on inspiratory phases<br>– No inference made to the severity levels of subjects<br>– Validation of system not reported |
| Key findings: 1) The perfomance of SVM classifier is independent of flow rate. 2) Overall performance of system is – Accuracy 94.6 ± 0.3%, sensitivity 94.2 ± 0.4% and specificity 95 ± 0.5% | | | | | | | |
| [6] | – 27 children<br>– All wheezy (age 1 day–12) | – Data was self-recorded<br>– Wheeze segments were validated by physician using only audio inspection of recordings | Mouth (No-contact) | Features extracted from power spectral density by autoregressive method and coupled with either SVM or logistic regression (LR) for wheeze identification in two classes – wheeze and non-wheeze | Not reported | Not reported | – Pathology of subjects not reported<br>– Data has been collected from upper airways<br>– Breathing maneuver not reported<br>– System was validated using 39 recordings |
| Key findings: 1) Overall performance of system with the SVM classifier on the validation set is sensitivity 71.4% and specificity 88.9%. 2) System shows better performance using the SVM classifier when compared to LR | | | | | | | |
| [27] | – 51 subjects (age 61.9 ± 24.7)<br>– 40 patients<br>– 11 normal subjects | – Data was self-recorded<br>– Wheeze segments were validated by physician<br>– Validation method not reported | Right upper interior chest wall | Spectral integration parameters, median frequency, peak frequency and bandwidth were calculated using power spectrum obtained by FFT for wheeze identification and parametric analysis | Not reported | Not reported | – Pathology of subjects not reported<br>– Breathing maneuver not reported<br>– Validation of system not reported |
| Key findings: 1) Spectral integration parameters introduced as possible features for wheeze identification. 2) Normal and wheeze sounds have shown statistical significant difference for all selected features except median frequency. 3) Overall performance of system is – sensitivity 91.5% and positive predictive values 100% | | | | | | | |

bell. This device was attached to the body through a wearable belt and data was transferred to a computer wirelessly. In [70], a diaphragm was attached to a polymer based soft chamber to transmit lung sounds through a microphone. The authors focused on designing a soft stethoscope for children that is small and flexible (non-rigid). In another study, Chen et al. [10] cut one section of a Y-shaped hose of a traditional stethoscope and placed a condenser microphone at this detached end which served as the output for recording signals.

Flow sensors (spirometers or pneumotachograph) have also been used by researchers to maintain constant air flow rate and to identify or determine the phases (inspiratory, expiratory) of a respiratory cycle. Simultaneous measurement and monitoring of air flow rate with respiratory sound data collection was observed in [16, 18, 23, 56]. Lung function values like force vital capacity (FVC), forced expiratory volume, $FEV_1$ and $FEV_1$% in 1 s and percentage, respectively in [16, 18, 23, 29, 37–40, 50, 56–59] have also been parameters of interest by researchers in the quest to observe or correlate wheeze with the degree of airway obstruction.

The aforementioned parameters have also been determined using a domestic deviceless approach [44]. Four studies [31, 36, 67, 70] indicated the severity of airway obstruction being determined solely by a physician. Similarly phases of respiratory cycles have also been segmented solely by physicians through an audio-visual inspection of the recorded respiratory sounds in [25, 32].

## Wheeze sound database

In the shortlisted studies, researchers have used recordings of respiratory sounds (wheezy and normal) from various sources such as, 1) databases – RALE [62], Marburg Respiratory Rounds (MARS) [21], ASTRA [2], 2) public internet data [1, 49, 67], 3) accompanying teaching and learning materials intended to train medical students in auscultation [65, 66, 69], and 4) self-collected data. RALE and MARS are two prominent databases. However, the RALE database is the only commercially available database for respiratory sound analysis. It comprises more than 50 recordings covering all age groups in healthy subjects and those with diseases. This database which is used to train medical students also provides information about respiratory patterns in young children [51]. In contrast, the MARS database is accompanied by lung function parameters and information on the respiratory phases, was only used by [57–59]. MARS consists of data that were collected according to the CORSA standards from mostly normal subjects and patients with asthma, COPD and pneumonia.

# Literature search results

## Wheeze detection or classification

### Logic-base algorithms

Wheeze detection involves the search for sets of peaks in the sound spectrum that meet the properties of wheezes. 11 articles [1, 16, 23, 31, 48, 53, 56, 58, 60, 64, 70] address the issue using logic-based algorithms. Generally, in this approach researchers attempt to smooth the spectrum, set threshold values and search for cluster(s) of peaks that meet some pre-defined criteria with the aim of increasing the accuracy, sensitivity and specificity of this process. Smoothing the spectrum generally focuses on window selection and averaging the periodogram. Thresholds are normally determined from the standard deviation of the peaks. A higher threshold value does not detect weak wheezes, and a lower threshold value detects false positives [48]. In addition, other criteria have been used by authors to characterize wheeze-like behavior, such as frequency >100 Hz, duration >100 ms, wheeze harmonics ≤4.

The algorithm developed by Shabtai-Musih et al. [53], detects wheezes by searching for peaks in the power spectrum that meet a set of defined rules. The authors applied their algorithm in an experiment where five healthy nonsmoking males performed forced expiratory vital capacity maneuvers. This algorithm used a logic-base threshold criteria (peaks defined as more than 3.5 times of the values normalized to the variance) and identified those peaks that formed a cluster (a set of nearby peaks) as wheezes, and separated them from the background [53]. However, the authors have not made any inference to the inspiratory and expiratory phases. Further, there was no mention of a minimum duration criteria applied to the determined clusters.

The study by Alic et al. [1], introduced a logic-based scoring algorithm to ensure the minimum wheeze duration criteria that includes a modification to the smoothing and threshold used in the algorithm developed by Shabtai-Musih et al. [53]. The resulting algorithm was applied to wheezy sounds of 26 asthmatic children amounting to seven from self-recordings and 19 obtained from RALE and online sources. Performance of the system for wheeze detection is given for recorded and online data separately – a) Recorded Data – 40 out of 43 true positive (TP), five out of seven doubtful (DB), and five false positive (FP) and

b) Online Data – true positive 22 out of 22, doubtful three out of three and four false positive [1]. It was noted that in this study, a uniform breathing maneuver could not be determined as the data used was obtained from various sources. Breathing maneuver plays a vital role in the characteristics of the generated wheeze [51] and should be considered in the data collection process.

Researchers of [23], developed a local adaptive wheeze detection algorithm (LAWDA) that introduces a grouping technique and a modification to the smoothing and threshold used in the algorithm developed by Shabtai-Musih et al. [53]. Wheezy sounds were collected from the trachea of 16 asthmatic patients, and normal sounds were obtained from 15 healthy (control) subjects. All subjects underwent forced respiratory maneuvers. The study focused on the exhalation airflow interval of 1.2–0.2 l/s. All wheeze segments were validated by a physician. After the initial peaks search, the algorithm attempts to group each peak with other nearest peaks by eliminating those with duration less than 80 ms and only accepting peaks more than 100 Hz. The LAWDA exhibits a sensitivity (%) of 100, 87 and 71 with airflow rates of 1.2–0.4 l/s, 0.4–0.2 l/s and 0.2–0.0 l/s, respectively. Sensitivity of algorithm was found to be highest at maximum flow rate attained in the expiratory phase and vice-versa. However, this study only considered the expiratory phase in the analysis.

Another study [58], developed a time-frequency wheeze detection algorithm (TF-WD) that introduces a peak coexistence criterion, i.e. the number of peaks at the same instance should not be greater than four. This algorithm was used in a pilot study consisting of 13 wheezing patients with COPD, asthma and pneumonia. The data from three patients (one with COPD, one with asthma and one with pneumonia) were used to select appropriate threshold for algorithm (training), and the data from 10 patients were used for analysis (testing) of the algorithm. The time-frequency representation was obtained by short time fourier transform (STFT) of the magnitude (dB) spectrum. A smoothing procedure was performed using box filtering (average or mean filter). For threshold setting, the frequency band between 100 and 1000 Hz was divided into four sub-bands (100–300, 300–500, 500–800, 800–1000), and the magnitude threshold for each band was determined. A pre-defined duration of 150 ms was used to characterize wheeze. Those identified peaks meeting all the other criteria were defined as wheezes, and all other non-wheezing peaks were discarded [58].

The TF-WD algorithm exhibits a performance with a total detectability rate (TDR, %) of 99.7% ± 1, a sensitivity (SE, %) of 95.5 ± 4.8 and a specificity (SP, %) of 93.7 ± 9.3. The robustness of this algorithm to noise, its accuracy and low computational complexity has been reported [58]. This work can be improved by increasing the number of frequency subbands, changing the wheeze duration criteria from 150 ms to 100 ms as per CORSA standards [55]. It was observed that only three subjects with different pathologies were engaged for setting the threshold, so this work can be improved by recruiting more subjects for the determination of threshold.

## Machine learning algorithms

Machine learning algorithm is the technique of feature extraction, learning a pattern through training a network and classification. Feature extraction involves the selection of essential characteristics from data which plays the major role in classification. For wheeze detection and classification, it has been observed now that the trend has changed over to machine learning from logic-base algorithms. Sixteen articles [2–8, 10, 25, 28, 29, 32, 35, 49, 52, 67] are related to machine learning algorithms.

One author, classified respiratory sounds into normal and wheeze categories using different feature extraction methods and classifiers. In articles [2–5], data from 12 wheezing subjects and 12 normal subjects were used for analysis. Bahoura and Pelletier [3] applied spectral analysis to wheezy sounds. Features were extracted from the energy spectrum using 20 coefficients obtained using Mel frequency cepstrum coefficient (MFCC) and classified using the vector quantization (VQ) approach. For comparison, the same data was analyzed using other feature extraction methods obtained by other researchers – 26 coefficients obtained using the fast fourier transform (FFT) algorithm, 20 coefficients obtained using linear prediction coding (LPC), 14 coefficients obtained through wavelet packet decomposition (WPD) and 24 coefficients obtained through the analysis of sub-band based cepstral parameters (SBC). A maximum performance of 77.5% for wheezing sounds was obtained with MFCC, and a maximum performance of 90.6% for normal sounds was obtained with FFT [3].

The algorithm developed by Bahoura [2], used breath sounds that was self-collected and obtained from RALE and ASTRA databases. Wheezes were segmented manually using Adobe Audition software through audio-visual inspection of spectrogram and recordings [2]. A total of 17 classifier systems were obtained through the combination of three classification techniques and four feature extraction methods [2]. Features were extracted from the data using STFT, auto-regressive (AR), MFCC, wavelet transform (WT) and wavelet packet transform (WPT) algorithms. The authors obtained the feature vectors from the power spectra, mean square prediction errors, amplitude spectra and energy bands. The finalized feature vector was then used in the learning, training and classification using the following supervised classifiers – vector quantization (VQ), Gaussian mixture model (GMM) and artificial neural network (ANN). It was observed that a maximum specificity of 91.9% and a sensitivity of 94.6% were obtained through the combination of MFCC and GMM [2]. This conclusion was also observed in the other similar works by [4, 5] albeit using various other features and classifiers. We have noted that in all of these works, the collected data did not receive any assistance or involve physicians. To the best of our knowledge, neither the segmentation nor classification results were validated by a physician. Further the subjects' age group which is considered important [19, 20] was not reported. No information on a uniform breathing maneuver could be identified.

The work by Sengupta et al. [52], used 72 samples from RALE database and other online sources (obtained from 30 subjects). A total of five classification systems were investigated through the combination of five individual feature extraction methods coupled with an ANN classifier. Features were extracted through linear prediction cepstral coefficients (LPCC), Perceptual LPCC (PLPCC), MFCC, Linear frequency cepstral coefficients (LFCC) and Inverted MFCC (IMFCC). The developed system gave the best performance for MFCC and worst performance for IMFCC for a two class classification (wheeze and other sounds). Results of system for wheeze sound with MFCC are sensitivity 97.91%, accuracy 95.83%, and specificity 95.83%. Similarly another study [10] extracted features through 13, 26 and 39 MFCC and applied the k-mean approach for feature clustering and a k-NN network for classification. Lung sounds of 20 males were collected through a custom made device. Rate of identification for wheeze sounds was observed at 90.5%. Both of these studies [10, 52] show good results with MFCC for classification for wheeze and other sounds. It has been observed that these studies have not provided certain important information, e.g. pathology of subjects, breathing maneuver and validation of breathing cycles segments.

The study by Mazić et al. [32], classified breath sounds into the wheeze and non-wheezes (inspiration, expiration, inspiratory stridor, expiratory stridor and snore) using a two-layer coarse-to-fine classification method. Wheezy sounds were collected from a single position on the lower lobe of the lungs in 16 children. For feature extraction, the respiratory sounds were first segmented by a physician using audio-visual inspection of the recordings and spectrogram. Eight to 12 MFCC features were extracted from the energy distribution. The author claimed that wheeze and stridor sounds have the same psychoacoustic and spectral properties. Thus, a cascaded classifier was used to distinguish wheeze types and thus eliminate false positive (stridor) detection. The first layer classifies respiratory sounds into wheeze and non-wheeze sounds. The second layer applied digital threshold to ensure at least five segments out of 10 consecutive segments should be classified as a wheeze. An overall classification of wheeze is only achieved if the outcomes are positive at both the layers. The overall mean reliability of the algorithm was reported as 97.68% [32]. Similarly, Bokov et al. [6], recorded respiratory sound from 27 wheezy children near the mouth (5–10 cm away) using a smartphone. Features were extracted using the autoregressive method on the power spectral density and fed into a SVM classifier. The system produced a sensitivity of 71.4% and specificity of 88.9%. It was observed that the authors in [6, 32] claimed that these algorithms are only suitable for children. Nevertheless, the wheeze sounds were collected from multiple pathologies in [6, 32] suggesting robustness of the algorithm to different diseases. However in Bokov et al. [6], breathing maneuver of subjects was not reported and data was collected using a smartphone near the mouth (non-contact) on patients in the emergency department. These circumstances probably dictate the observed out-of-practise procedures (as per CORSA standards) applied.

The study [25] introduces a feature extraction method based on temporal-spectral dominance. Breath sounds of 36 subjects was self-collected and obtained from CDs and books. The features were computed using the derivative of the spectrum to observe the dominant energy in the spectrum. A k-nearest neighbor (k-NN) classifier was used to separate normal, stridor, monophonic wheeze and polyphonic wheeze respiratory sounds. Overall accuracy for the four class classification with $k=3$ in the k-NN classifier was obtained as $92.4 \pm 2.9\%$ [25]. No information on a uniform breathing maneuver could be identified.

The article by Lozano et al. [29], introduced the ensemble empirical mode decomposition (EMMD) method to calculate a time-frequency representation to obtain the Hilbert spectrum (HS). Data was collected from 30 asthmatic patients. Instantaneous frequency and instantaneous envelope features were calculated and later classified using an SVM classifier into normal and wheeze sounds. Overall performance of system was reported as accuracy of $94.6 \pm 0.3$, sensitivity of $94.2 \pm 0.4$ and specificity of 99.51% [29]. It was noted that in this study, the wheeze segments were collected only from the inspiratory phase and was validated using audio-visual inspection by a physician.

#### Topological method

Two studies are related to topological methods [14, 15] for wheeze detection. Two studies [14, 15], introduced a new approach for wheeze detection. In this method, time-delay embedding is used to transform the digital signal to point clouds and extract its periodic behavior. Then, a topological approach is used to obtain barcodes for wheeze and non-wheeze signals. To improve efficiency and computational complexity of the system, random and maxmin algorithms are applied for point clouds sub-sampling and significant barcodes determined to differentiate barcodes of wheeze and non-wheeze signals. A 98.39% accuracy of system has been reported for this system [14]. Similarly, in another study, density base sub-sampling was done and significant barcodes were identified for the detection of wheeze signals. Sensitivity of this system has been reported as 98.39% [15]. However, in both these works, the authors did not mention the age range, subject group, breathing maneuver and the pathology related to the selected samples or subjects.

From our observations, only these two studies have used the topological method which transforms the raw-signal to point clouds then applies a topological method to differentiate wheeze and non-wheeze sounds. While most other researchers have worked in time-frequency and related domains to extract characteristics and features, an extension of this in the topological domain has been demonstrated by generating barcodes as features and distance measurements as discriminators.

## Wheeze characterization

### Determination of spectral parameters

The article by Fiz et al. [18] collected wheezy sounds from 22 asthmatic and COPD, and 15 normal subjects during forced respiratory maneuvers. Wheezes were detected using the algorithm developed by Shabtai-Musih et al. [53], with some modifications to the identification and grouping procedures. Validation of wheeze segments was done by a physician through audio inspection of the recordings. Statistical analysis using average three expiration phases was conducted on mean frequency of wheeze, number of wheezes detected and the percentage of duration of monophonic wheezes, polyphonic wheezes and non-wheezes [18]. These parameters were calculated to determine whether the wheezes of normal subjects and patients present different behaviors and the results reveal that the numbers of wheezes vary among patients and healthy subjects. Further, the mean frequency of wheezes is higher in normal subjects than obtained in patients. No significant difference was observed on the other measured parameters between the two groups. Similarly another study [27], performed an analysis of parameters on wheeze segments. Spectral features such as peak frequency, median frequency, bandwidth and, normalized and non-normalized spectral integration parameters for frequency bands 0–250 Hz, 250–500 Hz and 500–1000 Hz. Normalization was done with respect to frequency band 0–1000 Hz. These parameters were calculated to investigate the behavior of normal and wheeze sounds. The results revealed that normal and wheeze sounds showed significant statistical difference for all selected features except median frequency.

The article by Taplidou and Hadjileontiadis [57] estimated the nonlinear behavior of wheezes generated by asthmatic patients. The combination of wavelet transform with third-order statistics/spectra was used to characterize the nonlinear behavior (quadrature phase-coupling) in the inspiratory and expiratory phases of asthma patients. Results reveals that quadrature phase-coupling is predominantly present in expiratory wheezes than in inspiratory wheezes [57]. Results published by the study conclude that the wheezes in the inspiratory and expiratory phases of asthmatic patients are different.

The article by Taplidou and Hadjileontiadis [59] collected wheezy sounds from adults, specifically 10 COPD patients and 11 asthmatic patients, to analyze the nonlinear behavior of wheezes using 23 features calculated by continuous wavelet transform (CWT) with higher-order statistics. The frequency behavior of monophonic and polyphonic wheezes was investigated during the total breathing cycle, and the inspiratory and expiratory phases. The wheezes were segmented by two experts and categorized as polyphonic or monophonic by an audio-visual inspection of the spectrogram. Statistical analysis was performed to observe the association of wheezes between COPD and asthma. The analysis concludes that the majority of selected features, shows significant difference in discriminating wheeze in asthma and COPD patients during the total breathing cycles and the expiratory and inspiratory phases [59].

### Correlation of airway obstruction and spectra

Two studies [36, 50] have recorded prolonged tracheal breath sounds from one female [36] and 60 children [50] with tidal breathing and segmented full breath cycles. Subjects had asthma as pathology and their severity level was identified by a physician. A three class classification was performed by Oud [36]. The results in this study reveal that normalization of the power spectrum influenced the discriminatory power of the classifiers (ANN and k-NN). In Rietveld et al. [50], a comparison was done between humans and artificial intelligence (AI) classifiers in detecting features according to the level of obstruction from a bar graph spectrogram of breathing cycles. It was found that AI classifiers performed better than humans.

In contrast, asthma in other studies [37–40] was induced through the inhalation of dust mite allergen in two to three sessions. Respiratory sounds were collected during forced respiratory maneuver. At appropriate intervals (16 of them), the change in $FEV_1$ values were recorded. The trachea sound samples were recorded at approximately the same time the $FEV_1$ values were measured. Data was collected from 10 asthmatic subjects [37, 40], one male [39] and one female and one male [38]. In these studies, parameters of sound spectra for a full breath cycle (which contained wheeze) was interpolated to $FEV_1$ values.

The article by Oud et al. [40] calculated the power spectrum by Welch spectra and discrete Fourier transform (DFT) with different bin widths, and then normalized the spectrum using a Cox-Box transformation. Interpolation of sound spectra was then done using the k-NN classifier. Sound spectra were classified according to the degree of airway obstruction ($FEV_1$). The overall accuracy of classification of sound spectra for a full breath cycle (which contained wheeze) with either DFT or Welch spectra was 61%–87% according to the 16 $FEV_1$ values [40]. Results of these studies show that, classification of a sound spectrum according to severity, based on full spectral information is meaningful and feasible.

Another work [37] calculated the power spectrum of a full breath cycle with Welch spectra (59 Hz resolution), then normalized it using a Cox-Box transformation and applied principal component analysis (PCA) to reduce the number of components. Neural network was used for interpolation between parameters of sound spectra and $FEV_1$ values. The interpolation produced scores which ranged from $(26\pm2)\%$ to $(80.1\pm0.8)\%$ [37]. These results indicate a strong relationship between the lung function ($FEV_1$) and sound spectra.

## Discussion

The literature reveals that initially researchers observed peaks in breath sounds for wheeze detection using different techniques. These include finding peaks in time-expanded waveforms or spectra or a combination of both. Generally, this is done by applying rules and criteria based on amplitude, frequency and duration. However, it was noted that these techniques are dependent on the amplitude of the sound signal which inevitably led researchers towards detectors that were invariant to sound attenuation.

Recent studies suggest that the trend for wheeze detection is changing towards machine learning techniques from logic-based algorithms for wheeze sound analysis. From the literature, it can be noticed that very limited number of classifiers has been tested-out for wheeze classification and analysis. Future work can focus on other combinations of classifiers which has been experimented and investigated for other adventurous sounds in [41–43].

Studies on wheeze characteristics have shown that high-order statistics or spectra analysis can quantify and discriminate the nonlinear behavior of wheeze in the expiratory and inspiratory phases. It also has been noticed that analysis of full breath cycles and its subgroups, according to phase (inspiration, expiration) and frequency (monophonic and polyphonic), provide statistical evidence to differentiate wheeze in asthma and COPD pathologies. While it is known that wheeze manifests in a number of diseases like asthma, COPD, pneumonia, etc., discriminating them has only been observed in works conducted on asthma and COPD. Clearly, there is a need to explore the behavior of wheeze related to all other pathologies. This can be possibly done using combinations of sets of features obtained from the subgroups of breath cycle to explore novel facts about the underlying pathologies, lung physiology and patient condition.

Results of works related to correlation of airway obstruction and spectra shows that $FEV_1$ has strong relation to sound spectra. These studies reveal that airway obstruction can be deduced from computer-based respiratory sound analysis, but still remains an open area for research. In these studies, data was collected from asthma patients (some induced and others not induced) with force respiratory maneuvers and sound spectrum has been interpolated to 16 $FEV_1$ values, estimated at different intervals. It is well known that wheeze can also be produced in normal subjects with forced breathing [18, 23, 53] which shows that during forced exhalation wheeze is not always related to airway obstruction [17]. So, there is a need to implement system which can identify levels of airway obstruction with tidal breathing. This can help in the management and treatment of patients which requires the knowledge of severity condition of the patient [34, 61]. Such works are not available in the literature yet.

In the context of breathing maneuvers, CORSA standard has suggested two breathing maneuvers – tidal breathing and forced expiratory maneuver for data collection [51]. Breathing maneuvers is an important issue. Twenty-one out of 41 studies have not reported breathing maneuvers in their work. Also, the respiratory physiology of children and adults are different indicating that the generated sound behavior may also be diverse [19, 20]. It should be noted that change in physiology cannot be totally ignored within age groups. Hence, the selection of age group is also an important issue. Our search results indicate that 13 studies have not reported the age range of subjects and one study [49] selected a wide range, from newborn to 70 years of age. We believe that appropriate attention should be given to the selected population (subject group) and sample size. However, our findings reveal that most of the studies have collected data from a small number of subjects or subsequently worked with little data.

Another issue concerning data collection of breath sounds is the need for additional parameters, and the moment and duration of recording. The already existing devices, such as spirometers and peak expiratory flow meters used during forced respiratory maneuvers cannot be used during sleeping or long-term analysis [32]. This is another area that needs more exploration for wheeze related pathologies. It has been investigated that in the field of computer-based wheeze sound analysis, there is still a requirement to define breath sound characteristics to measure acuteness of the patient with normal or tidal breathing. In section “Correlation of airway obstruction and spectra”, only asthmatic patients have been discussed. So there is also need to explore degree of obstruction for COPD and other related pathologies.

Sensor selection for reliable data collection is also an important issue in this field. Two type of sensors – air-coupled or contact sensors (accelerometers or piezoelectric) are observed to be used to acquire lung sounds in the literature. For appropriate selection of sensors, its signal-to-noise ratio (SNR) is an important issue and it has been concluded that there is no difference in the SNR of both type of sensors [45]. But the flatness in the frequency response of air-coupled microphones is affected by width, depth and shape of chamber as revealed in [26, 68]. These works mention that frequencies less than 500 Hz are not affected by the depth of chamber and the recommended coupler size is of conical shape at 10–15 mm diameter and 2.5–5 mm depth. Air-coupled sensors also have the vent option for proper propagation of vibrations, but this adds ambient noise into the microphone chamber. On the other hand, contact sensors are directly attached to the skin so they are free from any type of distortion arising from the coupling chamber [63].

There are a few issues that must be looked into during data collection. One of the important matters is that the sensor should be preferably in contact at the location of acquisition. In one study [6], data was collected from near the mouth through a non-contact method which was susceptible to noise (20% of data was rejected due to poor SNR). While the results were satisfactory, the applied procedure is generally not aligned to the practices of a physician. As data collection can be time consuming, sensor attachment techniques should be pain free and not cumbersome. The literature reveals that most sensors are directly attached to the surface using constant pressure or adhesive tapes. In [27], the author has used a large sized belt to attach the sensor to the body for short-term recording, which may cause irritation to patients. It is also advisable that the data collecting environment should provide high SNR. This was observed in a majority of works in the literature where recordings were done in spaces with low ambient noise. Data collection posture is also important. While CORSA recommends the sitting posture for short-term recording, this may not be possible all the time in infants and children or for long-term recordings. In these situations, there is a need to develop devices that can capture data from subjects on a long-term basis without continuous assistance from medical personnel. For long-term data collection, we recommend that the sensor should be compact in size, low weight and with small contact area.

An important issue concerns the severity of the pathology. Seventeen studies (Table 1) reported the severity of airway obstruction of the selected subjects. However, the results in seven studies did not make any inference to the severity level. The remaining 10 studies referred to the severity level, in particular two studies [16, 18] mention that the percentage of wheeze increases with the severity level. However, these studies only covered moderate to severe airway obstruction, and the number of subjects and the obtained samples related to those severity levels were limited for analysis.

It can be seen from Table 1 that out of the 41 selected studies, 20 studies collected data from only the trachea, three studies from the chest (exact location unknown), three studies from the lower lung base, one from the upper and lower lung base, two from the right upper chest anterior, one from near the mouth and 11 studies from the trachea and different combinations of lower lung base, axilla or upper lung lobe and one study from the upper and lower lung base. Trachea and lower lung base are the positions selected by 96% of the authors for wheeze data collection. Hence, it can be deduced from the literature that the trachea and lower lung base are the most frequently chosen positions for wheeze sound data collection. These positions are optimal for the recording of high frequencies (wheezes) with maximum possible information about the underlying pathologies and conditions of the patients. For the implementation and validation of a meaningful real-time computer-based system, it is recommended that as much as possible, reliable and valid data be initially collected and thereafter used in the development and testing stages.

The validation process is also an important issue to be looked into to ensure reliability of the results and repeatability of the experiment. Two important areas of validation include the source of data (breath sounds, respiratory phases, wheeze segments, etc.) and the developed system. Our observation from the literature indicates that wheeze segments are often validated by audio-visual inspection of recordings and spectrogram by a physician, an expert or the authors themselves. Twelve studies have not reported the source of validation of the wheeze segments or breathing cycles. It can be noticed from the literature that so far most systems have not been validated. Results obtained from an initial sample using a developed system should be tested recursively on other samples (obtained from the same population and of similar size) to measure reliability and repeatability.

## Conclusion

This study provides an in-depth analysis of computer-based techniques used for wheeze sound analysis in the last 20 years or so. Looking at the increasing number of articles, it can be deduced that research in this area is gaining momentum. The present review reveals that wheeze detection has shifted from logic-base algorithms towards machine learning techniques. Our search results also reveal that most researchers conform to the location for data collection as recommended by CORSA, which is the trachea and lower lung base. However, the present review indicates that limited studies have concentrated on issues related to severity levels of airway obstruction. Currently, this measure is estimated from the lung function values ($FEV_1$, $FEV_1\%$) which are obtained using flow sensors and with forced respiratory maneuvers. Several studies reveal that severity levels of airway obstruction can be deduced using sound spectra analysis. Nevertheless, additional work is still needed to identify wheeze spectral behavior for various levels of airway obstruction. While wheeze manifests in a number of diseases, the current literature shows that significant differences in behavior has only been discovered for COPD and asthma. Hence, there is a need to explore and identify wheeze behavior for those other related pathologies and further extend the characterization to their corresponding levels of airway obstruction. With regards to this, some preliminary results have been obtained by using full breath cycles and its subgroups to extract features, from the group, or a combination of them, from the subgroups, for analysis.

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