Available online at www.sciencedirect.com

SciVerse ScienceDirect

journal homepage: www.elsevier.com/locate/bbe

Original research article

Machine learning in lung sound analysis: A systematic review

Rajkumar Palaniappan*, Kenneth Sundaraj, Nizam Uddin Ahamed

AI-Rehab Research Group, Universiti Malaysia Perlis (UniMAP), Kampus Pauh Putra, Perlis, Malaysia

ARTICLE INFO

Article history:
Received 10 September 2012
Accepted 19 November 2012
Available online 9 July 2013

Keywords:
Review
Lung sound
Lung disorder
Statistical
Machine learning

ABSTRACT

Machine learning has proven to be an effective technique in recent years and machine learning algorithms have been successfully used in a large number of applications. The development of computerized lung sound analysis has attracted many researchers in recent years, which has led to the implementation of machine learning algorithms for the diagnosis of lung sound. This paper highlights the importance of machine learning in computer-based lung sound analysis. Articles on computer-based lung sound analysis using machine learning techniques were identified through searches of electronic resources, such as the IEEE, Springer, Elsevier, PubMed and ACM digital library databases. A brief description of the types of lung sounds and their characteristics is provided. In this review, we examined specific lung sounds/disorders, the number of subjects, the signal processing and classification methods and the outcome of the analyses of lung sounds using machine learning methods that have been performed by previous researchers. A brief description on the previous works is thus included. In conclusion, the review provides recommendations for further improvements.

1. Introduction

Auscultation, which is the processes of listening to the internal sounds in the human body by using a stethoscope [1], has been an effective tool for the diagnosis of lung disorders and abnormalities for a number of years now. This process mainly relies on the physician. Thus, a professionally well-trained physician is required to recognize lung abnormalities and disorders using this process. The possibility of untrained physicians incorrectly recognizing abnormalities, which can be due to not calibrating the instrument and/or due to noisy environment, is very high using this method [2] and has thus led to the development of computerized lung sound analysis systems. Computerized lung sound analysis, which started to be found in the literature in the early 1980s, serves as a reliable tool for the diagnoses of lung abnormalities and disorders [3]. Several techniques have been implemented for recognizing lung disorders and abnormalities. However, lung sound analysis continues to attract researchers because past researchers focused on identifying lung sounds and very few researchers concentrated on developing lung disorder diagnostic tools. Therefore, this research area appears incomplete and has thus attracted many researchers in recent years. Machine learning algorithms are currently used in many applications. Machine learning algorithms possess artificial intelligence that learns from past experiences, which allow the tools to function more accurately [4,5]. This review briefly discusses the types and characteristics of lung sounds and their associated disorders. In addition, the previous research on computer-based lung sound analysis using machine learning algorithms, such as artificial neural

* *Corresponding author at*: AI-Rehab Research Group, Universiti Malaysia Perlis (UniMAP), Kampus Pauh Putra, Perlis, Malaysia.
E-mail address: prkmect@gmail.com (R. Palaniappan).

0208-5216/$ – see front matter © 2013 Nałęcz Institute of Biocybernetics and Biomedical Engineering. Published by Elsevier Urban & Partner Sp. z o.o. All rights reserved.
http://dx.doi.org/10.1016/j.bbe.2013.07.001

networks (ANNs), the hidden Markov model (HMM), *k*-nearest neighbor (*k*-nn) algorithm, Gaussian mixture model (GMM), genetic algorithms (GAs), and fuzzy logic, will be discussed. The next section discusses the types and characteristics of lung sounds and their associated disorders followed by the methodology and the overview of the literature search. The overview of the literature is further divided into four section namely, Instrumentation for Lung Sound Recording, Lung sound databases, Methods for Feature Extraction, and Methods for Classification. Finally, a discussion is carried out from the literature search results followed by the conclusion.

2. Characteristics of lung sounds

The lung sounds that are heard over the chest wall are caused by the airflow in the lungs during the inspiration and expiration phases. These sounds are non-stationary and non-linear signals, which make it difficult for physicians to recognize any abnormalities [6]. The types and characteristics of lung sounds are listed in Fig. 1 [1,2,7–12]. Each lung disorder is associated with one or more lung sounds [2,6]. The disorders that are associated with each sound are also detailed in Fig. 1. The dominant frequency of heart sounds is typically below 150 Hz, whereas the dominant frequency of lung sounds ranges between 150 and 2000 Hz. This difference in the frequencies makes it easier to filter the heart sounds from the lung sounds. The durations of the different types of lung sounds are also mentioned in Fig. 1.

3. Methodology

Any relevant articles were initially identified from searches of various electronic resources, such as IEEE, Springer, Elsevier, PubMed and ACM digital library databases. During the initial search, the keyword "lung sound analysis" was used and enormous number of articles where found. Another search was carried out within the previous search using the keyword "lung sound classification" which returned 169 articles. A selection criterion was finalized and every article was selected according to the selection criteria from the 169 articles. The selection criterion are (i) lung sound analysis, (ii) machine learning techniques in lung sound analysis, (iii) articles in English, (iv) duplicate articles were excluded, and (v) articles highlighting only the medical perspective of the lungs were excluded. A total of 169 articles were obtained from the initial search. Out of these 169 articles, 119 articles were excluded after a review of the title and the abstract of the articles. The remaining articles were studied in their entirety and 16 additional articles were excluded due to the lack of sufficient information provided in the text. A total of 34 articles, which satisfied all of the selection criteria, were included in the final selection of articles. Fig. 2 shows the flow chart of selection criteria.

4. Overview of the literature search

A brief overview of the 34 articles that satisfied the selection criteria is tabulated in Table 1. This overview provides

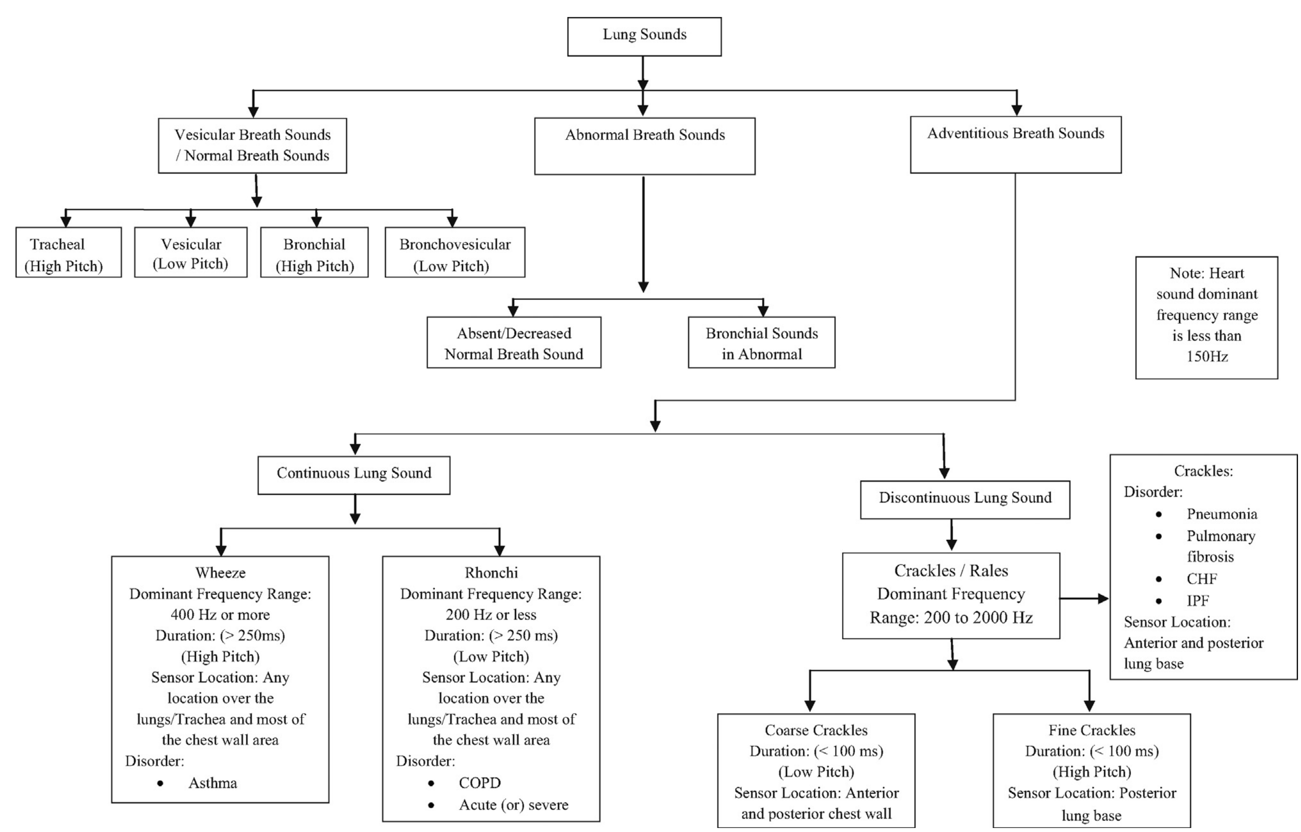

Fig. 1 – Characteristics of lung sounds.

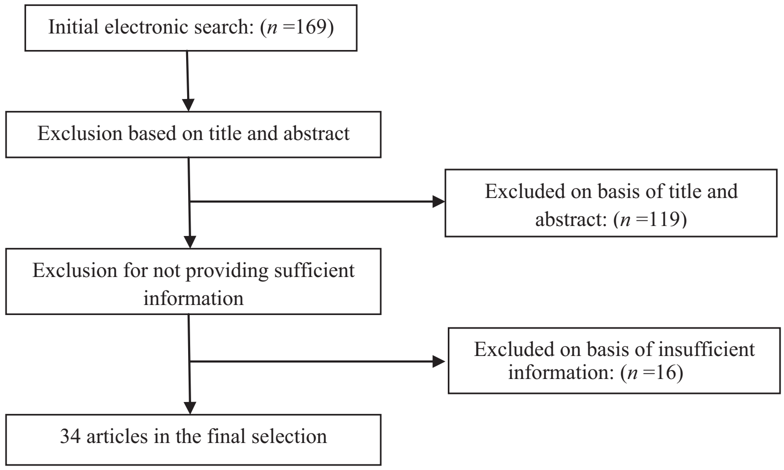

Fig. 2 – Flow chart of selection criteria.

Table 1 – Machine learning in computer based lung sound analysis systems.

Reference	Analyzed: sound/disorder	Sensor type	Number of subjects (n)	Real time (yes or no)	Method	Outcome
[36]	Lung sounds	Electret microphone (ECM44, Sony)	n = 69	No	k-nn classifier and quadratic classifier	The classification accuracies using k-nn and quadratic classifiers were 93.75% and 87.50%, respectively. Sensitivity and specificity were 100% and 71.4% respectively.
[37]	Wheeze and normal	Eight channel microphone	Not mentioned	No	ANN	The classification accuracies obtained using radial basis function networks with the training sets 1 and 2 were 93% and 96%, respectively.
[24]	Normal and pathology	Electret microphone (ECM140, Sony)	n = 69	No	k-nn	The overall classification accuracy was reported as 69.59%
[38]	Normal, wheeze and crackles	Electret microphone	n = 60	No	ANN	Classification accuracy of 95% was reported.
[39]	Airway obstructions in asthmatic patients	Electret microphone	n = 10	No	k-nn	Approximately 60% to 90% of the sounds where classified accurately using the k-nn classifier.
[40]	Normal and pathological	2 microphones (LS-60 Adult Precordial Sensors)	n = 17	No	ANN	The classification rate was 73%. This rate was 91% for the training tapes. Sensitivity and specificity were 87% and 95% respectively.
[41]	Normal and pathological	Electret microphone	Not mentioned	Yes	k-nn	Encouraging results were reported.
[42]	Wheeze and non-wheeze	Electret microphone	n = 24	No	Vector quantification	The classification accuracies for wheeze and non-wheeze were 75.80% and 77.50%, respectively.
[43]	Normal and pathological	Electret microphone	n = 20	No	Nearest mean classifier	The results obtained were satisfactory.
[22]	Normal and wheeze	Electret microphone	n = 24	No	GMM	The classification accuracy was improved using this technique compared to vector quantification and multilayer perceptron neural network.
[6]	Normal, wheeze, crackle, squawk, stridor, and rhonchus	Electret microphone	Not mentioned	No	ANN	A classification accuracy of 100% was obtained for the training set. A classification accuracy of 94.02% was obtained for the validation set.

Table 1 (*Continued*)

Reference	Analyzed: sound/disorder	Sensor type	Number of subjects (n)	Real time (yes or no)	Method	Outcome
[44]	Lung sounds	Electret microphone	Not mentioned	No	ANN	Classification accuracy of 97.8% was reported. Sensitivity and specificity were 97.8% and 89.6% respectively.
[45]	Lung sounds	Stethoscope, Acoustic analysis – sensor (Siemens EMT 25C)	$n = 8$	No	k-nn	A satisfactory classification accuracy was reported.
[33]	Normal, wheeze and crackles	Electret microphone	$n = 129$	No	ANN and GA based ANN	Classification accuracies of 81–91% and 83–93% were obtained using ANN and GA-based ANN, respectively.
[46]	Normal and abnormal lung sounds	Electret microphone	$n = 19$	No	ANN	A 87.68% classification accuracy was reported. Sensitivity and specificity were 81.36% and 83.64% respectively.
[47]	Wheeze	Electret microphone ECM-KEC-2738	$n = 30$	No	GMM	Classification accuracy of 90% was reported.
[23]	Fine and coarse crackles	Electret microphone	Not mentioned	No	GMM	95.1% classification accuracy was reported. Sensitivity and specificity were 95.6% and 63.3% respectively.
[48]	Lung sounds	2 ECM-77B microphone	Not mentioned	No	k-means clustering algorithm	The similarities between the lung sounds at short intervals were detected at a precession of 0.9711.
[30]	Normal and abnormal lung sounds	2 ECM-77B microphone	$n = 42$	Yes	k-nn and minimum distance classifier	The real-time implementation yielded 96% classification accuracy in the clinical trials. Sensitivity and specificity were 92% and 100% respectively.
[49]	Normal respiratory and abnormal respiratory sounds	Electronic stethoscope incorporating a piezoelectric microphone and condenser microphone	$n = 114$	No	HMM	The proposed method yields a classification rate that is 19.1% higher than previous methods that have been used.
[50]	Lung sounds	Electret microphone	$n = 24$	No	GMM	Sensitivity and specificity were reported to be 94.6% and 91.9% respectively.
[51]	Adventitious lung sounds	2 ECM-77B Electret microphone	Not mentioned	No	ANN	The classification using an incremental supervised neural network model gave improved results compared to the other conventional neural network models.
[19]	Wheeze	Electret microphone (ECM140, Sony)	Not mentioned	No	ANN	A 92.86% classification accuracy was obtained.
[52]	Normal and adventitious lung sounds	Electret microphone (ECM140, Sony)	Not mentioned	No	ANN	A classification accuracy of 92.36% was obtained.
[53]	Normal, crackles, and wheeze	2 ECM-77B Electret microphone	$n = 50$	No	GMM	A 98.75% accuracy was obtained for the reference library and 52.5% accuracy was obtained using the cross validation method.
[20]	Normal, wheeze and crackles	Electret microphone (ECM140, Sony)	$n = 279$	No	ANN	Confidence levels of 0.90, 0.87 and 0.89 were reported for normal, wheeze and crackles, respectively.
[54]	Asthma severity	Electronic stethoscope	$n = 28$	No	Fuzzy logic	The developed fuzzy expert system provided satisfactory results.
[21]	Lung sounds	2 ECM-77B Electret microphone	$n = 20$	No	k-means clustering algorithm	Accuracies of 98.2% and 95.5% were obtained for the tracheal recordings and the sounds recorded by an ambient microphone, respectively. Sensitivity and specificity were reported to be 98.2% and 95.2% respectively.
[55]	Normal and abnormal lung sound	25 acoustic sensors (Electret microphones)	$n = 27$	No	ANN	Classification accuracies of 75% and 93% were obtained for healthy subjects and patients, respectively. Sensitivity and specificity were reported to be 100% and 99.10% respectively.

Table 1 (*Continued*)

Reference	Analyzed: sound/disorder	Sensor type	Number of subjects (n)	Real time (yes or no)	Method	Outcome
[56]	Normal and pulmonary emphysema	Electronic stethoscope incorporating a piezoelectric microphone	$n = 168$	No	HMM	The classification accuracies for the proposed method were found to be 87.4% and 88.7% using the deterministic rule and the segment bigram rule, respectively.
[57]	Healthy and pathological	2 ECM-77B Electret microphone	$n = 21$	No	k-nn	An overall classification accuracy of 92.4 ± 2.9% was reported.
[58]	Crackles	Electret microphone (ECM 44, Sony)	$n = 26$	No	SVM	An overall classification accuracy of 97.20% was reported.
[14]	Pneumonia and Congestive Heart Failure (CHF)	Multichannel lung sound analyzer STG 16	$n = 257$	No	SVM	Classification accuracy of 86% and 82% was obtained for pneumonia and CHF respectively. Sensitivity and specificity were reported to be 79.50% and 86.50% respectively.
[59]	Normal and abnormal lung sounds	2 ECM-77B Electret microphone	$n = 36$	No	Empirical classification	Classification accuracy of 98.34% was reported.

Note: Squawks are wheezes with less intensity.

information on the machine learning techniques that have been used by previous researchers in lung sound analysis.

4.1. *Instrumentation for lung sound recording*

The sensors that are used most often in lung sound analysis are the piezoelectric microphones, contact microphones and the electret microphones, which can acquire a wide range of frequencies between 0 and 2000 Hz [13]. Few notable electret microphones used by earlier researchers are ECM 44 from Sony, ECM 140 from Sony, LS-60 Adult Precordial sensors, EMT 25C from Siemens, ECM-KEC-2738 from Kingstat Electronics, ECM 77B from Sony. There are also few commercially available multichannel lung sound analysis instruments. One notable instrument in the literature is STG 16 from Stethograpics [14]. Electronic stethoscopes are now commercially available. These stethoscopes provide advanced lung sound recordings that facilitate the filtering of the heart sounds from the lung sounds. In addition, standards have been developed for the placement of the sensors, such as computerized respiratory sound analysis (CORSA) [15].

4.2. *Lung sound databases*

There are three notable databases used by previous researchers namely, Marburg Respiratory Sounds (MARS) [16], R.A.L.E. repository [17], and European project CORSA [15]. However, R.A.L.E. repository is the only commercially available database. The Marburg Respiratory Sounds (MARS) database was compiled using Lung sound CDs which are commercially available for training doctors and nurses to understand lung sounds [16]. The European project CORSA was developed with an intension of standardizing the recording process of respiratory sounds [15].

4.3. *Methods for feature extraction*

The extraction of features, which is the process of identifying distinctive properties from a signal [18], plays a major role in the effective classification of lung sounds. The features can be extracted from the signals in one of three domains: the time domain, the frequency domain and the time–frequency domain. Feature extraction techniques that are most commonly used in computer-based lung sound analysis are autoregressive (AR) model, mel-frequency cepstral coefficient (MFCC), energy, entropy, spectral features, and wavelet [6,14,19–24]. The use of wavelet based features has proved effective in the work of Kandaswamy et al., with a classification accuracy of 100% for the training set using ANN [6]. The time–frequency analysis of lung sound signals was found to be limited in the literature. Time–frequency analysis on non-linear and non-stationary signals has proved to be effective in the past in other applications [25–27]. It is suggested for the future researchers to concentrate more on time–frequency analysis of the lung sounds.

4.4. *Methods for classification*

Table 1 briefs the overview of the various machine learning techniques that have been used in computer-based lung sound analysis by previous researchers. The ANN and k-nn algorithms are the machine learning techniques that are mostly used. A number of methods, such as ANN, k-nn, GMM, HMM, Fuzzy and GA are widely used in computer-based lung sound analysis. The use of support vector machines (SVMs) was found to be very limited in the literature. The most commonly used machine learning methods used for lung sound analysis are ANN and k-nn. The classification accuracy reported by Kandaswamy et al., was 100% for training and 94.02% for testing using ANN in classification of normal, wheeze, crackle, squawk, stridor, and rhonchus respiratory sounds [6]. This shows the effectiveness of ANN in classifying the lung sounds. The ANN has the ability to adapt well with complex non-linear data and classify it accurately and effectively [28]. The k-nn classifier is another machine learning technique which has attracted researchers to use it in lung sound classification. The advantage of using k-nn is its simplicity and robustness [29]. The work of Alsmadi and Kahya has reported a classification accuracy of 96% in real-time using k-nn classifier [30]. Their developed system can recognize normal and abnormal lung sounds and they trained the model with a large dataset comprising of 42 subjects. In spite of its advantages, the ANN and *k*-nn have few disadvantages too. The disadvantage of using ANN and *k*-nn in classification would be the computational burden caused for training the model and also it is required to have a very large dataset to train the model to effectively recognize the lung sounds accurately [28,29]. In spite of its disadvantage, ANN and *k*-nn serves as the most commonly used machine learning algorithms in lung sound analysis due to its ability to achieve better classification accuracy and detected the lung sounds accurately compared to other methods.

5. Discussion

Machine learning algorithms allow the computer to make decisions based on its previous experiences [31,32]. In the past decade, machine learning has been used in many research areas and its diversity has attracted the use of these algorithms for different applications. In the past few years, researchers have used machine learning algorithms in computer-based lung sound analysis. However, the use of machine learning techniques in computer-based lung sound analysis is still preliminary. The work of Güler, who used genetic algorithm-based artificial neural networks for the classification of lung sounds [33], shows the importance of using hybrid machine learning algorithms in computer-based lung sound analysis. Their resulting classification accuracy using GA-based ANN algorithms was reported to be 83–93%, which shows the significant improvement that can be achieved through the use of hybrid machine learning algorithms. The use of hybrid machine learning algorithms in lung sound analysis is very limited. However, the exploration of hybrid machine learning algorithms might help researchers improve the classification accuracy. It was observed from the literature that ANN yields good results in almost all the previous works and hence combining other methods with ANN would most probably yield better classification accuracy. The ability of ANN to discriminate both linear and non-linear data accurately gives it an advantage over other methods [34,35]. Alsmadi and Kahya developed a real-time classification system with a classification accuracy of 96% [30], which is satisfactory. Their system provides sufficient evidence that demonstrates the high possibility of the development of real-time computer-based lung sound analysis systems. The advantages of using a computer-based lung sound analysis algorithm include that this method is non-invasive, less time consuming and more accurate than other methods. In spite of its advantages, the computer-based lung sound analysis has not yet been developed to a level that can be used in a clinical setting. The development and commercialization of real-time computer based-lung sound analysis systems is a major area for future research approaches.

6. Conclusion

This review on the machine learning techniques that have been used by previous researchers in lung sound analysis provides in-depth knowledge on the various existing machine learning techniques. The types and characteristics of the lung sounds are briefly discussed in this manuscript. In addition, a brief overview of the types of sound/disorder analyzed, the number of subjects and methods used, and the outcomes of the previous research studies are reported. These overviews are followed by a few suggestions of potential future research areas in the discussion section. The authors strongly believe that this work will provide basic information of the works that have been performed by previous researchers on lung sound analysis using machine learning techniques. Future researchers should concentrate on the development of computer-based lung sound analysis using more advanced machine learning algorithms and also using hybrid machine learning techniques to improve the accuracy and intend to commercialize it as a product.

REFERENCES

[1] Earis J. Lung sounds. Thorax 1992;47:671–2.
[2] Pasterkamp H, Kraman SS, Wodicika G. Respiratory sounds. Am J Respir Crit Care Med 1997;156:974–87.
[3] Nissan M, Gavriely N. A microcomputer based lung sounds analysis. Comput Methods Programs Biomed 1993;40:7–13.
[4] Wolberg WH, Street WN, Mangasarian OL. Machine learning techniques to diagnose breast cancer from image-processed nuclear features of fine needle aspirates. Cancer Lett 1994;77:163–71.
[5] Kotsiantis SB. Supervised machine learning: a review of classification techniques. Amsterdam, Netherlands: IOS Press; 2007: 3–24.
[6] Kandaswamy A, Kumar CS, Ramanathan RP, Jayaraman S, Malmurugan N. Neural classification of lung sounds using wavelet coefficients. Comput Biol Med 2004;34:523–37.
[7] Chowdhury SK, Majumder AK. Frequency analysis of adventitious lung sounds. J Biomed Eng 1982;4:305–12.
[8] Korona Z, Kokar MM. Lung sound recognition using model-theory based feature selection and fusion. Appl Sign Proc 1998;5:152–69.
[9] Howell DCJ. In: Geoffrey JL, Steven DS, editors. Signs of respiratory disease: lung sounds. Oxford: Academic Press; 2006. pp. 35–41.
[10] Urquhart RB, McGhee J, Macleod JES, Banham SW, Moran F. The diagnostic value of pulmonary sounds: a preliminary study by computer-aided analysis. Comput Biol Med 1981;11:129–39.
[11] McGee S. Auscultation of the lungs. Philadelphia: W.B. Saunders; 2012: 251–66 [chapter 28].
[12] Steven M. Auscultation of the lungs. Saint Louis: W.B. Saunders; 2007: 326–45 [chapter 27].
[13] Welsby PD, Parry G, Smith D. The stethoscope: some preliminary investigations. Postgrad Med J 2003;79:695–8.
[14] Flietstra B, Markuzon N, Vyshedskiy A, Murphy R. Automated analysis of crackles in patients with interstitial pulmonary fibrosis. Pulm Med 2011.
[15] Sovijärvi ARA, Vanderschoot J, Earis JE. Standardization of computerized respiratory sound analysis. Eur Resp Rev 2000;10:585.
[16] Gross V, Hadjileontiadis LJ, Penzel T, Koehler U, Vogelmeier C. Multimedia database "Marburg Respiratory Sounds (MARS)", vol. 451. 2003; pp. 456–7.
[17] RALE: A computer-assisted instructional package. Respir Care 1990;35:1006.
[18] Bobrowski L, Łukaszuk T. Feature selection based on relaxed linear separability. Biocybern Biomed Eng 2009;29:43–59.

[19] Riella RJ, Nohama P, Maia JM. Method for automatic detection of wheezing in lung sounds. Braz J Med Biol Res 2009;42:674–84.
[20] Abbas A, Fahim A. An automated computerized auscultation and diagnostic system for pulmonary diseases. J Med Syst 2010;34:1149–55.
[21] Azarbarzin A, Moussavi Z. Unsupervised classification of respiratory sound signal into snore/no-snore classes; 2010;3666–9.
[22] Bahoura M, Pelletier C. Respiratory sounds classification using Gaussian mixture models; 2004;1309–12.
[23] Lu X, Bahoura M. An integrated automated system for crackles extraction and classification. Biomed Signal Process Contr 2008;3:244–54.
[24] Kahya YP, Guler EC, Sahin S. Respiratory disease diagnosis using lung sounds; 1997;2051–3.
[25] Cohen L. Time–frequency analysis. Prentice-Hall; 1995.
[26] Prosser WH, Seale MD, Smith BT. Time–frequency analysis of the dispersion of Lamb modes. J Acoust Soc Am 1999;105:2669–76.
[27] Gu YH, Bollen MHJ. Time–frequency and time-scale domain analysis of voltage disturbances. IEEE Trans Power Deliv 2000;15:1279–84.
[28] Tu JV. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. J Clin Epidemiol 1996;49:1225–31.
[29] Raniszewski M. The edited nearest neighbor rule based on the reduced reference set and the consistency criterion. Biocybern Biomed Eng 2010;30:31–40.
[30] Alsmadi S, Kahya YP. Design of a DSP-based instrument for real-time classification of pulmonary sounds. Comput Biol Med 2008;38:53–61.
[31] Meyfroidt G, Güiza F, Ramon J, Bruynooghe M. Machine learning techniques to examine large patient databases. Best Pract Res Clin Anaesthesiol 2009;23:127–43.
[32] Wang S, Summers RM. Machine learning and radiology. Med Image Anal 2012;16:933–51.
[33] Güler İ, Polat H, Ergün U. Combining neural network and genetic algorithm for prediction of lung sounds. J Med Syst 2005;29:217–31.
[34] Tsai C-F, Hsu Y-F, Lin C-Y, Lin W-Y. Intrusion detection by machine learning: a review. Expert Syst Appl 2009;36: 11994–2000.
[35] Jang J-SR, Sun C-T, Mizutan E. Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence. Prentice Hall; 1996.
[36] Sankur B, Kahya YP, Güler EC, Engin T. Comparison of AR-based algorithms for respiratory sounds classification. Comput Biol Med 1994;24:67–76.
[37] Forkheim KE, Scuse D, Pasterkamp H. A comparison of neural network models for wheeze detection; 1995;214–9.
[38] Rietveld S, Oud M, Dooijes EH. Classification of asthmatic breath sounds: preliminary results of the classifying capacity of human examiners versus artificial neural networks. Comput Biomed Res 1999;32:440–8.
[39] Oud M, Dooijes EH, van der Zee JS. Asthmatic airways obstruction assessment based on detailed analysis of respiratory sound spectra. IEEE Trans Biomed Eng 2000;47:1450–5.
[40] Waitman L, Clarkson K, Barwise J, King P. Representation and classification of breath sounds recorded in an intensive care setting using neural networks. J Clin Monit Comput 2000;16:95–105.
[41] Alsmadi SS, Kahya YP. Online classification of lung sounds using DSP; 2002;1771–2.
[42] Bahoura M, Pelletier C. New parameters for respiratory sound classification; 2003;1457–60.
[43] Baydar KS, Ertuzun A, Kahya YP. Analysis and classification of respiratory sounds by signal coherence method; 2003;2950–3.
[44] Folland R, Hines E, Dutta R, Boilot P, Morgan D. Comparison of neural network predictors in the classification of tracheal–bronchial breath sounds by respiratory auscultation. Artif Intell Med 2004;31:211–20.
[45] Gnitecki J, Moussavi Z, Pasterkamp H. Classification of lung sounds during bronchial provocation using waveform fractal dimensions; 2004;3844–7.
[46] Martinez-Hernandez HG, Aljama-Corrales CT, Gonzalez-Camarena R, Charleston-Villalobos VS, Chi-Lem G. Computerized classification of normal and abnormal lung sounds by multivariate linear autoregressive model; 2005;5999–6002.
[47] Jen-Chien C, Huey-Dong W, Fok-Ching C, Chung IL. Wheeze detection using cepstral analysis in Gaussian mixture models; 2007;3168–71.
[48] Masada T, Kiyasu S, Miyahara S. Unmixed spectrum clustering for template composition in lung sound classification. Adv Knowledge Discov Data Mining 2008;5012:964–9.
[49] Matsunaga S, Yamauchi K, Yamashita M, Miyahara S. Classification between normal and abnormal respiratory sounds based on maximum likelihood approach; 2009;517–20.
[50] Bahoura M. Pattern recognition methods applied to respiratory sounds classification into normal and wheeze classes. Comput Biol Med 2009;39:824–43.
[51] Dokur Z. Respiratory sound classification by using an incremental supervised neural network. Pattern Anal Appl 2009;12:309–19.
[52] Riella RJ, Nohama P, Maia JM. Methodology for automatic classification of adventitious lung sounds. Berlin, Heidelberg/Munich, Germany: Springer; 2010: 1392–5.
[53] Mayorga P, Druzgalski C, Morelos RL, Gonzalez OH, Vidales J. Acoustics based assessment of respiratory diseases using GMM classification; 2010;6312–6.
[54] Zolnoori M, Zarandi M, Moin M, Teimorian S. Fuzzy rule-based expert system for assessment severity of asthma. J Med Syst 2010;1–11.
[55] Charleston-Villalobos S, Martinez-Hernandez G, Gonzalez-Camarena R, Chi-Lem G, Carrillo JG, Aljama-Corrales T. Assessment of multichannel lung sounds parameterization for two-class classification in interstitial lung disease patients. Comput Biol Med 2011;41:473–82.
[56] Yamashita M, Matsunaga S, Miyahara S. Discrimination between healthy subjects and patients with pulmonary emphysema by detection of abnormal respiration; 2011;693–6.
[57] Feng J, Krishnan S, Sattar F. Adventitious sounds identification and extraction using temporal–spectral dominance-based features. IEEE Trans Biomed Eng 2011;58:3078–87.
[58] Serbes G, Sakar CO, Kahya YP, Aydin N. Feature extraction using time–frequency/scale analysis and ensemble of feature sets for crackle detection; 2011;3314–7.
[59] Xie S, Jin F, Krishnan S, Sattar F. Signal feature extraction by multi-scale PCA and its application to respiratory sound classification. Med Biol Eng Comput 2012;50:759–68.