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**Artificial intelligence techniques used in respiratory sound analysis - a systematic review**

Abstract: Artificial intelligence (AI) has recently been estab­lished as an alternative method to many conventional methods. The implementation of AI techniques for respira­tory sound analysis can assist medical professionals in the diagnosis of lung pathologies. This article highlights the importance of AI techniques in the implementation of com­puter-based respiratory sound analysis. Articles on com­puter-based respiratory sound analysis using AI techniques were identified by searches conducted on various electronic resources, such as the IEEE, Springer, Elsevier, PubMed, and ACM digital library databases. Brief descriptions of the types of respiratory sounds and their respective characteristics are provided. We then analyzed each of the previous studies to determine the specific respiratory sounds/pathology ana­lyzed, the number of subjects, the signal processing method used, the AI techniques used, and the performance of the AI technique used in the analysis of respiratory sounds. A detailed description of each of these studies is provided. In conclusion, this article provides recommendations for fur­ther advancements in respiratory sound analysis.

Keywords: artificial intelligence; lung disease; respiratory sounds; statistical computing; systematic review.

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**Introduction**

Auscultation is the process of listening to the internal sounds in the human body by using a stethoscope [15]. Since its invention by Rene Theophile Hyacinth Laennec in 1816, the stethoscope remains the most widely used instrument in clinical medicine [75]. In addition, it has been an effective tool for the diagnosis of respiratory pathologies for a number of years now. This process mainly relies on the medical professional and hence requires well-trained medical professionals to recognize lung pathologies from sounds. Computer-based respira­tory sound analysis started to appear in the literature in the early 1980s [52]. Several techniques have been imple­mented for the recognition of respiratory pathologies from sounds heard over the chest wall. However, computer- based respiratory sound analysis continues to attract the attention of researchers because it has not yet developed to a state where it can be used in clinical settings. AI techniques are currently used in many applications and possess intelligence that learns from past experiences, which allows these tools to function more accurately [77, 40]. This review briefly discusses the types and character­istics of respiratory sounds. Previous research studies on computer-based respiratory sound analysis using AI tech­niques, such as artificial neural networks (ANNs), hidden Markov models (HMMs), the ^-nearest neighbor (fc-nn) algorithm, Gaussian mixture models (GMMs), self-organ­izing maps (SOMs), genetic algorithms (GAs), and fuzzy logic, will be discussed. The organization of this article is as follows: the next section discusses the types and char­acteristics of respiratory sounds, followed by the methods and the overview of the literature result. The overview of the literature is further divided into four sections: res­piratory sound recording, respiratory sound databases, feature extraction methods, and AI techniques used in respiratory sound analysis. A discussion of the literature search results and the conclusions are then provided.

**Types and characteristics of respiratory sounds**

The literature on the types of respiratory sounds clearly shows that few modifications have been made to the fun­damentals since its invention by Laennec [51]. The lung sounds that are heard over the chest wall and trachea are caused by turbulent airflow in the air passage and lungs during the respiratory phases [57]. These lung sounds are non-stationary and non-linear signals [37]. It is possible that different pathological conditions cause similar res­piratory sound for which sophisticated signal processing techniques should be employed. A basic classification of lung sounds, based on their mechanism and basic acous­tic features, was proposed by Pasterkamp et al. [56, 57], and it is widely accepted. This classification divides res­piratory sounds into two groups: normal and abnormal or adventitious. The types and characteristics of normal lung sounds are listed in Figure 1 [16, 31, 39, 48, 49, 57, 73].

The common bandwidth of normal sounds depends on the recording area: chest wall or trachea. The frequency range of normal respiratory sounds is 100-1000 Hz [57, 75]. The frequency range of normal tracheal sounds is 100-3000 Hz [57]. The types and characteristics of adven­titious respiratory sounds are listed in Figure 2 [16, 31, 39, 48, 49, 57, 73]. Each respiratory disorder is associated with one or more lung sounds [37, 57].

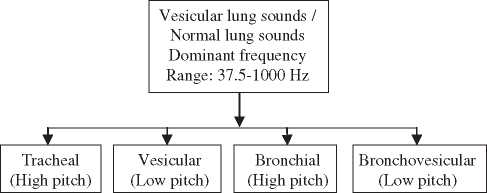


Figure 1 Characteristics of normal respiratory sounds.

The dominant frequency of heart sounds is typi­cally <1000 Hz [15], whereas the dominant frequency of lung sounds ranges from 150 to 2000 Hz. This overlapping frequency range makes it difficult to filter the heart sounds from the lung sounds. The use of an adaptive filter might be a possible solution for removing the heart sounds from the respiratory sounds because it would not remove any information of interest from the referred frequency band.

**Methods**

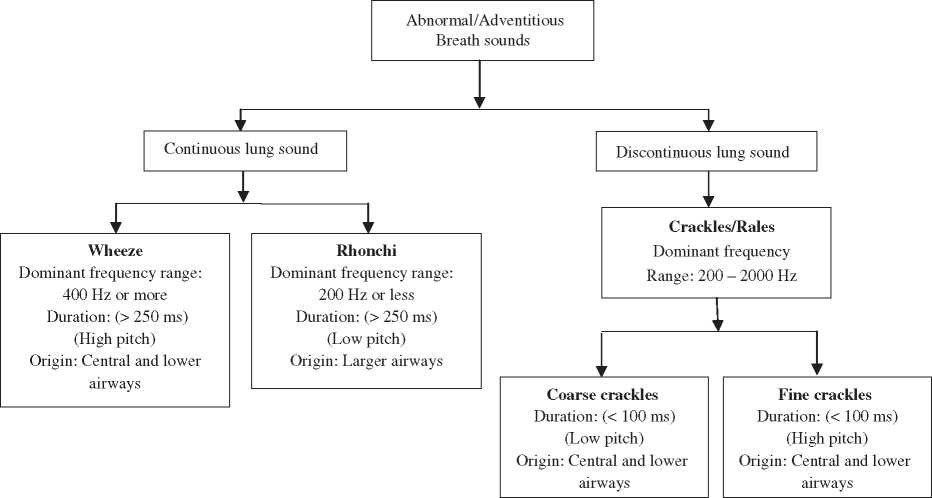


Figure 2 Characteristics of adventitious respiratory sounds.

All of relevant articles were initially identified from searches of various electronic resources, such as the IEEE, Springer, Elsevier, PubMed, and ACM digital library databases. During the initial search, the keywords used to identify the articles were “lung sound”, “breath sound”，“respiratory sound”，“abnormal lung sounds”, “adventitious lung sounds”，“lung sound classification”, “machine learning”, “wheeze detection”, “crackles detec­tion”, “lung sound detection”, and “abnormal lung sound classification”. The title and abstract of each study iden­tified were then read to exclude those articles that were not relevant, i.e., articles that did not exhibit the follow­ing selection criteria: (i) the article must describe a study on respiratory sound analysis; (ii) the article must be published; (iii) the article must be written in the English language; and (iv) the study must use the AI technique. A

total of only 52 articles satisfied all of the selection criteria and were thus included in this overview.

**Overview on computerized respiratory sound analysis using AI techniques**

A detailed overview of the 52 articles that satisfied the selection criteria is tabulated in Tables 1 and 2; the articles are divided into two tables based on the learning algo­rithm (supervised and unsupervised learning) used.

**Respiratory sound recording**

The sensors that are used most frequently in computer- based respiratory sound analysis are piezoelectric micro­phones, accelerometers, contact microphones, and electret microphones, which can attain a wide range of frequencies between 0 and 2000 Hz [57, 75]. Some of the famous elec- tret microphones used in the analyzed studies are the ECM 44 (Sony, Tokyo, Japan), ECM 140 (Sony, Tokyo, Japan), the LS-60 Adult Precordial Sensors (Tokyo, Japan), ECM-KEC- 2738 (Kingstat Electronics, New Taipei City, Taiwan), ECM 77B (Sony, Tokyo, Japan), and WM-61 (Panasonic, Osaka, Japan), and EMT 25C (Siemens, Berlin, Germany) is a well- known accelerometer used in respiratory sound analysis. There are also a few commercially available multichannel instruments for respiratory sound analysis. One notable instrument in the literature is STG 16 (Boston, MA, USA) from Stethographics [21]. In addition, electronic stetho­scopes are now commercially available. These stetho­scopes provide sophisticated respiratory sound recordings that facilitate the filtering of the heart sounds and ambient noise from the respiratory sounds. In addition, standards have been developed for the placement of the sensors, such as computerized respiratory sound analysis (CORSA) [70].

**Lung sound database**

There are three prominent databases used by previous researchers: Marburg Respiratory Sounds (MARS) [25], R.A.L.E repository [55], and European project CORSA [70]. However, the R.A.L.E repository is the only commercially available database. The MARS database was compiled using lung sound CDs that are commercially available for the training of medical professionals in auscultation [25].

The European project CORSA was developed with the aim of standardizing the recording process of respiratory sounds [70].

**Feature extraction methods**

Researchers have used various feature extraction methods in the analysis of respiratory sounds. This section provides an overview of these feature extraction methods. The extrac­tion of features, which is the process of identifying distinc­tive properties from a signal [12], plays a significant role in the effective recognition of the respiratory sounds. Features can be extracted from signals in the time domain, the fre­quency domain, or the time-frequency domain. The feature extraction method can be selected using two main factors: the domain and the characteristics of the feature vector [38]. The feature extraction techniques that are widely used in computer-based respiratory sound analysis are the autore­gressive (AR) model, mel-frequency cepstral coefficient, energy, entropy, spectral features, and wavelet [1, 7, 10, 21, 34, 37, 41, 62]. Kandasamy et al. [37] extracted wavelet-based features and reported a classification accuracy of 100% for the training set using ANN. The time-frequency analysis on non-linear and non-stationary signals has been proven to be effective in other applications [17, 26, 60]. Respiratory sounds are non-stationary signals, and various methods such as short-term Fourier transform and discrete wavelet transform can be applied for extracting the transient fea­tures of non-linear signals. However, the use of more sophis­ticated time-frequency domain features has been suggested. The feature extraction methods used in computer-based res­piratory sound analysis are listed in Tables 1 and 2.

**AI techniques in lung sound analysis**

Over the past few decades, AI algorithms have been widely developed for various applications. An AI algorithm can be based on either supervised or unsupervised learning frameworks. In the case of supervised learning, the inputs and the outputs are provided to the model. In contrast, in the unsupervised learning framework, only the input is provided and the output is predicted by the model itself [65]. Algorithms such as backpropagation, linear vector quantification (LVQ), and support vector machine (SVM) are classified as supervised learning, whereas algorithms such as radial basis function network, vector quantiza­tion, and SOMs are classified as unsupervised learn­ing. The selection of a suitable AI algorithm is the most important step in any pattern recognition application. To

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| --- | --- | --- | --- | --- |
| References | Sound/pathology  analyzed | Sensor type | Number of subjects (n) | Realtime (yes or no) |
| [67] | Lung sounds | Electret microphone (ECM44, Sony) | 69 | No |
| [58] | Wheeze, crackles, and normal | Electret microphone | 13 | No |
| [34] | Normal and pathological | Electret microphone (ECM140, Sony) | 69 | No |
| [59] | Wheeze, crackles, and normal | Electret microphone | 9 | No |
| [64] | Normal, wheeze, and crackles | Electret microphone | 60 | No |
| [53] | Airway obstructions in asthmatic patients | Electret microphone | 10 | No |
| [74] | Normal and pathological | Two microphones (LS-60 Adult Precordial Sensors) | 17 | No |
| [69] | Normal and asthma patients | Electronic stethoscope (Cardionics Inc.) | 20 | No |
| [4] | Normal and pathological | Electret microphone | 9 | Yes |
| [11] | Normal and pathological | Electret microphone | 20 | No |
| [35] | Normal and pathological | Four air-coupled electret microphones | 36 | No |
| [54] | Asthma and normal | Air-coupled electret microphone | 10 | No |
| [37] | Normal, wheeze, | Electret microphone | 8 | No |

crackle, squawk, stridor, and rhonchus

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| Autoregressive (AR) | /c-nn classifier | The classification accuracies using /c-nn |
| model | and quadratic classifier | and quadratic classifiers were 93.75% and 87.50%, respectively. The sensitivity and specificity were 100% and 71.4%, respectively. |
| Wavelet packet | ANN-LVQ | The overall sensitivity and positive |
| decomposition | (linear vector quantification) | predictivity were 22% and 15%, respectively. |
| AR model | k-n n | An overall classification accuracy of 69.59% was reported |
| Wavelet packet decomposition | ANN-LVQ | The sensitivity for wheeze classification was 58.7%, and the sensitivity for crackles classification was 71.2% |
| Fourier power | ANN- | A classification accuracy of 95% was |
| spectrum | feedforward  network | reported. |
| DFT spectra and Welch spectra | k-rm | Approximately 60% to 90% of the sounds were classified accurately using the /c-nn classifier. |
| Averaged power | ANN- | The classification rate was 73%. This |
| spectral density (PSD) | feedforward  network | rate was 91% for the training tapes. The sensitivity and specificity were 87% and 95%, respectively. |
| Wavelet coefficients | ANN-grow and learn (GAL) network | A classification accuracy of 98% was reported. |
| AR model | /c-nn | Encouraging results were reported. |
| Discrete-Fourier transformation (DFT) | Nearest mean classifier | The results obtained were satisfactory. |
| AR model coefficients | /c-nn | The classification accuracy, specificity, and sensitivity for /c-nn were 81.93%, 66.75%, and 91.75%, respectively. |
| Signal coherence | ANN-  feedforward  network | A maximum classification accuracy of 83% was reported. |
| Wavelet transform | ANN-  feedforward  network | A classification accuracy of 100% was obtained for the training set. A classification accuracy of 94.02% was obtained for the validation set. |

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| References | Sound/pathology  analyzed | Sensor type | Number of subjects (n) | Real time (yes or no) |
| [3] | Lung sounds | Electret microphone (Siemens EMT 25C) | 1 | No |
| [80】 | Healthy and pathological | Air-coupled-electret  microphones | 45 | No |
| [24] | Lung sounds | Stethoscope, acoustic analysis -sensor (Siemens EMT 2 5 C) | 8 | No |
| [27] | Normal, wheeze, and crackles | Electret microphone | 129 | No |
| [28】 | Chronic obstructive, restrictive lung disease, and healthy subjects | Two air-coupled electret microphones | 57 | No |
| [43] | Normal and abnormal lung sounds | Electret microphone | 19 | No |
| [36] | Normal and  pathological  (crackles) | Electret microphone (Sony- ECM4A) | 40 | No |
| [81】 | Normal and pathological | Fourteen air-coupled electret microphones (Sony-ECM 44) | 48 | No |
| [5] | Normal and abnormal lung sounds | Two ECM-77B microphones | 42 | Yes |
| [45] | Normal respiratory and abnormal respiratory sounds | Electronic stethoscope incorporating a piezoelectric microphone and condenser microphone | 114 | No |

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| --- | --- | --- |
| Average power, RMS, | ANN- | A classification accuracy of 91.7% was |
| WFD | feedforward  network | reported. |
| AR model | ANN- multi layer perceptron (MLP) network | A classification accuracy of 70±10% was reported. |
| Fractal dimension | k-nn | A satisfactory classification accuracy was reported. |
| PSD | ANN and GA-based ANN-MLP network | Classification accuracies of 81-91% and 83-93% were obtained using ANN and GA-based ANN, respectively. |
| AR model | ANN-MLP  network | A classification accuracy of 80-90% was reported. |
| AR model | ANN-  feedforward | A classification accuracy of 87.68% was reported. The sensitivity and specificity were 81.36% and 83.64%, respectively. |
| AR model | ANN-  feedforward and k-nn | The classification accuracy, specificity, and sensitivity for k-nn were 92.5%, 90%, and 95%, respectively. The classification accuracy, specificity, and sensitivity for ANN were 80%, 80%, and 80%, respectively. |
| AR model | k-n n | A classification accuracy of 77.8% was reported. The sensitivity and specificity were 79.2% and 80%, respectively. |
| AR model | k-nn and minimum distance classifier | The real-time implementation yielded a classification accuracy of 96% for clinical trials. The sensitivity and specificity were 92% and 100%, respectively. |
| Acoustic features | HMM | The proposed method yielded a classification rate that was 19.1% higher than previous methods that have been used. |

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| References | Sound/pathology  analyzed | Sensor type | Number of subjects (n) | Real time (yes or no) |
| [19] | Adventitious lung sounds | Two ECM-77B electret microphones | 18 | No |
| [62] | Wheeze | Electret microphone (ECM140, Sony) | 40 | No |
| [1] | Normal, wheeze, and crackles | Electret microphone (ECM140, Sony) | 279 | No |
| [62] | Asthma severity | Electronic stethoscope | 28 | No |
| [14] | Normal and abnormal lung sounds | Twenty-five acoustic sensors (electret microphones) | 27 | No |
| [79] | Normal and pulmonary emphysema | Electronic stethoscope incorporating a piezoelectric microphone | 168 | No |
| [20] | Healthy and pathological | Two ECM-77B electret microphones | 21 | No |
| [33] | Healthy and pathological | ECM-77B (Sony) | 21 | No |
| [66] | Healthy and pathological | Electret microphone | 6 | No |
| [29] | Wheeze and normal | Electronic stethoscope | 140 | No |
| [68] | Crackles | Electret microphone (ECM 44, Sony) | 26 | No |
| [21] | Pneumonia and congestive heart failure (CHF) | Multichannel lung sound analyzer STG 16 | 257 | No |

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Power spectrum ANN-GAL

network

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| --- | --- | --- |
| Spectral projection | | ANN-MLP  network |
| PSD | | ANN-MLP  network |
| Acoustic features | | Fuzzy logic |
| PSD, univariate | | ANN- |
| autoregressive (UAR), | | feedforward |
| and multivariate (MAR) autoregressive models | | network |
| Acoustic features | | HMM |
| Temporal spectral | k-n n | |
| dominance |  | |
| spectrogram |  | |
| Temporal | SVM | |
| spectraldominance |  | |
| spectrogram |  | |
| Energy index, | ANN- | |
| respiration rate, | feedforward | |
| dominant frequency, | network | |
| and strength of |  | |
| dominant frequency |  | |
| Wavelet transform | ANN-MLP | |
|  | network | |
| Spectral | SVM | |
| characteristics |  | |
| Statistical feature | SVM | |
| (median) |  | |

The classification using an incremental supervised neural network model gave improved results compared with the other conventional neural network models.

A classification accuracy of 92.86% was obtained.

Confidence levels of 0.90, 0.87, and 0.89 were reported for normal, wheeze, and crackles, respectively.

The developed fuzzy expert system provided satisfactory results.

Classification accuracies of 75% and 93% were obtained for healthy subjects and patients, respectively. The sensitivity and specificity were reported to be 100% and 99.10%, respectively.

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.

An overall classification accuracy of 92.4±2.9% was reported.

An overall classification accuracy of 92.7±2.9% was reported.

An overall classification accuracy of 98.7% was reported.

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An overall classification accuracy of 89.28% was reported.

An overall classification accuracy of 97.20% was reported.

Classification accuracies of 86% and 82% were obtained for pneumonia and CHF, respectively. The sensitivity and specificity were reported to be 79.50% and 86.50%, respectively.

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choose a suitable AI algorithm, one should know the size of the data set and the characteristics of the dataset, and evaluate the classifier [40]. The classifier is evaluated by calculating the classification accuracy. An unsatisfactory classifier accuracy can be due to a number of factors such as a too small training set, an unsuitable feature extrac­tion method, a too high dimensionality of the feature set, an unsuitable AI algorithm, and the absence of parameter tuning [13].

Tables 1 and 2 respectively give a brief overview of the various supervised and unsupervised AI techniques that have been used in computer-based respiratory sound analysis. The most commonly used AI techniques for res­piratory sound analysis are ANN and k-nn. ANN provides an alternative form of computation that attempts to mimic the functionality of the human brain [71]. The classifica­tion accuracies reported by Kandasamy et al. [37] using ANN for the classification of normal, wheeze, crackle, squawk, stridor, and rhonchus respiratory sounds were 100% and 94.02% for training and testing, respectively. This finding shows the effectiveness of ANN for the clas­sification of respiratory sounds. ANN has the ability to adapt well to complex non-linear data and to accurately and effectively classify these data [72]. The k-nn classi­fier is another AI technique that has attracted the inter­est of researchers for respiratory sound classification. The advantage of using k-nn is its simplicity and robustness [61]. This classifier computes the distances between dif­ferent points on the input features, and then assigns the points to the class of its k-nearest neighbors, where k is an important parameter; note that different k values will result in different performances [71]. The work conducted by Alsmadi et al. [5] showed a real-time classification accu­racy of 96% using a k-nn classifier. The system developed by these researchers can recognize normal and abnormal respiratory sounds, and these researchers trained the model with a large dataset comprising 42 subjects. Despite their advantages, the ANN and k-nn classifiers have a few disadvantages. The disadvantages of using an ANN clas­sifier include the computational burden required to train­ing the model and the requirement of a very large dataset to train the model to effectively and accurately recognize the respiratory sounds [61, 72]. Despite their disadvan­tages, ANN and k-nn classifiers are the most commonly used AI algorithms in respiratory sound analysis owing to their ability to achieve a better classification accuracy and accurately recognize the respiratory sounds. SOM is a type of ANN and is an unsupervised learning algorithm. In 1996, Malmberg et al. [42] proposed a method for clas­sifying normal and abnormal respiratory sounds using SOM and reported a classification accuracy of 78.1%. The

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| --- | --- | --- | --- | --- | --- | --- | --- |
| References | Sound/pathology  analyzed | Sensor type | Number of subjects (n) | Real time (yes or no) | Feature extraction method | Al technique used | Outcome |
| [23] | Wheeze and normal | Eight-channel  microphone | 6 | No | Fourier transform spectrum | ANN- radial basis function (RBF) network | The classification accuracies obtained using RBF networks with the training sets 1 and 2 were 93% and 96%, respectively. |
| [42] | Asthma, emphysema, fibrosing alveolitis, and healthy lungs | Air-coupled electret microphones | 32 | No | Fourier transform spectrum | SOM | An overall classification accuracy of 78.1% was reported. |
| [9] | Wheeze and non­wheeze | Electret microphone | 24 | No | Mel-frequency cepstrum coefficient (MFCC) | Vector  quantification | The classification accuracies for wheeze and non­wheeze were 75.80% and 77.50%, respectively. |
| [10] | Normal and wheeze | Electret microphone | 24 | No | Wavelet transform | GMM | The classification accuracy was improved using this technique compared with vector quantification and multilayer perceptron neural network. |
| [22】 | Lung sounds | Electret microphone | 9 | No | Frequency  spectrum | ANN-RBF | A classification accuracy of 97.8% was reported. The sensitivity and specificity were 97.8% and 89.6%, respectively. |
| [32] | Wheeze | Electret microphone ECM-KEC-2738 | 30 | No | MFCC | GMM | A classification accuracy of 90% was reported. |
| [41] | Fine and coarse crackles | Electret microphone | 22 | No | Fractal dimension | GMM | A classification accuracy of 95.1% was reported. The sensitivity and specificity was 95.6% and 63.3%, respectively. |
| [44] | Lung sounds | Two ECM-77B microphones | 30 | No | Power spectrum | /(-means  clustering  algorithm | The similarities between the lung sounds at short intervals were detected at a precession of 0.9711. |
| [8] | Lung sounds | Electret microphone | 24 | No | MFCC | GMM | The sensitivity and specificity were reported to be 94.6% and 91.9%, respectively. |
| [63] | Normal and adventitious lung sounds | Electret microphone (ECM140, Sony) | 40 | No | Discrete wavelet transform | ANN-RBF | A classification accuracy of 92.36% was obtained. |
| [47] | Normal, crackles, and wheeze | Two ECM-77B  electret  microphones | 50 | No | MFCC | GMM | A classification accuracy of 98.75% was obtained for the reference library and a classification accuracy of 52.5% was obtained using the cross-validation method. |
| [7] | Lung sounds | Two ECM-77B  electret  microphones | 20 | No | Energy features | /(-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. The sensitivity and specificity were reported to be 98.2% and 95.2%, respectively. |
| [46] | Wheeze, crackles, and normal | RALE database | RALE  database | No | Quantile vectors | GMM | The error rate was reported as 0%. |

Note: Squawks are wheezes with less intensity.

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number of subjects used in their work was 32. SVM is a supervised AI algorithm that classifies the data into two different classes or even multiple classes. SVM is particu­larly designed for binary classification. During the training phase, SVM builds a model, maps the decision boundary for each class, and specifies the hyperplane that separates the two different classes. Increasing the distance between the two classes by increasing the hyperplane margin helps increase the classification accuracy. SVM can be used to effectively perform non-linear classification [18, 71]. Serbes et al. [68] reported a classification accuracy of 97.20% using the SVM classifier. Their system can rec­ognize both normal and crackles sounds. The model was trained with a dataset comprising 26 subjects. The fuzzy- based AI technique is a computational approach based on predefined rules. In fuzzy logic, the degree of truth in a particular statement can range between 0 and 1, and there is no constraint to obtain 0 or 1. The use of fuzzy logic for the classification of crackles was implemented by Ayari et al. [6], who obtained a sensitivity of 98.34%. The previ­ous studies clearly suggest the possibility of developing a computer-based respiratory sound analysis system using AI algorithms that can be used in clinical settings.

**Discussion**

In the past few decades, researchers have used various AI techniques in computer-based respiratory sound analy­sis. However, the use of semi-supervised learning and reinforcement learning in computer-based respiratory sound analysis is limited. Similarly, the use of Hybrid Intelligent Systems (HIS), which combine two or more AI techniques for respiratory sound analysis, was found to be limited [50]. HIS have been effective in a wide range of real-world problems in the recent years [50]. Guler et al. [27], who used a GA-based ANN algorithm for the classifi­cation of respiratory sounds, illustrate the significance of implementing computer-based respiratory sound analysis using HIS. Their classification accuracy using GA-based ANN algorithms was 83-93%, which shows the considera­ble performance that can be achieved using HIS. Although the use of HIS in respiratory sound analysis is limited, it would be interesting to evaluate the performance of such AI techniques in respiratory sound analysis. The ben­efits of using computer-based respiratory sound analy­sis includes its non-invasive nature, the fact that it is less time consuming, and it is inexpensive [2]. This type of analysis can support medical professionals in the dif­ferential diagnosis of pathological conditions. Despite its benefits, computer-based respiratory sound analysis has not yet been developed to a level that can be used in a clinical environment.

**Conclusion**

This article presents a detailed overview of the AI tech­niques that have been used by previous researchers in computer-based respiratory sound analysis. The types and characteristics of respiratory sounds were briefly dis­cussed in this article. In addition, a brief overview of the types of sound/pathology analyzed, the number of sub­jects, the feature extraction techniques used, the AI tech­niques used, and the outcomes of the previous research studies are reported. After these overviews were detailed, a few suggestions on potential future research areas were presented in the Discussion section. Future researchers should focus on the development of computer-based res­piratory sound analysis using more sophisticated AI tech­niques and using HIS to improve the accuracy, and intend to commercialize it for use in a clinical environment.

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