Machine learning and deep learning in respiratory/lung sound analysis: A systematic review

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Abstract

Respiratory disorders, including severe conditions like lung carcinoma, are on the rise globally, posing a growing health burden. Early and accurate diagnosis is essential for effective treatment. Recent innovations in machine learning (ML) and deep learning (DL) have shown considerable promise in supporting pulmonary diagnostics through enhanced prediction accuracy in imaging and acoustic analysis. These methods facilitate automated respiratory sound evaluation by extracting and analyzing key audio features, reducing noise, and identifying pathological patterns. This study reviews the application of ML and DL in computer-aided lung sound analysis, drawing from major databases such as Elsevier, Springer, IEEE, and PubMed. Key aspects explored include types of respiratory sounds, related pathologies, dataset characteristics, preprocessing strategies, classification methods, and model performance. The review concludes with insights into current limitations and future directions for advancing intelligent respiratory sound diagnostics.

Keywords: Lung sound analysis, Respiratory sound, Machine learning, Deep learning.

Introduction

Auscultation using a stethoscope remains a fundamental and widely adopted clinical method for evaluating respiratory function. Historically, it was one of the earliest diagnostic techniques employed by physicians to detect various pulmonary disorders [1]. The method is non-invasive, cost-effective, safe, and simple to perform. Different types of lung sounds—such as tracheal, bronchial, bronchovesicular, vesicular, and oral—can be detected depending on the anatomical site of auscultation [2]. Notably, the majority of respiratory sound energy is concentrated below 200 Hz [3]. Under normal physiological conditions, healthy lungs generate typical breath sounds. In contrast, pathological lungs often produce adventitious sounds, categorized as either continuous or discontinuous. The detection and interpretation of these abnormal sounds—based on their location, acoustic properties, and surrounding clinical context—can aid physicians in identifying underlying respiratory conditions [4]. However, this process requires substantial clinical experience. Inexperienced practitioners may misinterpret lung sounds due to external noise interference, suboptimal instrument calibration, or limited training [10]. To address these challenges, several automated algorithms have been developed for the detection and classification of lung sounds [5]. Computational analysis enables systematic identification of respiratory anomalies by automatically extracting acoustic features from recorded signals [3,6]. Numerous techniques have been employed to detect irregularities in respiratory sounds; yet, earlier research has focused on the recognition of pulmonary sounds rather than on comprehensive diagnostic systems. Consequently, respiratory sound analysis remains an active area of investigation [7].

This review presents an overview of respiratory sound types, acoustic features, and associated pathological conditions. Furthermore, it summarizes previous studies that have applied machine learning techniques to automated respiratory sound analysis. These include Support Vector Regression (SVR), Principal Component Analysis (PCA), Mel-Frequency Cepstral Coefficients (MFCC), k-Nearest Neighbors (KNN), Gaussian Support Vector Machines (SVM), Neural Networks (NN), Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT), Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (BiGRU), Convolutional Bidirectional Long Short-Term Memory (C-BiLSTM), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN).

The subsequent sections elaborate on the categories and distinguishing characteristics of respiratory sounds, as well as related medical conditions. A detailed summary of prior research is provided, covering aspects such as respiratory sound acquisition using hardware devices, datasets used, feature extraction techniques, and classification algorithms. Finally, the paper concludes with an evaluation of the reviewed methods and a discussion of their outcomes.

Breathing sounds

Respiratory sounds are generated by the movement of air through the airways and the respiratory tract. In healthy individuals, these sounds are typically smooth and soft, reflecting unobstructed airflow. In contrast, abnormal or pathological respiratory sounds often indicate underlying medical conditions. Normal breath sounds are generally categorized into three types: vesicular, bronchovesicular, and bronchial. Abnormal respiratory sounds are typically classified as adventitious sounds, which may be either continuous or discontinuous in nature [1,2]. Due to their irregular and often non-stationary characteristics, adventitious lung sounds can be challenging for clinicians to detect and interpret accurately [8]. Figure 2 illustrates the classification and defining features of various respiratory sounds, including both normal and abnormal types [1,2,4,5,9].

Each respiratory pathology is commonly associated with specific acoustic signatures that vary in frequency content, ranging from low to high pitch, depending on their origin and characteristics [9]. Moreover, Figure 2 provides a comprehensive overview of the diseases associated with different respiratory sound types.

Methodology

This section will examine the search methodology and inclusion and exclusion parameters for selected publications.

Search Methodology

A comprehensive literature search was conducted across major scientific databases, including Scopus, Elsevier, Springer, IEEE, and PubMed. The search focused on studies related to lung sound analysis, respiratory signal processing, and machine learning-based classification of lung sounds. Relevant English-language articles were identified using keywords found in the title, abstract, and author-specified terms, without restrictions on publication year. Initially, 182 records were retrieved. After a preliminary screening based on titles and abstracts, 120 articles were excluded. Of the remaining 62, an additional 23 were removed due to insufficient methodological or experimental detail. Ultimately, 39 studies met the inclusion criteria and were selected for in-depth review

Guidelines for Inclusion and exclusion

This comprehensive analysis includes Studies that identified severe breathing-related conditions using machine learning techniques and breathing sound characteristics. An investigation considered for inclusion in this comprehensive assessment had to meet a certain threshold of training, cross-validation evaluation, or analysis of data sets. This is because algorithms need methods for resizing to have a higher likelihood of correctly generalizing on unrelated databases. The age of those involved in the lung condition investigation varies [11]. The most common cause of sickness and mortality in people is chronic breathing-related conditions, which are the focus of this comprehensive investigation. This thorough investigation uses machine learning techniques and lung sounds to recognize breathing-related conditions. Additionally, patients from one specific non-target illness group or those who were healthy were omitted from the adverse or non-disease classification since these individuals have more fundamental issues with little medical significance.

Here, we used pulmonary sound analysis to analyze the early stages of respiratory illness. The one pulmonary sound consists of two or more lung diseases. Similarly, the basis for this inquiry is separated breathing noises.

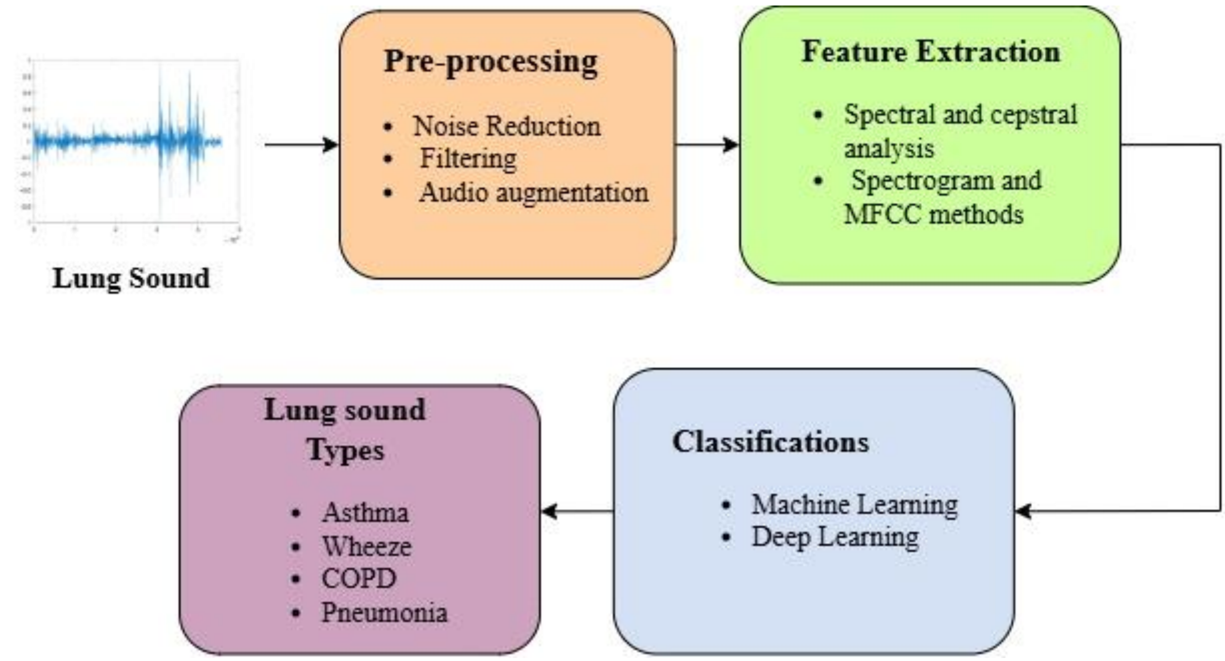
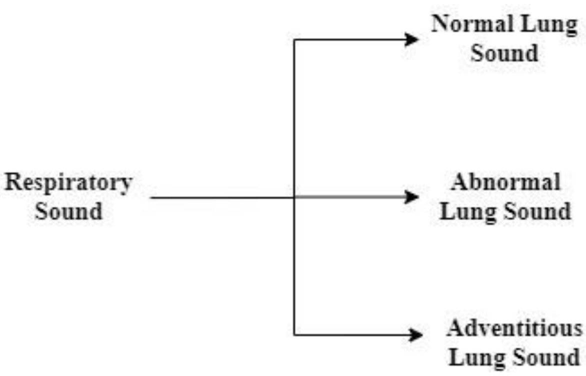
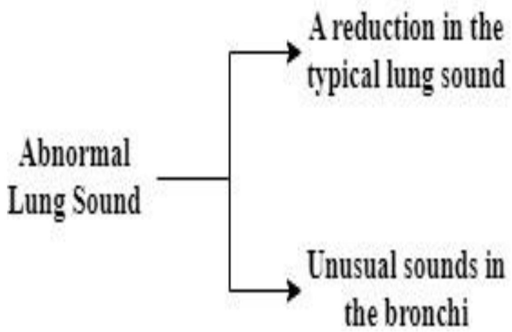


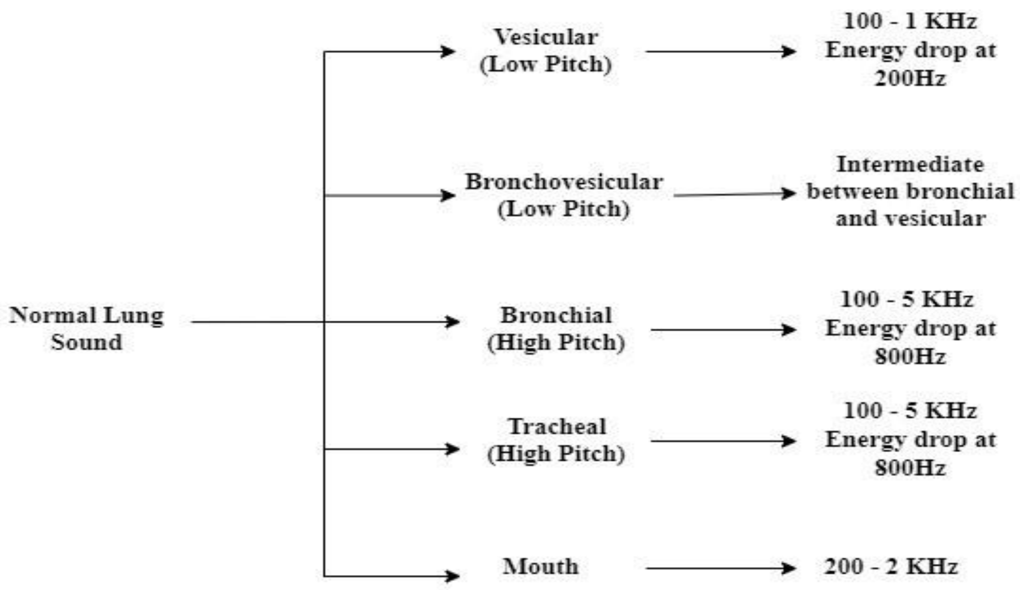
Fig.1 Workflow for lung sound classification



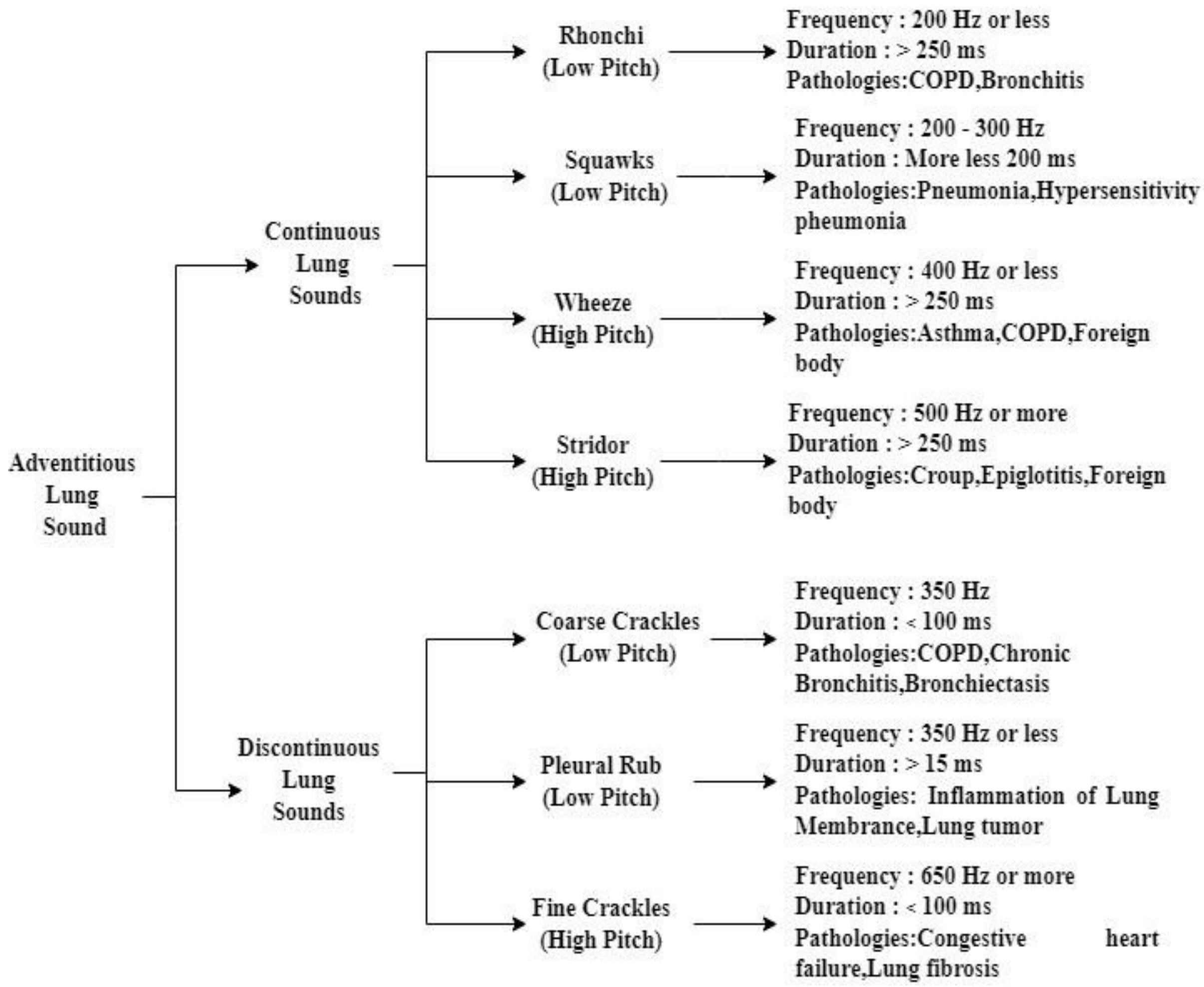
(a) Respiratory Sound



(b) Abnormal Lung Sound



(c) Normal Lung Sound



(d) Adventitious Lung Sound

Fig. 2 Lung sounds and their types. (a) shows respiratory sound types. (b) shows abnormal lung sounds. (c) various normal lung sounds and their frequency range. (d) The two kinds of adventitious lung sounds and their frequency range, time duration for respiration, and associated lung diseases [1, 2-5, 8, 9, 12].

A brief description review of the literature

The machine learning and deep learning algorithms investigators previously used to investigate lung sounds are covered in this discussion. The eligibility requirements based on selected 39 publications are summarized in the Table. 1.

Lung sound recording devices

Many researchers use real-time respiratory lung sound records with different devices for auscultation. Here, we see some auscultate devices. Samples were acquired using an inexpensive electronic stethoscope, recording at 44.1 kHz. Concurrently collecting background sounds, a separate Sony-ICD-UX71-81 sensor [13] was attached to the stethoscope's front. [14] proposed the use of two instruments to capture tracheal noises. A digital stethoscope that connects to a mobile is called HF-Type-2. The components of the HF-Type-3 include a mobile device, an earpiece, an abdominal part, and a stethoscope cable. The mobile phone uses an application designed to capture the bronchial sounds it obtained. The microphone device comprised a signal processing system, a notebook PC, and an electro-stethoscope with a broad-spectrum sound detector (Bio-Sound Sensor BSS-01) [15, 16] affixed to the interior of a diaphragm. [17] An audio device is fixed to the back of the upper body, while another receives data using a flow sensor, which is employed to time the respiration sounds. Hence, they correspond with the inhalation and exhalation processes. The lung sound detector is an air-coupled electret instrument (Sony ECM-44) that measures a lung cavity's shape. A tape-fixed and an audio detector were placed on the chest area. An audio connector converts the sound input to digital form at 48 kHz and 24 bits per data and stores it on a laptop drive [18]. The researchers recorded the respiratory sounds using mobile phone applications. The electronic stethoscope is used to auscultate the lung sounds and separate lung sounds from heart sounds.

Respiratory sound dataset

Here, we see three central lung sound databases that earlier researchers used, such as e International Conference on Biomedical and Health Informatics (ICBHI) 2017 Challenge Respiratory Sound Database [19, 20, 22], Computerized Respiratory Sound Analysis (CORSA) [23, 24], R.A.L.E. (Respiration Acoustics Laboratory Environment) [25, 26], RespiratoryDatabase@TR [27], and Kaggle platform [28, 29]. Then, many researchers created their own datasets. Many investigators primarily use the ICBHI dataset. ICBHI also details the subject's respiratory condition chest status, data collection device, collecting method, and age and gender. Of the 6898 phases, 1864 fall under wheezes, 886 as crackles, 506 as having both occurrences and 3642 as having none [19 - 22]. Several lung sound databases, such as the Lung audio dataset, Respiratory sound database, Physiological Signal Analysis System (PhiSAS), and Marburg Respiratory Sounds (MARS), are movable online. The dataset was created with the help of a stethoscope. A stethoscope that is sold publicly was used for gathering data from the lungs [30].

Feature extraction algorithm

In this section, the procedure for categorizing a significant incoming signal with numerous of the same elements can be simplified to a lesser number of typical characteristics that can precisely define the source signal [31]. Numerous characteristics can be extracted from sounds in the frequency, time, and frequency-time domains, and those characteristics have served as the foundation for techniques for analysing sound [31 - 33]. A machine learning algorithm uses characteristics to differentiate across the various respiratory sound categories. Respiratory sounds are fundamentally irregular, so their character cannot be predicted by just one characteristic [22]. Existing computational implementations of computerized lung sound identification have utilized Mel frequency domain analyses. These characteristics enable the feature minimization stage to choose precisely the appropriate attributes for every category assignment by offering broad knowledge of the audio spectrum and in-depth analyses of particular frequencies [34]. The capacity to differentiate between distinct irregular adventitious sounds and typical respiration sounds is necessary for practical respiratory sound assessment [35]. For respiratory sound data evaluation, a variety of spectrum methods for analysis employed in the research, such as autoregressive, Fourier transform (FT), AR-Burg, autoregressive moving average, Mel-frequency cepstral coefficients (MFCC), and fast Fourier transform (FFT)-Welch.

Classification methods

Table 1. Review the kind of machine and deep learning algorithms used by earlier investigators for computerized lung/respiratory sound analysis. The CNN and SVM algorithms have often been utilized in previous research. The various machine learning algorithms primarily served in this review study.

Table 1. Machine and Deep learning-based lung/Respiratory sounds analysis

Study	Sound type	Auscultation	No. of inputs	Database	Method	Results
[21]	Normal, crackles, and wheeze	Digital stethoscope with audio recorder	n = 770	Own database	K – fold cross validation	For usual vs. unusual, crackles vs. wheezing, normal vs. crackles, and normal vs. wheezing, the algorithms verification accuracy values included 83.68%, 83.67%, 80.94%, and 90.42%, correspondingly. The precision rates of the future assessment included 82.22%, 67.74%, 67.80%, and 81.36%, in that order
[22]	COPD and Pneumonia	-	n = 703	ICBHI 2017 database	Quadratic discriminate	Quadratic discriminate attained 99.70% of precision value.
[23]	Wheeze	-	n = 111	CORSA	k-NN	The highest performance for MFCC-based element categorization is 99%, 90%, and 89% for mild, moderate, and severe specimens. 93% of wheezes were detected on the median. The telemedicine software was determined to be 57%, 72%, and 76% for mild, moderate, and severe stages.
[24]	COPD	stethoscope with a microphone attached	n = 51	Own database	STFT	86.6% for moderate COPD, 69.2% for severe COPD, and 84.5% for extremely severe COPD are the true positive signs.
[26]	Lung Sounds	-	-	R.A.L.E database	CNN	We succeeded in raising the precision to 95.56% from 95.10%.

[27]	COPD	Littmann3200 digital stethoscope	n = 42	RespiratoryDatabase@TR	SVM	SVM classification required 0.836 seconds to provide an early COPD severe assessment.
[28]	Lung Sounds	Electronic stethoscope with audacity software	n = 920	Kaggle Dataset	GB	It was discovered that the gradient boosting algorithm predicted the pneumonia cases with a greater precision of 97%.
[30]	Lung Sounds	electronic stethoscope and sound recording device HF-Type-1	-	HF_Lung_V1	CNN–BiGRU	The developed model displayed the potential to classify breathing as DASs wrongly; a fresh database with better-matched input or a different training technique is necessary to
						overcome this issue. We developed the DAS identification algorithm using sound records with a D label.
[35]	Lung Sounds	Electronic stethoscope	n = 500	Own database ICBHI 2017 database	Fine Gaussian SVM	A Fine Gaussian SVM algorithm yielded 99% accuracy, 99.04% sensitivity, and 99.2% specificity
[36]	Lung Blowing sound	Microphone	n = 188	Own database	Quadratic Linear Discriminant	94.69% accuracy, 94.45%sensitivity and 99.45%specificity they attained.
[37]	Cough sound	Smartphone microphone	n = 150	Own database	ResNet50 +SVR	Combination displays exceptional assessment of the condition of the lungs measures while coughing, enabling the realization of an easy and quick assessment for patients with pneumonia.

[38]	Lung sounds	Electronic stethoscope with microphone	n = 532	Own database	ALSD-Net	Methodology obtained 94.24% precision by using methods of data enhancement for several classifications along with instruction of pulmonary sounds.
[39]	Lung sounds	-	n = 126	ICBHI 2017 database Peking University (PKU) respiratory dataset	CNN	When developed on the ICBHI+PKU database, our algorithm outperforms all of them significantly. Specificity is 95.80%.
[40]	Respiratory sounds	Electronic stethoscope and mobile phone	n = 145	Own database ICBHI 2017 database	lightweight MobileNetV2,	The classification accuracy is 89.23%.
[41]	Lung sounds	-	n = 126	ICBHI 2017 Respiratory sound database	CNN	In the 2 Class Crackling sounds, CNN_dualInput reached 99.6% precision rate and 99.6% AUC; during the 2 Class Wheezes, CNN_dualInput reached 98.6% precision and 98.4% AUC. CNNs performed higher in the two assignments.
[42]	Cough sound	SONY ICD-LX30 portable digital recorder and an ECM-CS10 microphone	n = 42	Own database	C-BiLSTM	The algorithm has an outstanding quality with a specificity rating of 99.82%.
[43]	Lung sounds	Electronic stethoscope	n = 105 n = 126	Own database ICBHI 2017 database	Boosted decision tree	Boosted decision tree algorithm performed the most well, as indicated by its greatest levels of spe (98.55%),sen 91.5%), and acc (98.20%).

[44]	Lung sounds	-	n = 126	ICBHI 2017 database	Multilayer Perceptron	Obtained a maximum precision of 99.22% (AUC = 0.9993) using a collection of data that is accessible to the public.
[45]	Lung sounds	Electronic stethoscope, Eight electret microphones	n = 261	HF_Lung_V1	CNN	Lastly, the precision of respiratory sound evaluation was enhanced with the use of a CNN, particularly in the continuous adventitious sound identification work.
[46]	Lung sounds	Electronic stethoscope	n = 1630	Own database	CNN and SVM	CNN and SVM attained 86% of precision rate.
[47]	Asthma COPD	3 M Littmann Classic II SE Stethoscope	n = 240	Own database	Decision tree	The investigated report is to have succeeded with the most excellent categorization precision at 99.3%.
[48]	COPD, Asthma, lower and upper respiratory tract infection	-	n = 126	ICBHI 2017 database	Mel-Frequency Cepstral Coefficients	Out of all the Librosa machine learning library characteristics, "MFCC" is indicated to be more accurate for identifying COPD, according to the studies performed.
[49]	Respiratory sound	3M™ Littmann® Electronic Stethoscope 3200, 3M Littmann StethAssist Software	n = 50	BRACETS	CNN + LSTM	Our approach allows for calculating spirometric values from the airflow curve without the dimensions obtained using the respiration sound data.

[50]	Respiratory sound	-	-	ICBHI 2017 database	VMD-ELM	Manhattan distance-based VMD-ELM disclosed a precision of 95.39% for the 2-class categorization while the study was conducted; for the 3-class categorization, Euclidean distance-based VMD-ELM according to a precision of 90.61%; as well as for the 4-class categorization, VMD-ELM indicated a precision of 89.27%.
[51]	Lung sounds	-	-	ICBHI 2017 database Lung sound dataset	CNN	Our CNN model's most excellent precision of 91.04% was attained with multilayered visualization of features,
						highlighting the significance of integrating various sounds' innate characteristics to identify fresh feature sets in a particular respiratory sound area illness.
[52]	Lung sounds	Electronic stethoscope	n = 1152	Own database	VGGish-BiGRU	With an overall detection rate of 87.41%, the suggested algorithm is able to identify pulmonary sounds more accurately.
[53]	Respiratory sounds	-	n = 126	ICBHI 2017 database	k-NN	The k-NN attained 84.38% of the precision rate.

[54]	Wheeze	Microphone	n = 112	-	ANN	The findings demonstrate that, when utilizing collections of breathing cycles collected from a similar subject, the recommended method obtains 92.86% precision for wheezing identification and 84.82% performance for wheezing identification for a single breathing period.
[55]	Respiratory sounds	-	-	Own database R.A.L.E. database-CD ASTRA database-CD	B-MFCC/GMM	The suggested technique B-MFCC/GMM works better than frequently utilized techniques (p<0.05).
[56]	Lung sounds	-	n = 126	ICBHI 2017 database	CNN	The best use would be a digital stethoscope to train and test a lightweight convolutional neural network. It would enable the doctor to differentiate between healthy and unhealthy respiratory illnesses instantly.
[57]	Lung sounds	Digital stethoscope	n = 137 n = 84	RA-ILD dataset CTD-ILD dataset	Deep neural network	The critical roles played by the Knn and LogitBoost algorithms in improving the accuracy of the auscultations of the DNN processes and getting up the information set.
[58]	Respiratory sounds	Digital stethoscope via bluetooth	n = 920	Respiratory sound database	LSTM	The predicted precision rate is 98.82%.
[59]	Lung sounds	Microphone	n = 85	Own database R.A.L.E database	k-NN	Model and used characteristics RSFS chose to obtain F-Measure scores of 94.1%.

[60]	Respiratory sounds	microphone	n = 126	ICBHI 2017 dataset Own database EMTprep	1D-CNN-LSTM	With its excellent diagnostic precision and capacity to process ongoing information, this novel wheeze counter may be handy for identifying respiratory illnesses from overtime respiration habits.
[61]	Respiratory sounds	-	n = 126	ICBHI 2017 database	Dual-channel CNN-LSTM	The predicted precision rate and f1 score are 99.01% and 0.99.
[62]	Respiratory sounds	-	n = 2840	Own database	CNN	The predicted precision rate and mean AUC are 85.7% and 0.92.
[63]	Cough, Breath and Speech	Microphone	n = 6000	Own database	DNN classifiers	With an area under the ROC curve (AUC) of 0.982 for cough, 0.942 for breath, and 0.923 for speech, the top-
						performing COVID-19 classification resulted.
[64]	Respiratory sounds	Digital stethoscope	n = 23,592	Kaggle dataset	D-Cov19Net	With an AUC of 0.972 and a sensitivity of 0.983, this algorithm is accurate and clinically helpful.
[8]	Lung sounds	Microphone	n = 126	Own database	ANN	ANN attained precision rate is 94.02% but the training precision rate is 100%.

The methods commonly used in computerized lung/respiratory sound analysis are CNN, k-NN, SVM, ANN, GB, LSTM, and DT. Here, CNN is the most widely employed lung/respiratory sound detection technique. The online database of ICBHI 2017 is widely used for lung and respiratory sound detection. Then, the investigators generate their respiratory sound datasets for research purposes. The ICBHI 2017 database contains 126 subjects, including 920 annotated audio samples, 6,898 respiratory cycles, of which 1,864 had crackles, 886 contained wheezes, and 506 featured both crackles and wheezes [39, 40, 44, and 48]. Here, CNN-LSTM, Decision tree, MLP, CNN, and SVM-FG attained 99% for the classification of lung and respiratory sounds. But in this review, Naqvi et al. [22] achieved an accuracy of 99.70%, 99.40%, and 99.20% accuracy on multiple pairings of 85, 97, and 116 characteristics in the classification method of SVM-FG for classifying the Chronic obstructive pulmonary disease (COPD) and pneumonia. SVM is a supervised machine learning technique that works on classification and regression methods. Another deep learning method that has drawn interest from investigators for application in identifying respiratory sounds is the CNN algorithm for classification. Since deep learning is a thorough method, extracting characteristics is unnecessary. Deep learning models get their original data [56]. Deep neural network classification algorithms for speech, breath, and cough sounds to identify COVID-19. ROC curve (AUC) of 0.982 for cough, 0.942 for breath, and 0.923 for speech, the top-performing COVID-19 classification resulted [63]. Using cough sound, machine learning and deep learning methods were employed for COVID-19 detection [65].

Discussion

In this study, we outline the methodologies employed in a comprehensive review of research integrating machine learning (ML) and deep learning (DL) techniques with respiratory sound features for the diagnosis of chronic pulmonary diseases. Key patterns emerging from the analysis are synthesized to highlight technological and methodological advancements. While earlier studies relied on conventional recording systems, recent investigations have utilized digital stethoscopes, smartphones, audio sensors, and mobile applications to acquire lung sound data.

All reviewed studies involved the analysis of respiratory sounds collected from participants to predict pulmonary conditions. It was observed that traditional ML approaches, dependent on handcrafted feature extraction, have been largely surpassed by newer DL-based models, even when trained on limited datasets. Respiratory disorders that exhibit characteristic lung sound signatures have shown high diagnostic accuracy when assessed using either sound features alone or in combination with clinical indicators.

For instance, artificial neural networks (ANNs) demonstrated a classification accuracy of 92.86% for multi-cycle wheeze detection and 84.82% for single-cycle analysis. Although only a limited number of ML algorithms have been specifically applied to lung sound classification, hybrid approaches—combining ANNs with other techniques—show potential for enhancing diagnostic precision. In one such case, an ANN model trained on a custom dataset achieved a precision rate of 94.02% and a training accuracy of 100%.

Compared to traditional methods, computer-aided lung sound analysis offers several advantages, including improved accuracy, non-invasiveness, and faster processing. However, despite its promise, such systems are not yet widely adopted in clinical practice. Future research should focus on the real-time implementation and deployment of automated respiratory sound assessment tools to bridge this translational gap.

Conclusion

This survey presents a comprehensive overview of the various machine learning (ML) and deep learning (DL) methodologies previously employed in the analysis of respiratory and lung sounds. It explores the characteristics and classifications of different types of pulmonary sounds and associated pathologies. Additionally, the paper provides a structured summary of the disorders investigated, participant counts, signal processing techniques, and classification methods utilized in prior studies, along with their corresponding outcomes. Based on this review, the discussion section outlines recommendations and potential directions for future research in the domain of automated respiratory sound analysis.

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