

REVIEW

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Deep learning-based lung sound analysis for intelligent stethoscope

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Abstract

Auscultation is crucial for the diagnosis of respiratory system diseases. However, traditional stethoscopes have inherent limitations, such as inter-listener variability and subjectivity, and they cannot record respiratory sounds for offline/retrospective diagnosis or remote prescriptions in telemedicine. The emergence of digital stethoscopes has overcome these limitations by allowing physicians to store and share respiratory sounds for consultation and education. On this basis, machine learning, particularly deep learning, enables the fully-automatic analysis of lung sounds that may pave the way for intelligent stethoscopes. This review thus aims to provide a comprehensive overview of deep learning algorithms used for lung sound analysis to emphasize the significance of artificial intelligence (AI) in this field. We focus on each component of deep learning-based lung sound analysis systems, including the task categories, public datasets, denoising methods, and, most importantly, existing deep learning methods, i.e., the state-of-the-art approaches to convert lung sounds into two-dimensional (2D) spectrograms and use convolutional neural networks for the end-to-end recognition of respiratory diseases or abnormal lung sounds. Additionally, this review highlights current challenges in this field, including the variety of devices, noise sensitivity, and poor interpretability of deep models. To address the poor reproducibility and variety of deep learning in this field, this review also provides a scalable and flexible open-source framework that aims to standardize the algorithmic workflow and provide a solid basis for replication and future extension: <https://github.com/contactless-healthcare/Deep-Learning-for-Lung-Sound-Analysis>.

Key words Deep learning, Lung sound analysis, Respiratory sounds

Background

Lung disease has been a leading cause of mortality worldwide for many years, especially since the onset of corona virus disease 2019 (COVID-19)[1-3]. Various clinical methods have been developed to diagnose and evaluate lung health conditions, including computed tomographic scans, chest X-rays, and pulmonary function tests (PFTs)[4,5]. However, these methods are often limited to high-end clinics due to their complexity and high costs[6]. In contrast, auscultation offers a noninvasive, low-cost, and portable way of working where paramedics use a conventional acoustic stethoscope to diagnose lung diseases, including asthma, chronic obstructive pulmonary disease (COPD), and pneumonia[7-9], based on

the patient's lung sound.

Although the stethoscope has been widely used in clinics, it has several associated challenges. First, the interpretation of lung sounds requires a trained paramedic, limiting stethoscope use in low-resource areas[10]. Second, the medical-decisions made based on auscultation are subject to inter-listener variability in proficiency[11]. The subjectivity of the diagnosis is further amplified by the lack of a recording function in the conventional stethoscope that prevents other personnel from analyzing the sounds heard during the consultation[12]. These challenges need to be resolved to improve the quality and efficiency of lung disease diagnosis.

To this end, the digital stethoscope has been developed to record lung sounds by digitizing acoustic signals[13]. It enables the visualization and retrospective analysis of lung sounds. In addition, wireless transmission (e.g., Bluetooth or WiFi) allows it to be used for remote diagnosis, further increasing the convenience of application[14-16]. The emergence of digital stethoscopes combined with related physics study[17] has contributed to our understanding of lung sounds including,

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their production, transmission, and characteristics under healthy and pathological conditions[18].

Based on this understanding, the recognition of lung sound patterns using machine learning has been achieved, providing an objective and quantitative method for lung health assessment[19]. Earlier study focused on the feature engineering of lung sounds and exploitation of shallow machine learning tools for abnormal lung sound detection[20]. Zhang *et al.*[21] conducted a clinical trial showing that support vector machine (SVM)-based diagnosis performed better than general pediatricians in abnormal lung sound detection, achieving an accuracy of 77.7% and 59.9% for crackles and wheezes, respectively. This demonstrates the potential of machine learning in intelligent lung sound recognition.

More recently, deep learning-based models were proposed to detect the patterns related to lung diseases and distinguish abnormal lung sounds from normal ones and have shown promising performance[22]. Compared with shallow machine learning, most deep learning-based methods adopt an end-to-end learning approach to automatically learn the representation of lung sounds from raw acoustic signals without the need for handcrafted feature engineering. They can also leverage transfer learning to increase the adaptability of the learned models in new environments, which reduces the amount of data needed for training[23,24]. It is important for clinical applications due to the difficulty of acquiring a large amount of patient data. Pham *et al.*[25] applied convolutional neural networks (CNNs) to learn temporal-frequency information from spectrograms, and achieved 89% specificity and 82% sensitivity in normal and abnormal lung sound classification. Perna *et al.*[26] used recurrent neural networks (RNNs) to mine the context information of lung sounds over time, obtaining an accuracy of 99% in recognizing COPD patients. In addition, Altan *et al.*[27] proposed a deep belief network-based model combined with a three-dimensional (3D)-second order

difference plot of lung sound signals to distinguish the severity of COPD patients. These methods demonstrate the feasibility of implementing deep learning-based intelligent stethoscopes that can automate the detection of pulmonary disease and its severity. Moreover, deep learning-based quantitative results overcome the disadvantages of subjective auscultation diagnosis caused by inter-listener difference and the need for clinical proficiency, thus supporting medical diagnosis and treatment. Thus, deep learning-based approaches can significantly improve the quality of healthcare in underdeveloped countries with limited clinical resources; examples of their applications include community-acquired pneumonia detection and the domiciliary management of COPD.

To increase the understanding of deep learning-based lung sound analysis, in this paper, we systematically review deep learning methods proposed for lung sound analysis. This review, organized as shown in Fig. 1, outlines the system of lung sound analysis, including the pathological fundamentals of lung sounds, existing digital stethoscopes, and deep learning-based methods. The fundamentals of lung sounds guide and motivate the design of reasonable deep learning methods, and in turn, the application of digital stethoscope-based deep learning methods verifies the understanding of observations. In contrast to previous reviews[6,19,28-31], this paper emphasizes the applications of deep learning-based lung sound analysis, including the system framework, basic model selection, and the advancement of deep methods in respiratory medical tasks, also highlighting the challenges that need to be overcome. The main contributions of this review are as follows: 1) it provides an in-depth review of the fundamentals of lung sounds under normal and pathological conditions that motivates the design of deep-learning models and guides the design of signal processing algorithms (spectrograms, typical signatures, and their definitions); 2) it provides a thorough overview of the algorithmic framework of deep learning-

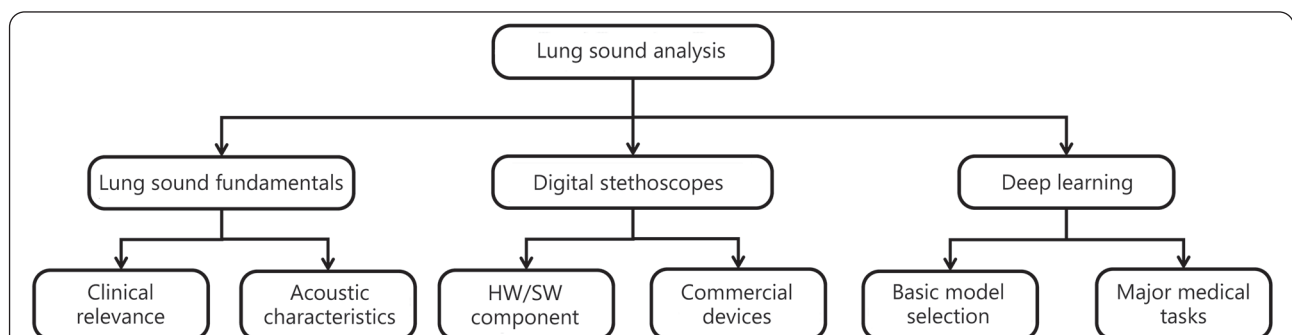


Fig. 1 An overview of deep learning in lung sound analysis.

The fundamentals of lung sounds include clinically relevant knowledge and its acoustic characteristic, which guides and motivates the design of the digital stethoscope in hardware and software. In turn, the application of digital stethoscope-based deep learning methods verifies the understanding of observations

based lung sound analysis, with a detailed introduction to each processing step, including the pros and cons of deep models and challenges they face; and 3) it provides a unified open-source deep learning-based framework that aims to standardize algorithmic components and establish a strong base that facilitates replication, bench-marking, and future extension.

The remainder of this paper is structured as follows. First, the fundamentals of lung sounds are presented. Then, the existing digital and wireless stethoscopes that can be used for clinical purposes are described, followed by an overview of the framework of deep learning in lung sound analysis including the main tasks, preprocessing, public datasets, and related research. Furthermore, an open-source framework for deep learning-based lung sound analysis is introduced. Finally, the conclusions of this review are presented.

Fundamentals of lung sounds

This section provides an overview of lung sound to improve

our understanding of its definitions, as summarized in Table 1, which is important for designing and implementing methods for lung sound analysis. Lung sound, also termed respiratory sound, can be categorized into two types according to the health condition: 1) normal lung sound, which refers to the sounds generated by the airflow passing through the healthy respiratory system[32]; 2) abnormal lung sound, which is generally caused by lung diseases, exemplified by the presence of additional sounds overlaying the normal lung sound, the absence or reduction of normal lung sound, and asymmetry between left and right lung sounds[28]. Figure 2 portrays these separately.

Normal lung sound

Normal lung sound mostly consists of tracheal, bronchial, vesicular, and bronchovesicular sounds[33]. The differences between regarding the mechanism of generation, auscultation location, appearance timing, and acoustic characteristics are shown in Table 1.

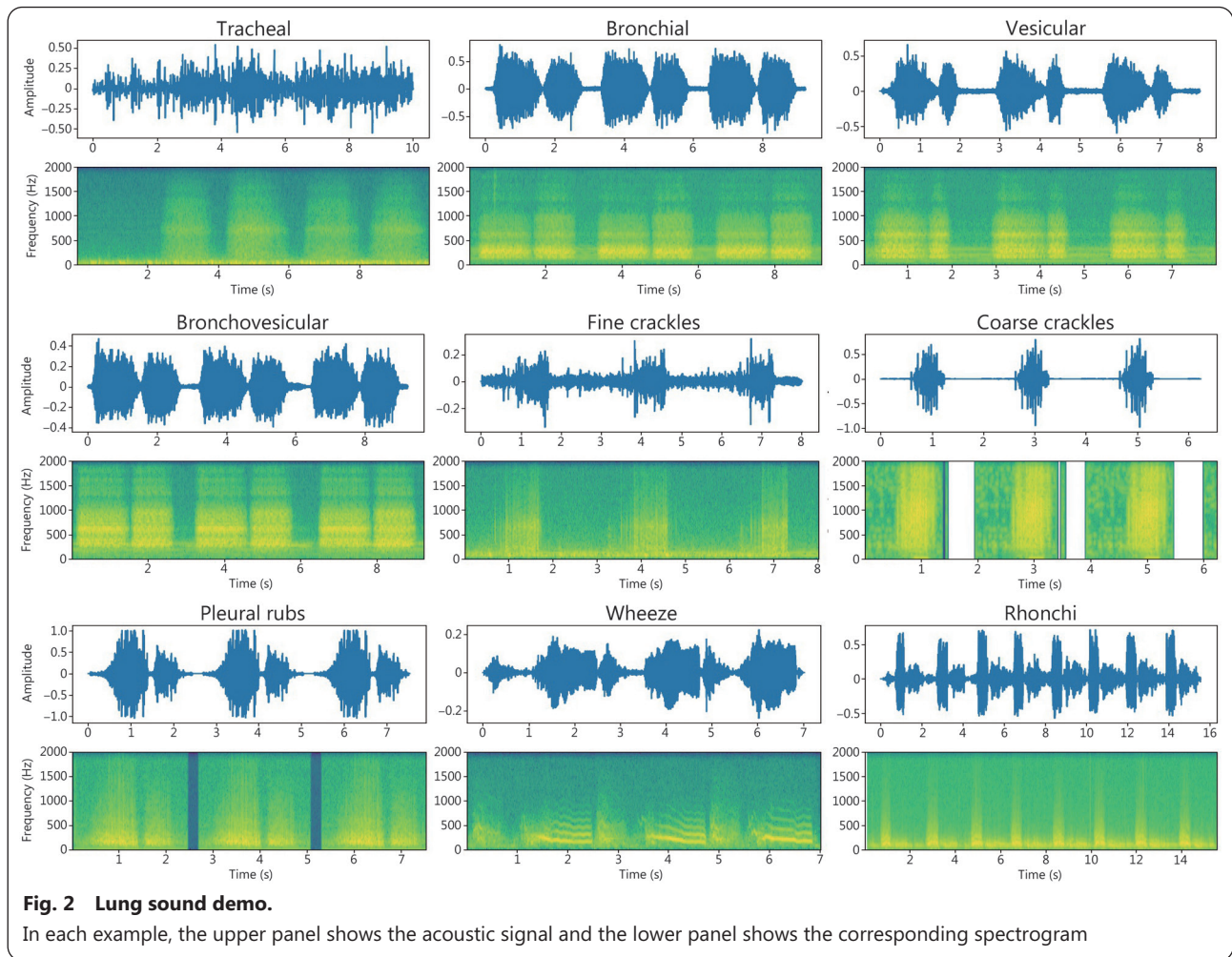
Table 1 The understanding of normal and abnormal lung sounds

| Categories of lung sounds | Produce/Cause | Timing | Acoustics characteristics | Associated disease |
|---------------------------|---|--|---|---|
| Normal | | | | |
| Tracheal | Turbulent airflow through pharynx and glottis | Both inspiration and expiration | Hollow, non-musical, harsh; High-pitch, 100-5000 Hz, drop at 800 Hz | - |
| Bronchial | Airflow traversing from trachea to the main airways | Inspiration, mostly expiration | Soft, non-musical, tubular; High-pitch, similar to tracheal | - |
| Vesicular | Airflow through smaller airways and alveoli | Inspiration, early expiration | Soft, non-musical; Low-pitch, 100-1000 Hz, drop at 200 Hz | - |
| Bronchovesicular | Airflow through bronchi and alveoli | Both inspiration and expiration | Frequency between vesicular and bronchial | - |
| Abnormal | | | | |
| Fine crackle | Explosive opening of small airways or the alveoli | Mid-to-late inspiration, occasionally expiration | Explosive, non-musical; High-pitch, 650 Hz; Duration: 5 ms | Interstitial lung fibrosis, pneumonia, pulmonary fibrosis, asbestosis |
| Coarse crackle | Air bubble in larger airways | Expiratory, mostly early inspiratory | Explosive, non-musical; Low-pitch, 350 Hz; Duration: 15 ms | COPD, bronchiectasis, asthma |
| Pleural rub | Pleural membrane rubbing against each other | Biphasic | Non-musical, rhythmic; Low-pitch, 350 Hz; Duration: 15 ms | Pleural inflammation, pleural tumors |
| Wheeze | Airflow limitation, airway narrowing | Inspiratory, mostly expiration | Musical, sibilant; High-pitch, >100 Hz; Duration: >80 ms | COPD, asthma, foreign body |
| Rhonchi | Thickening of secretions in bronchial tree | Inspiratory, mostly expiratory | Musical, sibilant; Low-pitch, 200 Hz; Duration: >80 ms | Bronchitis, COPD |
| Stridor | Upper airway obstruction | Mostly inspiratory, sometimes both | Musical, sibilant; High-pitch, 500 Hz; Duration: >250 ms | Epiglottitis, foreign body, croup, laryngeal oedema |

"-" none; COPD. Chronic obstructive pulmonary disease

Tracheal sound is produced by the turbulent airflow passing the tracheal tissues of the respiratory system[34]. When auscultation is carried out over the trachea, particularly above the sternum, this sound can be heard clearly during both the inspiratory and expiratory phases. The tracheal sound lasts for

a similar duration in both phases, and the pause between the two phases is obvious[35]. Since its transport occurs in the straighter part of the trachea with a larger diameter, the tracheal sound is typically high-pitched, hollow, non-musical, harsh, and louder than other normal lung sounds[36,37]. The normal



tracheal sound has a wide energy distribution of 100–5000 Hz, and the energy usually drops at 800 Hz[38].

Bronchial sound is generated by the airflow traversing from the trachea to the main airways, and can usually be heard near the second and third intercostal spaces[37]. Like the tracheal sound, it appears in both phases but mainly in the expiratory phase, twice as long as in the inspiratory phase[39]. In general, the bronchial sound is generally soft, non-musical, loud, high-pitched, and tubular, with a similar frequency energy distribution as the tracheal sound[28,40].

Vesicular sound is created by the airflow passing through the smaller airways and alveoli (tiny air sacs) in the lungs[41]. It is audible in most of the lung fields across the whole inspiration phase and the early expiration phase[35,42,43]. The vesicular sound is typically soft, non-musical, and low-pitched and its frequency range is from below 100–1000 Hz with an energy drop at 200 Hz[40,44].

Bronchovesicular sound can be heard between the scapulae in the posterior chest, and in the central region of the anterior chest[40]. It has a similar duration in the expiratory and

inspiratory phases[39]. In sound analysis, the bronchovesicular sound is softer than the bronchial sound but approximates the tubular sound, similar to the sound between the bronchial and vesicular sounds. Additionally, the frequency band of bronchovesicular sounds is between that of vesicular and bronchial sounds[44].

Abnormal lung sound

Abnormal lung sounds can be distinguished as discontinuous and continuous abnormal sounds according to their acoustic properties. The former has a shorter duration of less than 25 ms including fine crackle, coarse crackle, and pleural rub, whereas the latter typically has a longer duration of more than 250 ms[28], including wheeze, rhonchi, and stridor. Table 1 presents a description of these lung sounds in terms of their causes, appearance timing, clinical characteristics, acoustic characteristics, and the associated diseases.

Fine crackle arises due to the explosive opening of small airways or alveoli that were previously collapsed or closed[45]. It is commonly audible in mid-to-late inspiration and sometimes in the expiration phase, changing or disappearing

with the body position[35]. Clinical study has reported that fine crackle is caused by several diseases, such as interstitial lung fibrosis and pneumonia[35]. It can be used as a biomarker for detecting specific diseases such as idiopathic pulmonary fibrosis and asbestosis, showing good sensitivity and specificity[46]. Fine crackle presents as high-pitched (close to 650 Hz), non-musical, and explosive, with a duration of nearly 5 ms [47].

Coarse crackle is probably caused by air bubbles in larger airways that open and close intermittently[48]. Upon auscultation, it can be heard in both phases, mostly in the early inspiratory phase[49]. Due to intermittent airway opening, it is associated with some obstructive diseases, for example, COPD, bronchiectasis, and asthma[28,50]. In contrast to fine crackle, coarse crackle is low-pitched (close to 350 Hz) and has an approximative duration of 15 ms[51].

Pleural rub is generated by the rubbing of the pleural membranes against each other and is relevant to pleural inflammation and pleural tumors[35]. It is typically biphasic with the expiratory sequence of sounds mirroring the inspiratory sequence[37]. Pleural rub is non-musical, rhythmic, and low-pitched (<350 Hz). Its duration is longer than 15 ms.

Wheeze is produced by airflow limitations due to airway narrowing and is normally detected in both phases, mostly in the expiration phase[52]. Wheezing sounds are typically caused in asthma and COPD, possibly by a foreign body (e.g., a tumor) blocking the airway[35]. In general, wheeze is musical, sibilant, and high-pitched (more than 100 Hz). Its duration is generally more than 80 ms[53].

Rhonchi are related to the thickening of secretions in the bronchial tree and can be heard mostly in the expiration phase and sometimes in the inspiratory phase. Rhonchi are reported to be associated with bronchitis and COPD[35]. The acoustic characteristics of rhonchi are similar to those of wheeze sounds but with a relatively low pitch (<200 Hz)[53].

Stridor is created by the turbulent airflow in the bronchial tree, which is relevant to upper airway obstruction. Upon auscultation, it can be detected mostly in the inspiration phase, but in certain situations, it can be heard in both phases[28]. Diseases related to upper airway obstruction may cause stridor, including croup and laryngeal edema. Stridor is a sibilant and musical sound that has a high pitch above 500 Hz with a duration longer than 250 ms.

Digital stethoscopes

For deep learning-based lung sound analysis, the data acquisition process depends on digital stethoscopes that record

the lung sound by converting acoustic waves into electrical signals. Thus, this section focuses on digital stethoscopes currently available in the market and widely used in clinics, with an emphasis on their limitations and potential directions for improvement.

Implementation of digital stethoscopes

A digital stethoscope generally consists of a diaphragm, sensor, pre-amplifier, microcontroller, and transmission module[54,55], as shown in Fig. 3. Its workflow is as follows in Fig. 3a, b. First, the diaphragm is placed on the chest piece to capture the sound wave of the internal body[56]. Then, either piezoelectric sensors or electret microphones are commonly used to convert the sound waves into electrical signals[57,58]. The pre-amplifier enhances the extremely weak acoustic signal that is picked up by the sensor[59]. Next, the microcontroller processes the amplified signal, which includes controlling the audio processing circuitry and managing the user interface and display. Finally, under the control of the microcontroller, the transmission module (e.g., Bluetooth), transmits data to the terminals in a lossless way as far as possible[60,61].

Available digital stethoscopes

Here, we focus on digital stethoscopes that have been used as clinical devices, including 3M LITTMAN 3200, Thinklabs digital stethoscope, and Clinicloud digital stethoscope, as shown in Fig. 3c–e.

3M LITTMAN 3200

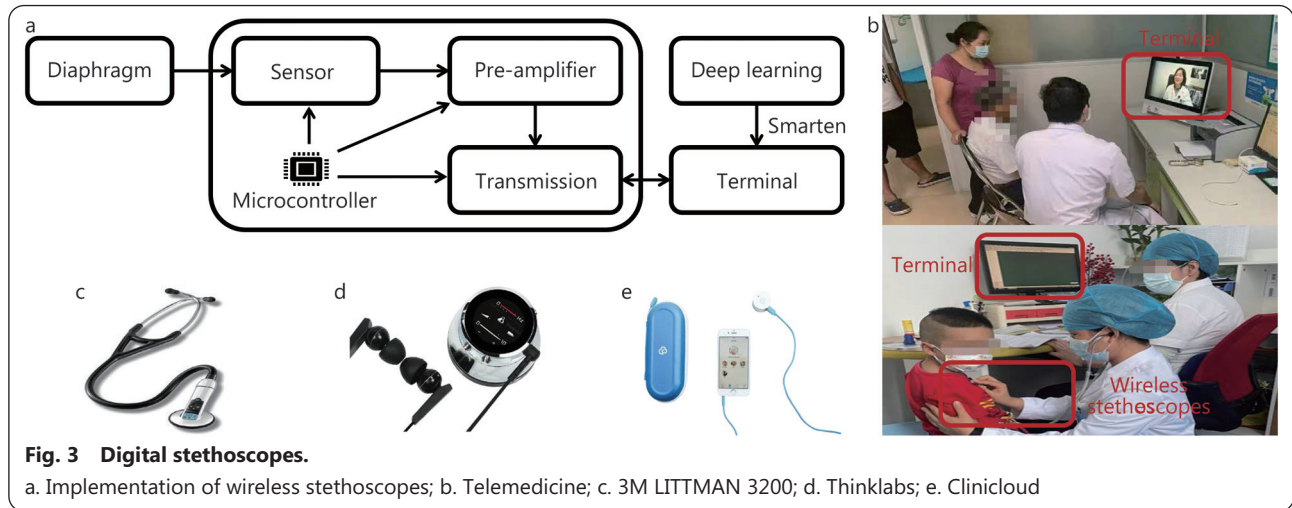
The most popular stethoscope, it amplifies 24 times for acoustic signals with a denoised module and offers a mobile applications system for lung health management. A clinical trial showed that the diagnostic accuracy of medical interns was improved upon using LITTMAN 3200 compared to the traditional acoustic stethoscope[62]. Some studies also used machine learning to automatically detect abnormal lung sounds and diagnose lung diseases in offline clinical studies, wherein the 3M LITTMAN 3200 was applied to collect and transmit lung sounds[10,63,64].

Thinklabs digital stethoscope

This is a tube-free device that can amplify acoustic signals 100-fold, remove noises that have different frequency bands by using multiple frequency filters, and provide a mobile APP. This stethoscope has been clinically investigated for pneumonia detection[65] and the analysis of the frequency characteristics of normal lung sounds[66].

Clinicloud digital stethoscope

This stethoscope has been designed without the function of signal amplification. It was used in a clinical trial at Melbourne Hospital and showed accurate abnormal sound detection (ASD) in children[67].



Limitations and future improvements

Although the abovementioned stethoscopes are capable of recording and transmitting lung sounds, they still face some challenges. First, the high price of existing digital stethoscopes limits their scope of application in low-resource areas. Such areas desperately need low-cost and easy-to-operate medical devices since they cannot afford expensive equipment and manpower. Second, the available commercial digital stethoscopes are single-channel devices, making it difficult to monitor the left and right lungs synchronously. The diagnostic accuracy of single-channel devices can be improved by extending them to multiple channels[68-70]. Third, the difference in sound quality between these stethoscopes may cause deviations in the performance of algorithms for lung sound analysis[71]. Gairola *et al.*[72] performed device-based fine-tuning to improve the quality of detection; however, it is not practical to tune all these devices. To solve these challenges, future research should focus on the implementation of low-cost and highly-reliable digital stethoscopes. Specifically, the development of each component of the device can facilitate this goal. For example, the expensive commercial

diaphragm can be replaced with 3D-printed materials[73]. For signal transmission, the lung sound signal can be transmitted by matured technologies such as Bluetooth Low Energy[74] and Zigbee[75], allowing stethoscopes to be a part of the Internet of Medical Things to provide more comprehensive lung health assessments[76]. Furthermore, the development of wearable devices is also conducive to all-weather lung health monitoring. Meanwhile, the endurance and intelligence of digital stethoscopes need to be improved by introducing new technologies regarding the battery, processor, and embedded algorithms to cope with medical situations in low-resource areas.

Deep learning in lung sound analysis

This section reviews deep learning studies for lung sound analysis including the system framework, common datasets, preprocessing, feature extraction, and deep learning methods designed for different medical tasks, as shown in Fig. 4.

System framework

Clinically, auscultation results depend on the doctor’s interpretations of lung sounds, which are often subjective based on the proficiency of the listener. As a result, the clinical

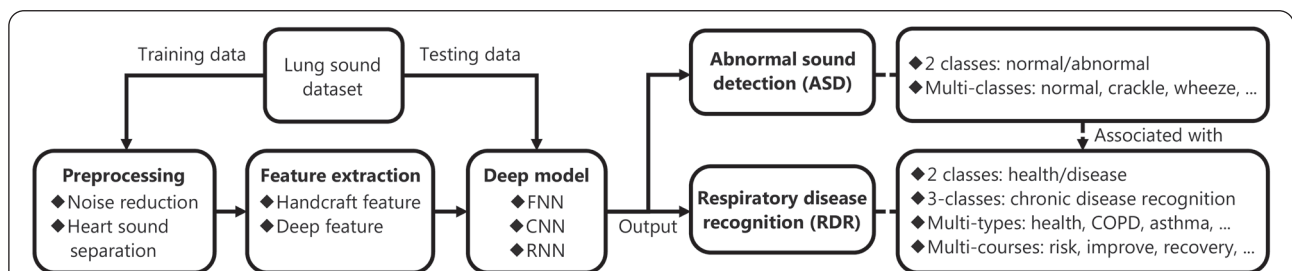


Fig. 4 Deep learning-based framework for lung sound analysis.

For two different medical tasks (ASD and RDR), the training set is used to construct the model including the steps of preprocessing, feature extraction, model selection. Finally, the test set is used to evaluate the performance of model. FNN. Fully connected neural network; CNN. Convolutional neural network; RNN. Recurrent neural network; COPD. Chronic obstructive pulmonary disease

decisions made for the same patient may vary between physicians, promoting misdiagnosis and missed diagnosis. To solve this issue, machine learning methods (SVM, CNN, and random under-sampling boosting) have been proposed in different clinical contexts to provide quantitative and objective results on different types and degrees of lung disease[21,77,78]. However, most shallow machine learning-based lung sound analysis methods were evaluated based on a self-collected dataset of only a few subjects that was saturated at a low accuracy of approximately 80%[79-81].

Recently, deep learning has shown great potential in lung sound analysis, with a more accurate and robust performance compared with shallow machine learning[82]. Its improved performance may be attributed to the following features. (1) Representation: deep learning methods automatically learn task-relevant features in a data-driven manner without the need for manual feature engineering, and the learned features can capture complex patterns and structures in the raw data[22]; (2) Context information: deep learning methods show the advantages of capturing temporal context information, such as RNNs, which is significant for lung sound analysis in mining periodic lung sound changes caused by disease[26]; (3) Transfer learning: deep learning methods can use the common knowledge shared with related fields (e.g., AudioSet[83], a large audio dataset) to improve lung sound analysis, which reduces the amount of data required for training[24]. This property is significant for clinical applications since clinical data are often scarce due to the challenge of organizing clinical trials.

Generally, most deep learning-based lung sound analyses follow the paradigm of sequentially executing data acquisition

and preprocessing, feature extraction, and classification. First, a digital stethoscope is used to collect lung sound data, following which preprocessing is applied to suppress environmental noise in the recorded lung sound signals. Thereafter, feature extraction is used to convert high-dimensional preprocessed lung sound data into a lower-dimensional space to obtain a more discriminative representation. Finally, the classifier is designed to create a mapping between the features and classes of relevant diseases.

Datasets for lung sound analysis

To evaluate performance, many deep learning-based lung sound analysis methods were benchmarked on public datasets for a fair comparison. The public lung sound datasets[84-88] are summarized in Table 2. The most widely used dataset is the ICBHI 2017 Respiratory Sound Database[84] which consists of 920 recordings from 126 subjects who were diagnosed with respiratory pathological conditions, such as pneumonia, bronchiectasis, bronchiolitis, and COPD. Those recordings had different sampling rates (e.g., 4000 Hz, 10,000 Hz, and 44,100 Hz) and their duration ranged from 10 s to 90 s. For annotation, the medical teams labeled the beginning and end of the breathing cycles in each recording as well as the presence/absence of crackles and wheezes. This dataset collected 6898 breath cycles, with 3642 normal cycles, 1864 with crackles, 886 with wheezes, and 506 with both, where the cycle duration of all recordings varied from 0.2 s to 16 s, with a mean duration of 2.7 s.

Recently, many new datasets have emerged for lung sound analysis. Fraiwan et al.[85] collected 112 lung sound recordings from 112 subjects who were healthy or diagnosed with asthma, pneumonia, COPD, bronchitis, heart failure, lung fibrosis, and

Table 2 Public lung sound datasets

| Dataset | Subject | Audio recording | Duration | Annotation | Diagnosis |
|----------------------------|---------|-----------------|----------|--|---|
| ICBHI 2017[84] | 126 | 920 | 10-90 s | Normal, crackle, wheeze, both crackle and wheeze | Lower respiratory tract infections, upper respiratory tract infections, pneumonia, COPD, asthma, bronchiolitis, bronchiectasis, cystic fibrosis |
| Fraiwan et al.[85] | 112 | 112 | 5-30 s | Inspiratory, expiratory, wheezes, crackles, normal | Normal, asthma, pneumonia, COPD, bronchitis, heart failure, lung fibrosis, pleural effusion |
| HF_Lung_V1[86] | 261 | 9765 | 15 s | Inhalation, exhalation, stridor, rhonchus, crackle | Acute respiratory failure, chronic respiratory failure, acute exacerbation of COPD, COPD, pneumonia, acute respiratory distress syndrome, emphysema |
| HF_Lung_V2[87] | 303 | 14,138 | 15 s | Inhalation, exhalation, stridor, rhonchus, crackle | Acute respiratory failure, chronic respiratory failure, acute exacerbation of COPD, COPD, pneumonia, acute respiratory distress syndrome, emphysema, long-term mechanical ventilation |
| RespiratoryDatabase@TR[88] | 77 | 77 | >17 s | COPD 0-5, wheezing, crackle | Asthma, COPD, bronchitis, healthy |

COPD. Chronic obstructive pulmonary disease

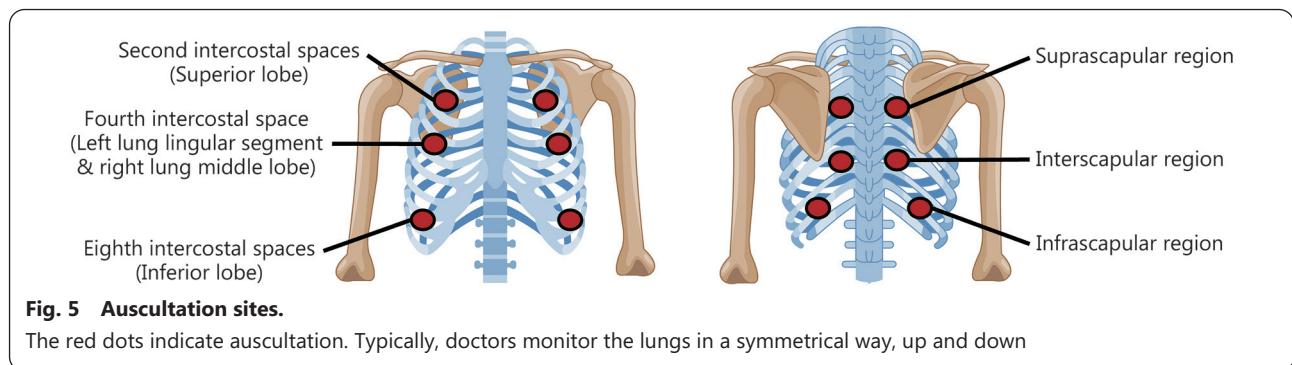
pleural effusion. Each recording was annotated according to the different lung sound events, including normal, inspiratory, expiratory, crepitations, crackles, and wheezes. Hsu *et al.*[86] proposed a new dataset called HF_Lung_V1, which consists of 9765 lung sound recordings with a duration of 15 s from 261 subjects. These recordings were collected using a single-channel device (3M LITTMAN 3200) and a multi-channel device (self-customized device, HF-Type-1). HF_Lung_V1 marked 34,095 inspiratory segments, 18,349 expiratory segments, 13,883 continuous adventitious sound segments, and 15,606 discontinuous adventitious sound segments. Moreover, Hsu *et al.*[87] collected lung sounds from 42 new subjects to expand HF_Lung_V1 into a new dataset, namely HF_Lung_V2. More details about these public datasets are given in Table 2.

In addition, the need for the management of chronic pulmonary disease like COPD has also gradually attracted the attention of clinicians and researchers[89], where the assessment of disease severity is a prerequisite for determining medical interventions[90]. Altan *et al.*[88] released a dataset called RespiratoryDatabase@TR that collected lung sounds from patients diagnosed with asthma, bronchitis, and different severities of COPD (0–5). In the trial, each subject underwent the examinations of chest X-rays, PFTs, and cardiopulmonary auscultation. The resulting dataset consists of 77 recordings from 77 subjects, with each recording sampled at 4000 Hz and containing 4 channels of heart sounds and 12 channels of lung sounds. For annotation, two pulmonologists validated and

labeled the sound records as murmur, crackle, or wheezing, with reference to the gold standards of chest X-rays and PFTs. RespiratoryDatabase@TR has been widely used to assess the severity of COPD[27,91,92].

Data acquisition and preprocessing

In the clinical procedure for acquiring lung sound data, the digital stethoscope should be placed on specific parts of the thoracic surface for certain durations (e.g., 15 s, 30 s, or even longer) to depict the overall lung condition. As shown in Fig. 5, the monitoring of the superior lung lobe requires the digital stethoscope to be placed on both the left and right second intercostal spaces on the anterior chest, along with the suprascapular region at the equivalent horizontal level. The fourth intercostal space and the interscapular region are correspondingly affiliated with the superior lobe of the left lung (the lingular segment) and the middle lobe of the right lung. To assess the inferior lobes of the lung, auscultation should be performed on the left and right eighth intercostal spaces as well as the infrascapular region. Through this process, the lung sound data from the audio recorded by the stethoscope are extracted in the form of electrical signals. However, since lung sound is fragile to environmental noise and the disturbance caused by internal heartbeat sounds, it is necessary to preprocess the raw recordings to ensure that lung sound is the dominant component of the recordings[93]. According to the different noise sources, the preprocessing can be subdivided into two types, namely external noise reduction and heart sound separation.



External noise reduction methods are generally based on three different technologies. (1) Filter-based: this technology has the ability to quickly process a large amount of data but it is difficult to remove noise, with frequency information overlapping with lung sounds[94-96]; (2) Wavelet-based: this can decompose the mixed signal based on its time-frequency information to obtain the denoised signal; however, its denoising effect is easily affected by the selection in the wavelet basis function and threshold function[97-99]; and

(3) Empirical mode decomposition (EMD)-based: this eliminates different types of noise in the audio signal but requires high computational complexity and reasonable parameter selection[100,101]. For example, Meng *et al.*[102] decomposed the noisy signal into seven sub-signals using wavelet decomposition and located the position of the lung sound in each sub-signal using autocorrelation coefficients to extract the effective lung sound components. Haider *et al.*[103] used EMD to decompose the noisy signal and integrated Hurst

analysis for intrinsic mode function (IMF) selection to reduce the noise from the lung sound recording. Based on prior knowledge of lung sound signals, Emmanouilidou *et al.*[11] processed the noisy signal in short-time windows and used the current frame's signal-to-noise information to dynamically extract the interested components of lung sound.

To separate the lung sound and heart sound, various methods have been proposed based on blind source separation (BSS), such as filter-based methods, independent component analysis (ICA), wavelet-based methods, and non-negative matrix factorization (NMF)[104-109]. Grooby *et al.*[110] presented an NMF-based method that separates the raw sound recording into both the heart sound and lung sound. Although these methods have shown their effectiveness, the results of ICA-based separation are varied due to the selection of the number of iterations and convergence criteria, resulting in uncertainties in the phase, amplitude, or ranking order of separated signals. In the NMF-based method, the spectrogram of mixed signals is decomposed into two nonnegative matrices,

minimizing the difference between the product of the two non-negative matrices and the original matrix. Since the minimization process involves non-convex optimization, the decomposed signal is easily limited to the local optimal solution, resulting in poor noise reduction. In addition, the periodicity of heart sound has been applied to differentiate heart sound from lung sound[111,112]. For example, Ghaderi *et al.*[113] applied singular spectrum analysis to locate and separate different trends of heart sound and lung sound.

Feature extraction

The high variability of lung sound is caused by many factors, such as age, sex, lung disease, and body position. The feature extraction method is important for obtaining distinctive feature representations for classification. As shown in Fig. 6, the representations of lung sound rely on two different types of feature extraction: traditional handcrafted feature extraction and deep learning-based feature extraction[114], which are discussed below.

The traditional handcrafted features have quantifiable

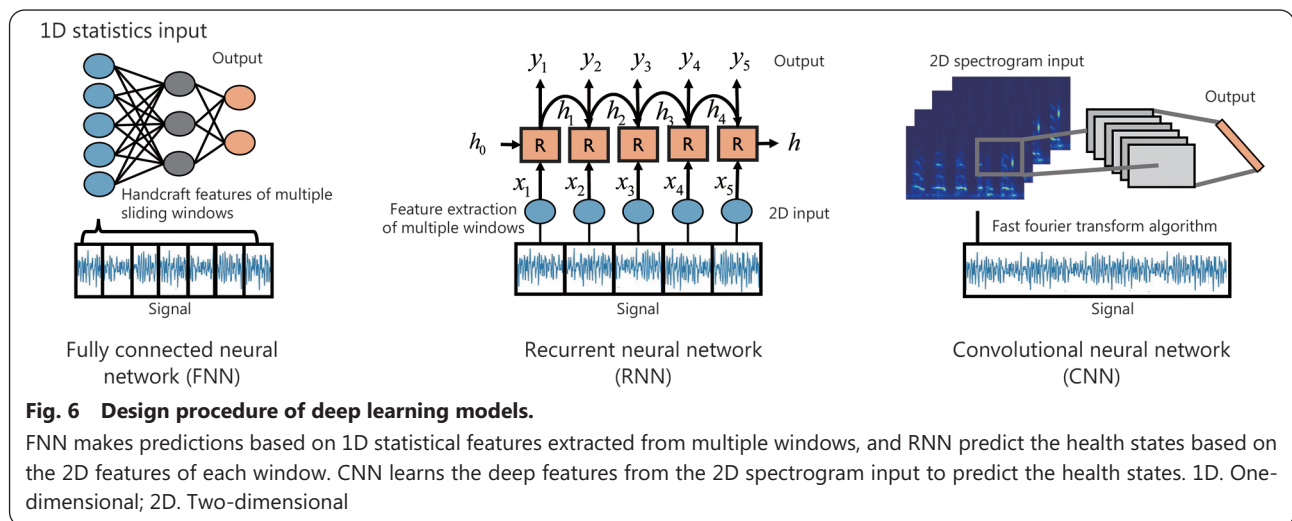


Fig. 6 Design procedure of deep learning models.

FNN makes predictions based on 1D statistical features extracted from multiple windows, and RNN predict the health states based on the 2D features of each window. CNN learns the deep features from the 2D spectrogram input to predict the health states. 1D. One-dimensional; 2D. Two-dimensional

characteristics of audio signals that can be used to differentiate various sounds, which can be subdivided as follows: 1) time-domain features, which capture information related to lung sound variations over time, such as zero-crossing rate, root mean square, and signal envelope; 2) frequency-domain features, which provide information about the distribution of energy across various frequency bands, such as spectral centroid, spectral roll-off, and spectral flux. Mel-frequency cepstral coefficients (MFCCs) are a commonly used feature in lung sound analysis derived from the Fourier transform, which can capture the distribution of energy in different frequency bands[115,116]; and 3) time-frequency domain features, which record the distribution of energy across different frequency bands over time, providing valuable insights into

the non-stationary and transient nature of lung sounds, such as wavelet transform and spectrogram[117-119]. Researchers generally use a combination of multiple-domain handcrafted features as representations for lung sound analysis[120]. Among them, the statistical feature is a commonly used combination representation derived from a short temporal sliding window that divides the signal into multiple segments to extract multidomain features. The statistical values of each feature across multiple segments, such as mean, variance, skewness, and kurtosis, are calculated as the representation. Deep learning-based feature extraction is a data-driven approach that learns features directly from the raw data without the need to design manual features[121-123]. The CNN, with the input of the spectrogram, is commonly used to

capture complex and hierarchical patterns within data and can learn more discriminative and robust representations. Pham *et al.*[124] explored the effect of different types of spectrograms and the spectral-time resolution in deep learning-based lung disease detection. Long short-term memory (LSTM) is another important method for feature extraction based on raw data or frequency-domain features. Fraiwan *et al.*[125] used CNN to extract the time-frequency information of multiple windows from the raw signal, then used LSTM to mine the continuous time-frequency change information for pulmonary disease recognition.

In summary, traditional handcrafted features are manually designed based on the human understanding of audio signals that emphasize different characteristics of lung sounds in different targeting domains. These handcrafted features are usually easy to interpret and computationally efficient. Initially, the 1D handcrafted features combined with fully connected neural networks (FNNs) were often used for lung sound analysis by projecting the feature vectors into the specified task space[117]. However, handcrafted features are more sensitive to noise, suffering from quality drops when unexpected events emerge (e.g., talking, footsteps, and coughing)[93]. Unlike handcrafted features, deep learning-based feature extraction does not fully rely on the human understanding of acoustics or audio content, but automatically learns the task-relevant features from a large amount of lung sound data. Here, CNN combined with the input of 2D spectrogram representation is the most commonly used method, wherein the spectrogram records the raw signal information in the time-frequency domain, and the convolutional kernel is used to integrate the frequency and time domain features to generate high-level semantic representations. The features learned by the deep learning model have the clear advantage of high complexity and dimensionality; however, they lack interpretability since the procedure of network optimization (e.g., backpropagation) is not transparent. Furthermore, this approach requires more computing resources.

Deep learning methods

This section outlines the existing deep-learning methods for lung sound analysis[10,22-27,33,72,77,82,91,92,117,122-157], as shown in Table 3. Many aspects of deep learning-based lung analysis are overviewed: basic model selection, the advancement of medical tasks, and limitations and future directions.

Basic model selection

The construction of a specific deep-learning model is based on the structure of input data, as shown in Fig. 6. FNNs can be used to extract information from a 1D representation, such as

the 1D statistical features of lung sound data. For RNNs, the lung sounds will be divided into continuous time windows, and the acoustic features will be extracted from each window to form a 2D lung sound representation. Then, the RNN uses the hidden layer to learn the temporal changes of lung sounds for disease classification. CNNs are more suitable for 2D data representation, such as images (e.g., 2D spectrograms of lung sound). Therefore, the construction of deep learning can be done based on the selection of a specific deep learning model according to its input structure. The basic models can be referred to[33,126,127]. Preferably, the model undergoes some tailoring or tuning of its structure based on the classification task and optimization strategy[24,128,129]. For example, the FNN-based method transforms the lung sound into a combination representation of acoustic characteristics, then feeds it to the FNN for abnormal sound identification[18]. Charleston-Villalobos *et al.*[118] extracted power spectral density as the representation of lung sound, then used a FNN to distinguish between healthy subjects and interstitial lung disease (ILD) patients, achieving a mean accuracy of 84% with a self-collected dataset. The RNN-based method analyzes the temporal dynamics of lung sounds, which provides insight into the progression of respiratory diseases over time[127]. Perna *et al.*[26] exploited the temporal information of lung sounds by using an RNN to recognize abnormal lung sounds, achieving 85% specificity and 62% sensitivity. The CNN-based method learns the temporal-frequency features from the 2D spectrogram of lung sounds to detect abnormal patterns and infer health conditions[33,121]. Based on the ICBHI 2017 dataset, Yu *et al.*[130] extracted global and local features from the Mel spectrogram with a CNN to recognize normal lung sounds, crackle, wheeze, and both, achieving 84.9% specificity and 84.5% sensitivity.

Advancement of medical tasks using lung sound analysis

For medical purposes, deep learning methods can be sorted for two main tasks. (1) ASD: this is a diagnostic auxiliary task that involves the detection of specific abnormal lung sounds, usually crackling and wheezing, as the basis for the diagnosis of specific diseases; and (2) Respiratory disease recognition (RDR): this is an automated diagnostic task that directly distinguishes respiratory patients from healthy subjects or identifies patients with different types of respiratory diseases, such as patients with COPD, pneumonia, and asthma. The relationship between them is shown in Fig. 4.

ASD consists of two sub-tasks. (1) 2-classes abnormal lung sound detection. As a binary classification, this focuses on distinguishing abnormal lung sounds from normal lung sounds without concrete labels or on detecting one type of

Table 3 Deep learning methods in lung sound analysis

| Task | Year | Reference | Basic method | Dataset | Outcome |
|------|-------|-----------------------------------|-------------------------------------|--|--|
| ASD | 2013 | [126] | Wavelets, FNN | Self-collected, 13 healthy, 13 pathological | Normal or crackle: ACC–71.55% |
| | 2014 | [117] | Wavelets, FNN | Lehrer’s dataset | Normal, wheeze or crackle: ACC–99.26% |
| | 2016 | [132] | MFCCs, LFCCs, FNN | RALE database, IIT Kharagpur, Salt Lake, Kolkata | Normal, wheeze or crackle: ACC–97.61%, SEN–97.41%, SPE–98.33% |
| | 2018 | [33] | Spectrogram, CNN | RALE dataset | Coarse crackle, fine crackle, polyphonic wheeze, monophonic wheeze, normal, squawk, stridor: ACC–95.56% |
| | 2018 | [127] | MFCCs, RNN | Self-collected, 10 healthy, 5 idiopathic pulmonary fibrosis | Inspiration: F1–87%; Expiration: F1–84.6%; Crackles: F1–72.1% |
| | 2018 | [147] | LSTM | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SEN–58.4%, SPE–73.0%, AS–65.7% |
| | 2019 | [133] | Spectrogram, CNN | Self-collected, 50 pediatric patients | Wheeze, rhonchi, fine crackle, or coarse crackles: recall–76.5%, precision–53.0%, SPE–83.6%, F1–62.5% |
| | 2019 | [148] | Spectrogram, CNN | CBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SEN–31.12%, SPE–68.20%, AS–50.16% |
| | 2020 | [23] | Mel spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SEN–48.63%, SPE–84.14%, AS–66.38% |
| | 2020 | [131] | Mel spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: AS–78.4%; Normal and abnormal: AS–83.7% |
| | 2020 | [136] | Mel Spectrogram, CNN | ICBHI 2017 | Normal, wheeze or crackle: ACC–98.6%, F1–98.4% |
| | 2020 | [149] | Spectrogram, LSTM, CNN, autoencoder | Self-collected, 22 patients | Inspiration or expiration: ACC–92% |
| | 2020 | [150] | Spectrogram, CNN | Self-collected, 25 pediatric patients | Normal, wheeze or crackle: crackle PPA–95%, NPA–99%; wheeze PPA–90%, NPA–97% |
| | 2020 | [151] | Spectrogram, CNN | RALE database, Think labs lung sound library | Normal, crackles, wheezes, or rhonchi: ACC–83.78% |
| | 2021 | [22] | Spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE–85.44%, SEN–70.93%, AS–78.18% |
| | 2021 | [72] | Mel spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE–72.3%, SEN–40.1%, AS–56.2%; Normal or abnormal: SPE–80.9%, SEN–73.1%, AS–77.0% |
| | 2021 | [77] | CNN | Self-collected, 1918 respiratory sound record | Normal, abnormal (crackles, wheezes, rhonchi): ACC–84.8%, precision–81.4%, recall–81.7%, F1–81.4% |
| | 2021 | [152] | Spectrogram, CNN, autoencoder | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE–69%, SEN–29%, AS–49% |
| | 2023 | [82] | Spectrogram, CNN | Self-collected, 105 health, 189 patients | Normal, crackles, or rhonchi: ACC–83% |
| | 2022 | [130] | Mel spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: ACC–84.7%, SEN–84.5%, SPE–84.9%, precision–84.4%, recall–89.0%, F1–86.6% |
| 2022 | [134] | Spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE–85.6%, SEN–29%, AS–57.3% | |
| 2022 | [135] | Mel spectrogram, TCN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE–86.1%, SEN–65.3%, AS–75.7% | |
| 2022 | [137] | LSTM, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE–82.46%, SEN–47.37%, AS–64.92% | |
| 2022 | [146] | Spectrogram, Mel spectrogram, CNN | ICBHI 2017 | Crackles or others: ACC–86.4%; Wheezes or others: ACC–78.2%; Crackles, wheezes, or others: ACC–84.5% | |
| RDR | 2013 | [153] | Statistical feature, FNN | Self-collected, 27 healthy and 33 tuberculosis | Healthy or pulmonary tuberculosis subject: ACC–73% |
| | 2014 | [138] | FNN | Self-collected, 10 healthy and 20 pathological | Normal and abnormal subject: ACC–92.86%, SEN–86.30%, SPE–86.90% |
| | 2018 | [27] | Deep belief networks | RespiratoryDatabase@TR | Risk level or interior level: ACC–95.84%, SEN–93.34%, SPE–93.65% |
| | 2018 | [91] | Extreme learning machines | RespiratoryDatabase@TR | COPD or health: ACC–92.22%, SEN–89.44%, SPE–95.00% |
| | 2018 | [154] | Deep extreme learning | RespiratoryDatabase@TR | COPD or health: ACC–95.0%, SEN–93.33%, SPE–93.53% |
| | 2019 | [123] | Spectrogram, CNN | ICBHI 2017 | All diseases classification: ACC–97% |

(Continued)

| Task | Year | Reference | Basic method | Dataset | Outcome |
|----------|------|-----------|--|---|---|
| | 2020 | [155] | Boltzmann machines | RespiratoryDatabase@TR | COPD or healthy subject: ACC -93.67%, SEN-91%, SPE-96.33% |
| | 2020 | [122] | Convolutional RNN | Self-collected, 16 healthy and 7 pulmonary fibrosis | Health or idiopathic pulmonary fibrosis: precision-100%, SEN-85.9%, F1-92.4% |
| | 2020 | [139] | Mel spectrogram, CNN | ICBHI 2017 | Non-COPD, COPD, or healthy subject: SEN-98.5%, SPE-99.0%, AS-98.7% |
| | 2020 | [143] | Extreme learning machines | RespiratoryDatabase@TR | Five severity degrees of COPD: ACC-94.31%, SEN-94.28%, SPE-98.76% |
| | 2020 | [156] | Statistical feature, FNN | ICBHI 2017 | Health or diseases: ACC-82%, precision-87% |
| | 2021 | [140] | EMD, wavelet, CNN | ICBHI 2017 | Non-COPD, COPD, or healthy subject: precision-98.90%, recall-98.90%, ACC-98.92%, F1-98.90%; Six diseases: precision-98.70%, recall-98.27%, ACC-98.70%, F1-98.47% |
| | 2021 | [144] | Deep belief network | RespiratoryDatabase@TR | Mild, moderate, or severe COPD: ACC-71.74%, SEN-70.08%, SPE-73.53% |
| | 2022 | [125] | CNN, LSTM | Self-collected, 103 patients | Health or five diseases: ACC-98.16%, SEN-90.06%, SPE-98.61%, precision-92.13% |
| | 2022 | [141] | Wavelet, CNN, LSTM | ICBHI 2017 | Health, COPD, asthma, or pneumonia: ACC-88.86%; Health, COPD, or non-COPD: ACC-66.54% |
| | 2022 | [142] | FNN, CNN, LSTM | ICBHI 2017 | URTI, COPD, pneumonia, and bronchiolitis and healthy: ACC-94%, precision-94%, recall-94%, F1-93% |
| | 2022 | [157] | Statistical feature, FNN | ICBHI 2017 | Health or diseases: SPE-97.6%, SEN-98.2% |
| | 2023 | [10] | CNN, LSTM | Self-collected, 198 patients | Disease, symptom relief, or health: 1) subject-dependent: SEN-96.98%, SPE-97.43%, AS-97.20% 2) subject-independent: SEN-43.26%, SPE-39.61%, AS-41.44% |
| | 2023 | [92] | Mel spectrogram, pretrained MobileNet-V1 | RespiratoryDatabase@TR | Risk level or interior level: ACC-99.25%, SEN-99.18%, SPE-99.36%; Five severity degrees of COPD: ACC-96.14%, SEN-95.94%, SPE-98.89% |
| | 2023 | [129] | CNN | Self-collected, 126 subject | Health, asthma, COPD, ILD, pneumonia, bronchiectasis: precision-92.81%, SEN-92.22%, SPE-98.50% |
| ASD, RDR | 2019 | [26] | MFCCs, LSTM | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: ACC-74%, SPE-85%, SEN-62%, AS-74%; Normal or abnormal: ACC-81%; Health or diseases: ACC-99%, SPE-82%, SEN-99%, AS-91%; Health, COPD, or non-COPD: ACC-98%, SPE-82%, SEN-98%, AS-90% |
| | 2020 | [25] | Spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE-89%, SEN-72%, AS-80%; Normal or abnormal: SPE-89%, SEN-82%, AS-85%; Health or diseases: SPE-71%, SEN-99%, AS-85%; Health, COPD, or non-COPD: SPE-71%, SEN-95%, AS-83% |
| | 2021 | [124] | Spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE-90%, SEN-68%, AS-79%; Normal or abnormal: SPE-90%, SEN-78%, AS-84%; Health or diseases: SPE-86%, SEN-98%, AS-92%; Health, COPD, or non-COPD: SPE-86%, SEN-95%, AS-91% |
| | 2021 | [128] | Mel spectrograms, CNN | ICBHI 2017 | Normal, crackles, or wheezes: SPE-82%, SEN-61%, AS-72%; COPD, healthy, and pneumonia: SPE-92%, SEN-98%, AS-95% |
| | 2021 | [145] | Spectrogram, inception | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE-73%, SEN-30%, AS-52%; Health, COPD, or non-COPD: SPE-100%, SEN-75%, AS-85% |
| | 2022 | [24] | Spectrogram, CNN | ICBHI 2017 | Normal, crackles, wheezes, and both crackles and wheezes: SPE-78.55%, SEN-35.97%, AS-35.97%; Normal or abnormal: SPE-79.34%, SEN-50.14%, AS-64.74%; Health, COPD, or non-COPD: SPE-91.77%, SEN-93.68%, AS-92.72%; Health or diseases: SPE-91.77%, SEN-95.76%, AS-93.77% |

ACC. Accuracy; AS. Average score of specificity and sensitivity; ASD. Abnormal sound detection; COPD. Chronic obstructive pulmonary disease; CNN. Convolutional neural network; EMD. Empirical mode decomposition; FNN. Fully connected neural network; ILD. Interstitial lung disease; LFCCs. Linear frequency cepstral coefficients; LSTM. Long short-term memory; MFCCs. Mel-frequency cepstral coefficients; NPA. Negative percent agreement; PPA. Positive percent agreement; RDR. Respiratory disease recognition; RNN. Recurrent neural network; SEN. Sensitivity; SPE. Specificity; IIT. Indian Institute of Technology; F1. F1-score; URTI. Upper respiratory tract infection

abnormal lung sound (e.g., crackle, wheeze, and stridor). Serbes *et al.*[126] explored the effect of different wavelet types and window sizes in FNN-based crackle detection, where Gaussian, Hanning, Hamming, and Rectangular windows were considered, while Morlet, Mexican Hat, and Paul wavelets were applied to lung sound recognition. Nguyen *et al.*[131] proposed the methods of temporal stretching and vocal tract length perturbation for data augmentation to solve the issue of limited training samples, then used a CNN as the backbone for abnormal lung sound detection. (2) Multi-classes abnormal lung sound recognition. This is used to distinguish between specific abnormal sounds including crackles, wheezes, and rhonchi, where the number of classes is dependent on the number of types of abnormal sounds. Sengupta *et al.*[132] extracted statistical features based on MFCCs for lung sound, then fed a FNN to distinguish normal, wheeze, and crackle sounds. Their experiment was carried out on 30 subjects and showed that MFCC-based statistical features outperformed wavelet-based features in finding abnormal sounds. Bardou *et al.*[33] extended the types of abnormal lung sounds to include normal, coarse crackle, fine crackle, monophonic wheeze, polyphonic wheeze, squawk, and stridor, then used a spectrogram-based CNN to identify these types. Grzywalski *et al.*[133] conducted a clinical trial to compare the accuracy of abnormal lung sound detection between an artificial intelligence (AI) algorithm and doctors, where a CNN was trained to detect four types of lung sound: wheezes, rhonchi, and fine and coarse crackles. This trial suggested that CNN-based abnormal lung sound detection is more accurate than doctors in regard to the metrics of sensitivity and F1-score. With the release of the ICBHI 2017 dataset, the number of studies on ASD for detecting normal sound, crackles, wheezes, and both crackles and wheezes exploded[23,130,134,135]. Rocha *et al.*[136] separately trained a classifier for crackle detection, wheeze detection, and mixture detection (crackle, wheeze, and others) and used four different machine learning methods to evaluate its effectiveness (e.g., boosted trees, SVM, and CNN). Gairola *et al.*[72] proposed a concatenation-based augmentation to solve the unbalanced class issue, and used the ResNet block for abnormal lung sound detection. For a limited training sample, Song *et al.*[22] proposed an abnormal lung sound detection method that encourages intra-class compactness and inter-class separability by comparing samples from different classes during the training phase. To explore the temporal and frequency information of lung sound, Petmezas *et al.*[137] integrated a CNN and an RNN for abnormal lung sound detection, where the former extracts the deep temporal-frequency features from spectrograms, and the latter uses the

deep features to mine the change of lung sound over the time.

For RDR, most studies were evaluated on ICBHI 2017 and focused on 4 sub-tasks. (1) 2-classes respiratory pathology recognition. This is used to distinguish patients from healthy people. Messner *et al.*[122] collected lung sounds from healthy subjects and patients with idiopathic pulmonary fibrosis, then applied a convolutional RNN to lung sound analysis for binary classification (e.g., healthy vs. pathological). Mondal *et al.*[138] extracted the statistical feature combination of kurtosis, sample entropy, and skewness from lung sounds and used FNN to infer lung health conditions. (2) 3-classes respiratory chronic disease recognition. This divides populations into three groups: healthy subjects, chronic patients (e.g., COPD, bronchiectasis, and asthma patients), and non-chronic patients (e.g., those with upper and lower respiratory tract infection, pneumonia, and bronchiolitis). García-Ordás *et al.*[139] converted lung sounds into Mel spectrogram representations to train CNNs to recognize respiratory pathologies, meanwhile using variational autoencoders to generate new samples for minority classes to solve the issues of unbalanced data. Shuvo *et al.*[140] decomposed the preprocessed signal using EMD to obtain an IMF signal that had a high correlation with the lung sound signal, then applied the continuous wavelet transform to extract a discriminative representation for training a lightweight CNN model. Their proposed method was evaluated on ICBHI 2017 and outperformed other lightweight models. Shi *et al.*[141] explored the temporal-frequency information of different scales with the dual wavelet analysis module, and used the attention module to extract the salient difference information for respiratory chronic disease recognition. (3) Multi-types specific RDR. This task is used to distinguish between specific respiratory diseases (e.g., COPD, asthma, and pneumonia), where the number of classes depends on the total class of the disease. Tariq *et al.*[123] applied a variety of data augmentation methods to solve the issue of unbalanced classes (e.g., time stretching, pitch shifting, and dynamic range compression) and used a CNN to extract pathological features from the spectrogram to recognize seven respiratory diseases. Kwon *et al.*[142] explored the performance of different combinations of feature extraction methods and classifiers in detecting lung conditions (e.g., healthy lungs, upper respiratory tract infection, COPD, pneumonia, and bronchiolitis). (4) Multi-courses respiratory disease severity recognition. This task aims to distinguish the severity of respiratory diseases, in which the number of classes generally depends on the medical definition of disease progression. Morillo *et al.*[158] adopted principal component analysis and FNN to detect whether COPD patients were aggravated by pneumonia, with a sensitivity

and specificity of 72.0% and 81.8%, respectively. Based on the RespiratoryDatabase@TR dataset, Altan *et al.*[27] proposed the method of using a 3D-second order difference plot to analyze lung sound signals, then using pre-trained deep belief networks to distinguish the risk level from the interior level for COPD patients. This approach demonstrated the validity of pre-trained deep-learning architectures in RDR. Huang *et al.*[10] proposed a hybrid model based on pre-trained VGGish networks and BiLSTM to identify the severity of community-acquired pneumonia among children, including pneumonia-confirmation, spontaneous resolution, and recovery. Altan *et al.*[143] adopted the cuboid and octant-based quantization methods to extract characteristic abnormalities from a 3D-second order difference plot, then used a deep extreme learning machine classifier to separate five COPD severities. Yu *et al.* [144] explored the ability of multiple methods (SVM, decision tree, and deep belief network) to identify the severity of COPD, where the deep belief network achieved 93.67% accuracy in distinguishing between patients with mild, moderate, and severe COPD.

More recently, some studies proposed deep learning-based methods that can be used for both RDR and ASD[25,124,145], as shown in Table 3. Perna *et al.*[26] extracted the MFCCs of multi-window from lung sound signals to generate representations, then used an RNN-based model. Li *et al.*[128] proposed a knowledge distillation-based method that transfers the weights of a CNN learned from multiple centers into a fuzzy decision tree, which provides an interpretable model for abnormal lung sound detection and chronic RDR. Nguyen *et al.*[24] introduced different methods to adapt a pre-trained model to a new environment, including fine-tuning, cotuning, stochastic normalization, and their combination, for ASD and RDR. In their experiments, the authors noted that varying performance was caused by differences in equipment and introduced spectrum correction to solve this issue[159].

Limitations and future directions

Table 3 summarizes the state-of-the-art deep learning approaches for ASD and RDR. It shows that most methods use specificity, sensitivity, and the confounding index between the two for ASD, while evaluation metrics (e.g., accuracy, precision, recall, and F1) are added based on the evaluation metrics of ASD for RDR. In terms of the model, a CNN with the input of a spectrogram and Mel spectrogram is currently the most widely-used method for both tasks, achieving over 80% specificity and 60% sensitivity in the ICBHI 2017 dataset for ASD and having over 90% accuracy, recall, precision, and F1 for RDR. In addition, most methods recently used a structure that applies a CNN to extract deep features from

multiple consecutive temporal windows, then uses the deep features of successive windows as the input of RNN to learn the contextual information for RDR. Table 3 shows that deep learning has made progress regarding lung sound-based medical tasks, demonstrating the capability to identify different abnormal sounds, pulmonary diseases, and disease severity. However, the clinical application of deep learning-based lung sound analysis still faces some challenges, as discussed below.

The main challenge is that most deep learning-based lung sound analysis methods have poor interpretability[128]; thus deep learning-based methods currently only play a supporting role in clinical applications. Specifically, physicians rely on the interpretation of lung sounds for medical decision-making. However, the black-box operation of deep learning makes it difficult for physicians to understand how the model works in the diagnosis, that is its mechanism is not fully clear. As a result, physicians cannot fully trust or rely on the results given by the model. Potential solutions to improve interpretability include the following. (1) Symptom localization: intuitively, the segmentation network can highlight the segments of lung sound in the respiratory cycle to locate the symptoms caused by the disease. These segments can be used not only for disease diagnosis, but also for physicians to confirm the final outcome based on intermediate supporting results[160]. The appearance and localization of abnormal sounds in specific respiratory diseases can be exploited as the trigger of intelligibility by combining them with clinical knowledge; (2) Input visualization: gradient-weighted class activation mapping analyzes input and gradients to generate interpretable heatmaps that can be used to understand which regions the model focuses on when making decisions[161]. This can present the intermediate results of the model during the decision-making process, which may convince the clinician of its reliability[162]; (3) Knowledge distillation: this can distill the knowledge learned from complex models to another model with interpretability, such as decision trees or linear regression, to achieve an interpretable recognition process with high performance[128]; (4) Surrogate model: this generates a simple, interpretable local model for each specific input to approximate the behavior of the original complex model given the input, such as local interpretable model-agnostic explanations (LIME)[163]. Thus, LIME can help explain the predictions of complex models on specific inputs.

Another challenge is that deep learning-based lung sound analysis lacks robustness under some conditions. (1) Noise sensitivity: most methods have performance degradation due to an increased noise level[136], meaning that the reliability of deep learning methods will be compromised in disease

diagnosis due to distortions, resulting in misdiagnosis and missed diagnosis; (2) Device difference: due to the difference between devices regarding sensors, timbre, and sound quality, the performance of a model trained on a single device will fluctuate or drop when tested on other devices[23,24]; (3) Physiological diversification: Fernandes *et al.*[146] reported that physiological differences between patients, including age, sex, and body mass index, caused deviations in the performance of models for ASD. To address this problem, transfer learning which mines invariant features under different factors (e.g., noise, devices, and physiological differences) for lung sound analysis, may be an option. It can map the data with differences into aligned data distributions to improve generalizability[164,165]. Moreover, multi-input models that take these differences as input and force the model to dynamically adjust its weight based on the input to improve generalizability may be effective.

In addition, due to differences in the morbidity of pulmonary diseases, the data distribution of lung sound is a long-tail distribution, which may cause the poor recognition ability of models for rare categories. Most methods adopt data augmentations to address this issue[22,72,139]; however, they are still unreliable in real clinical applications since the data augmented by perturbations are different from patient data in practice. To address this issue, few-shot learning might be a useful tool that aims to extract the representative features from a limited number of training samples to exhibit good generalization when faced with new, unseen data[166]. For example, prototypical networks achieved remarkable results in audio event classification with the long-tail distribution[167,168]. The key idea is to learn the prototype representation of each class, then perform the classification by calculating the distance between the new sample and each prototype[169]. In addition, contrastive learning can be applied to lessen long-tail distribution issues by increasing the distance between different classes in the feature space. Li *et al.*[170] integrated the idea of prototypical networks to first generate a set of targets uniformly distributed on a feature space, then make the features of different classes converge to these distinct and uniformly distributed targets during training. This forces all classes, including a few, to remain uniformly distributed by the constraints of targeted supervised contrastive learning on the feature space during the optimization process to improve class boundaries.

It is worth noting that most existing lung sound studies only focus on accuracy rather than taking computational resource consumption into account, tending to use models with a large number of parameters that demand more memory and high

computational resources[6,14,122]. This poses challenges to implementation on the chips of portable devices with limited computation power as compared to servers or personal computers, especially considering the cost-effective hardware solutions that are important for large-scale deployment in poor-resource areas for healthcare improvement. The edge computing of intelligent stethoscopes allows the processing of lung sound data on the device, which reduces the time delay in decision-making and monitoring caused by data transmission in cloud computing, protects the privacy of patients, and reduces the cost of maintaining the cloud server. Such a device is also suitable for disease or well-being management at home by tracking and predicting recovery. Therefore, we consider portable digital stethoscopes equipped with deep learning methods to be a major research direction in this field. Here, we present three strategies to embed deep learning models into the chip of a stethoscope for edge computing. (1) Lightweight model: a large number of methods, such as knowledge distillation and pruning, have been used to lightweight large-scale models to reduce computational requirements[171]; (2) Hardware acceleration: characteristics of hardware, such as parallel processing capabilities, high-speed memory access, and customized computation units, are proven to accelerate computation in deep models[172]; and (3) Operational optimization: the complexity and computation of deep models can be dropped by optimizing basic operators (e.g., depthwise separable convolution decomposes the convolution operation into two separate layers, a depthwise convolution layer and a pointwise convolution layer)[173]. With the above three strategies, deep learning models can be implemented in the chips of digital stethoscopes in the near future, turning the devices into intelligent stethoscopes that not only make recordings of lung sounds, but also give prompt predictions on potential diseases, which can better assist clinicians in consultation.

Open-source framework

Due to the poor reproducibility caused by the variety of deep learning methods, an open-source framework intended to build a solid foundation for replication and extension has been released to facilitate progress in this field. This framework provides the commonly used methods (e.g., FNN with acoustic feature input and CNN with spectrogram input) and demonstrates them on the ICBHI 2017 dataset as an example of bench-marking. In addition, the framework decomposes the algorithm into four major modules: preprocessing for segmentation and noise reduction, feature extraction for input representation, evaluation metrics for performance assessment,

and classifier design for training and testing. Thus, researchers can focus on improving specific steps while keeping the rest identical, which can largely improve the efficiency and agreement of the benchmark. This framework was developed based on PyTorch, and each module contains a main function that is called upon to execute the corresponding task.

The preprocessing module consists of two main operations. (1) Noise suppression. Since lung sounds are easily contaminated in the real environment, this framework executes basic noise suppression based on the band-pass filter to retain the frequency band information of interest for lung sounds. In addition, it provides candidates for noise suppression, including EMD, wavelet denoising, ICA, etc. 2) Segmentation. This step segments the input audio recording into intervals to form a uniform input to train the deep model. For the ICBHI 2017 dataset, each audio recording has each respiratory cycle annotated, i.e., the cycles with abnormal lung sounds (crackles and wheezes) are annotated as 1 and the other as 0. This module splits the recording with such labels. If the duration of the segment is insufficient, smart padding[131] or zero padding is used.

The feature extraction module transforms the 1D sound signal into a representation suitable for the model input. For FNNs and RNNs, lung sound analysis methods adopt the statistical features extracted from segmentation as the representation to train and test the model. This framework performs extraction using pyAudioAnalysis[174]. For CNNs, spectrogram-based input is generally employed for training and testing, where the framework uses the Librosa library to extract different spectrograms, including the Mel spectrogram.

The evaluation metrics module provides the data-splitting strategies and the commonly used evaluation metrics for the experiment setting. To date, there are two data-splitting strategies for lung sound analysis: 1) subject-dependent experiment[22,130,131] that randomly splits the entire dataset into training and testing sets. Here, the data from one subject exist in both the training set and the testing set; and 2) subject-independent experiment[10,24,175] that splits the entire dataset into training and testing sets in a subject-wise manner. Here, the data from one subject only appear in the training set or testing set to implement the cross-subject benchmark. The choice of evaluation metrics has been referred to[84], including accuracy, specificity, sensitivity, and ICBHI score.

The classifier design module is based on PyTorch to automate lung sound analysis, where the training and testing set is loaded based on different dataset splitting strategies. This module is formed by the model design, evaluation metrics, training and testing function, and recording

function. For model design, a commonly used basic model is implemented (e.g., FNN, CNN, and RNN). For evaluation metrics, specificity, sensitivity, and the ICBHI score (the mean of specificity and sensitivity) are applied to evaluate the performance of the model according to previous studies[84]. The recording function is applied to visualize the training information including loss, specificity, and sensitivity.

To develop and evaluate deep learning methods, the above modules can be used as a basis or starting point, providing general functional performance as demonstrated on the ICBHI 2017 dataset. Customized functions can be added on top of each module in future research.

Conclusions

This review provides a systemic overview of the development of deep learning-based lung sound analysis for intelligent stethoscopes. Deep learning has shown effective performance in detecting, classifying, and assessing respiratory conditions from lung sound recordings, especially the CNN model with 2D spectrogram-based input. While there are still challenges to be addressed, including noise reduction, the interpretability of the model, and the robustness of performance, the potential benefits of deep learning-based lung sound analysis are significant regarding the intelligent stethoscope. With further development and refinement, we expect deep learning to empower the digital stethoscope for automatic and intelligent diagnosis. In addition, it can be a part of 5G telemedicine based on video and audio streams, where deep learning-based intelligent stethoscopes provide in-body information (e.g., lung sound and heart sound) and the video provides out-body information (e.g., affective and pain level).

Abbreviations

ACC. Accuracy; AS. Average score of specificity and sensitivity; ASD. Abnormal sound detection; BSS. Blind source separation; COPD. Chronic obstructive pulmonary disease; CNN. Convolutional neural network; EMD. Empirical mode decomposition; FNN. Fully connected neural network; ILD. Interstitial lung disease; ICA. Independent component analysis; LFCCs. Linear frequency cepstral coefficients; LSTM. Long short-term memory; MFCCs Mel-frequency cepstral coefficients; NMF. Non-negative matrix factorization; NPA. Negative percent agreement; PPA. Positive percent agreement; RDR. Respiratory disease recognition; RNN. Recurrent neural network; SVM. Support vector machine; SEN. Sensitivity; SPE. Specificity; 1D. One-dimensional; 2D. Two-dimensional; 3D. Three-dimensional.

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Declarations

Ethics approval and consent to participate

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Competing interests

The authors declare that they have no competing interests.

References

- Williamson EJ, Walker AJ, Bhaskaran K, Bacon S, Bates C, Morton C, et al. Factors associated with COVID-19-related death using OpenSAFELY. *Nature*. 2020;584(7821):430–6.
- Wu Y, Wang X, Li X, Song L, Yu S, Fang Z, et al. Common mtDNA variations at C5178a and A249d/T6392C/G10310A decrease the risk of severe COVID-19 in a Han Chinese population from Central China. *Mil Med Res*. 2021;8(1):1–10.
- Jin Y, Cai L, Cheng Z, Cheng H, Deng T, Fan Y, et al. A rapid advice guideline for the diagnosis and treatment of 2019 novel coronavirus (2019-nCoV) infected pneumonia (standard version). *Mil Med Res*. 2020;7(1):1–23.
- Singh D, Agusti A, Anzueto A, Barnes PJ, Bourbeau J, Celli BR, et al. Chronic obstructive lung disease: the GOLD science committee report 2019. *Eur Respir J*. 2019;53(5):1900164.
- Wu K, Jelfs B, Ma X, Ke R, Tan X, Fang Q. Weakly-supervised lesion analysis with a CNN-based framework for COVID-19. *Phys Med Biol*. 2021;66(24):245027.
- Landge K, Kidambi BR, Singhal A, Basha A, et al. Electronic stethoscopes: brief review of clinical utility, evidence, and future implications. *J Pract Cardiovasc Sci*. 2018;4(2):65.
- Palaniappan R, Sundaraj K, Sundaraj S. A comparative study of the SVM and k-NN machine learning algorithms for the diagnosis of respiratory pathologies using pulmonary acoustic signals. *BMC Bioinform*. 2014;15:223.
- Sakai T, Kato M, Miyahara S, Kiyasu S. Robust detection of adventitious lung sounds in electronic auscultation signals. In: *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*. Tsukuba, Japan; 2012, p. 1993–6.
- Oweis RJ, Abdulhay EW, Khayal A, Awad A. An alternative respiratory sounds classification system utilizing artificial neural networks. *Biomed J*. 2015;38(2):152–61.
- Huang D, Wang L, Wang W. A multi-center clinical trial for wireless stethoscope-based diagnosis and prognosis of children community-acquired pneumonia. *IEEE Trans Biomed Eng*. 2023;70(7):2215–26.
- Emmanouilidou D, McCollum ED, Park DE, Elhilali M. Adaptive noise suppression of pediatric lung auscultations with real applications to noisy clinical settings in developing countries. *IEEE Trans Biomed Eng*. 2015;62(9):2279–88.
- Mills GA, Nketia TA, Oppong IA, Kaufmann EE. Wireless digital stethoscope using Bluetooth technology. *Intern J Eng Sci Technol*. 2012;4(8):3961–9.
- Leng S, Tan RS, Chai KTC, Wang C, Ghista D, Zhong L. The electronic stethoscope. *Biomed Eng Online*. 2015;14:66.
- Lee SH, Kim YS, Yeo MK, Mahmood M, Zavanelli N, Chung C, et al. Fully portable continuous real-time auscultation with a soft wearable stethoscope designed for automated disease diagnosis. *Sci Adv*. 2022;8(21):eabo5867.
- Hirosawa T, Harada Y, Ikenoya K, Kakimoto S, Aizawa Y, et al. The utility of real-time remote auscultation using a bluetooth-connected electronic stethoscope: open-label randomized controlled pilot trial. *JMIR Mhealth Uhealth*. 2021;9(7):e23109.
- Yilmaz G, Rapin M, Pessoa D, Rocha BM, de Sousa AM, Rusconi R, et al. A wearable stethoscope for long-term ambulatory respiratory health monitoring. *Sensors (Basel)*. 2020;20(18):5124.
- Dai Z, Peng Y, Mansy HA, Sandler RH, Royston TJ. Comparison of poroviscoelastic models for sound and vibration in the lungs. *J Vib Acoust*. 2014;136(5):0510121–5101211.
- İçer S, Gengeç Ş. Classification and analysis of non-stationary characteristics of crackle and rhonchus lung adventitious sounds. *Digit Signal Process*. 2014;28:18–27.
- Palaniappan R, Sundaraj K, Ahamed NU. Machine learning in lung sound analysis: a systematic review. *Biocybern Biomed Eng*. 2013;33(3):129–35.
- Sen I, Saraclar M, Kahya YP. A comparison of SVM and GMM-based classifier configurations for diagnostic classification of pulmonary sounds. *IEEE Trans Biomed Eng*. 2015;62(7):1768–76.
- Zhang J, Wang HS, Zhou HY, Dong B, Zhang L, Zhang F, et al. Real-world verification of artificial intelligence algorithm-assisted auscultation of breath sounds in children. *Front Pediatr*. 2021;9:627337.
- Song W, Han J, Song H. Contrastive embedding learning method for respiratory sound classification. In: *ICASSP 2021–2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. Toronto, ON, Canada; 2021. p. 1275–79.
- Acharya J, Basu A. Deep neural network for respiratory sound classification in wearable devices enabled by patient specific model tuning. *IEEE Trans Biomed Circuits Syst*. 2020;14(3):535–44.
- Nguyen T, Pernkopf F. Lung sound classification using co-tuning and stochastic normalization. *IEEE Trans Biomed Eng*. 2022;69(9):2872–82.
- Pham L, McLoughlin I, Phan H, Tran M, Nguyen T, Palaniappan R. Robust deep learning framework for predicting respiratory anomalies and diseases. In: *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. Montreal, QC, Canada; 2020. p. 164–7.
- Perna D, Tagarelli A. Deep auscultation: predicting respiratory anomalies and diseases via recurrent neural networks. In: *2019 IEEE 32nd International Symposium on Computer-Based Medical Systems (CBMS)*. Cordoba, Spain; 2019. p. 50–5.
- Altan G, Kutlu Y, Pekmezci AÖ, Nural S. Deep learning with 3D-second order difference plot on respiratory sounds. *Biomed Signal Process Control*. 2018;45:58–69.
- Pramono RXA, Bowyer S, Rodriguez-Villegas E. Automatic adventitious respiratory sound analysis: a systematic review. *PLoS One*. 2017;12(5):e0177926.
- Palaniappan R, Sundaraj K, Ahamed NU, Arjunan A, Sundaraj S. Computer-based respiratory sound analysis: a systematic review. *IETE Tech Rev*. 2013;30(3):248–56.
- Jácome C, Marques A. Computerized respiratory sounds in patients with COPD: a systematic review. *J Chronic Obstr Pulm Dis*. 2015;12(1):104–12.
- Rao A, Huynh E, Royston TJ, Kornblith A, Roy S. Acoustic methods

- for pulmonary diagnosis. *IEEE Rev Biomed Eng*. 2018;12:221–39.
32. Chang GC, Lai YF. Performance evaluation and enhancement of lung sound recognition system in two real noisy environments. *Comput Methods Programs Biomed*. 2010;97(2):141–50.
 33. Bardou D, Zhang K, Ahmad SM. Lung sounds classification using convolutional neural networks. *Artif Intell Med*. 2018;88:58–69.
 34. Pasterkamp H, Kraman SS, Wodicka GR. Respiratory sounds: advances beyond the stethoscope. *Am J Respir Crit Care Med*. 1997;156(3):974–87.
 35. Bohadana A, Izbicki G, Kraman SS. Fundamentals of lung auscultation. *N Engl J Med*. 2014;370(8):744–51.
 36. Olson DE, Hammersley JR. Mechanisms of lung sound generation. *Semin Respir Crit Care Med*. 1985;6(3):171–9.
 37. Sarkar M, Madabhavi I, Niranjana N, Dogra M. Auscultation of the respiratory system. *Ann Thorac Med*. 2015;10(3):158–68.
 38. Gavriely N, Palti Y, Alroy G. Spectral characteristics of normal breath sounds. *J Appl Physiol*. 1981;50(2):307–14.
 39. Weiss EB, Carlson CJ. Recording of breath sounds. *Am Rev Respir Dis*. 1972;105(5):835–9.
 40. Forgacs P, Nathoo AR, Richardson HD. Breath sounds. *Thorax*. 1971;26(3):288–95.
 41. Kraman SS. Vesicular (normal) lung sounds: how are they made, where do they come from, and what do they mean?. *Semin Respir Crit Care Med*. 1985;6(3):183–91.
 42. Kraman SS. Determination of the site of production of respiratory sounds by subtraction phonopneumography. *Am Rev Respir Dis*. 1980;122(2):303–9.
 43. Kraman SS. Does laryngeal noise contribute to the vesicular lung sound?. *Am Rev Respir Dis*. 1981;124(3):292–4.
 44. Gavriely N, Nissan M, Ruben AH, Cugell DW. Spectral characteristics of chest wall breath sounds in normal subjects. *Thorax*. 1995;50(12):1292–300.
 45. Vyshedskiy A, Alhashem RM, Paciej R, Ebril M, Rudman I, Fredberg JJ, et al. Mechanism of inspiratory and expiratory crackles. *Chest*. 2009;135(1):156–64.
 46. Flietstra B, Markuzon N, Vyshedskiy A, Murphy R. Automated analysis of crackles in patients with interstitial pulmonary fibrosis. *Pulm Med*. 2011;2011:590506.
 47. Munakata M, Ukita H, Doi I, Ohtsuka Y, Masaki Y, Homma Y, et al. Spectral and waveform characteristics of fine and coarse crackles. *Thorax*. 1991;46(9):651–7.
 48. Forgacs P. The functional basis of pulmonary sounds. *Chest*. 1978;73(3):399–405.
 49. Jones A. A brief overview of the analysis of lung sounds. *Physiotherapy*. 1995;81(1):37–42.
 50. Murphy R, Vyshedskiy A. Acoustic findings in a patient with radiation pneumonitis. *N Engl J Med*. 2010;363(20):e31.
 51. Bohadana AB, Peslin R, Uffholtz H. Breath sounds in the clinical assessment of airflow obstruction. *Thorax*. 1978;33(3):345–51.
 52. Nagasaka Y. Lung sounds in bronchial asthma. *Allergol Int*. 2012;61(3):353–63.
 53. American Thoracic Society, et al. Updated nomenclature for membership reaction. *ATS News*. 1977;3:5–6.
 54. Luo Y. Portable bluetooth visual electrical stethoscope research. In: 2008 11th IEEE International Conference on Communication Technology. Hangzhou, China; 2008. p. 634–6.
 55. Chamberlain D, Mofor J, Fletcher R, Kodgule R. Mobile stethoscope and signal processing algorithms for pulmonary screening and diagnostics. In: 2015 IEEE Global Humanitarian Technology Conference (GHTC). Seattle, WA, USA; 2015. p. 385–92.
 56. Schuman AJ. Electronic stethoscopes: what's new for auscultation. *Contemp Pediatr*. 2015;32(2):37–41.
 57. Behere S, Baffa JM, Penfil S, Slamon N. Real-world evaluation of the eko electronic teleauscultation system. *Pediatr Cardiol*. 2019;40:154–60.
 58. Wang W, Xu Q, Zhang G, Lian Y, Zhang L, Zhang X, et al. A bat-shape piezoresistor electronic stethoscope based on MEMS technology. *Measurement*. 2019;147:106850.
 59. Kajor M, Grochala D, Iwaniec M, Kantoch E, Kucharski D. A prototype of the mobile stethoscope for telemedical application. In: 2018 XIV-th International Conference on Perspective Technologies and Methods in MEMS Design (MEMSTECH). Lviv, Ukraine; 2018. p. 5–8.
 60. Lakhe A, Sodhi I, Warriar J, Sinha V. Development of digital stethoscope for telemedicine. *J Med Eng Technol*. 2016;40(1):20–4.
 61. Vasudevan RS, Horiuchi Y, Torriani FJ, Cotter B, Maisel SM, et al. Persistent value of the stethoscope in the age of COVID-19. *Am J Med*. 2020;133(10):1143–50.
 62. Mesquita CT, dos Reis JC, Simões LS, de Moura EC, Rodrigues GA, Athayde CC, et al. Digital stethoscope as an innovative tool on the teaching of auscultatory skills. *Arq Bras Cardiol*. 2013;100(2):187–9.
 63. Elgendi M, Bobhate P, Jain S, Guo L, Rutledge J, Coe Y, et al. Spectral analysis of the heart sounds in children with and without pulmonary artery hypertension. *Int J Cardiol*. 2014;173(1):92–9.
 64. Elgendi M, Bobhate P, Jain S, Rutledge J, Coe JY, Zemp R, et al. Timedomain analysis of heart sound intensity in children with and without pulmonary artery hypertension: a pilot study using a digital stethoscope. *Pulm Circ*. 2014;4(4):685–95.
 65. Scrafford C, Basnet S, Ansari I, Shrestha L, Shrestha S, Ghimire R, et al. Evaluation of digital auscultation to diagnose pneumonia in children 2 to 35 months of age in a clinical setting in Kathmandu, Nepal: a prospective case-control study. *J Pediatr Infect Dis*. 2016;11(2):28–36.
 66. Ellington LE, Emmanouilidou D, Elhilali M, Gilman RH, Tielsch JM, Chavez MA, et al. Developing a reference of normal lung sounds in healthy Peruvian children. *Lung*. 2014;192(5):765–73.
 67. Kevat AC, Kalirajah A, Roseby R. Digital stethoscopes compared to standard auscultation for detecting abnormal paediatric breath sounds. *Eur J Pediatr*. 2017;176:989–92.
 68. Zheng L, Li Y, Chen W, Wang Q, Jiang Q, Liu G. Detection of respiration movement asymmetry between the left and right lungs using mutual information and transfer entropy. *IEEE Access*. 2017;6:605–13.
 69. Jean S, Cinel I, Tay C, Parrillo JE, Dellinger RP. Assessment of asymmetric lung disease in intensive care unit patients using vibration response imaging. *Anesth Analg*. 2008;107(4):1243–7.
 70. Ren S, Li Y, Li W, Zhao Z, Jin C, Zhang D. Fatal asymmetric interstitial lung disease after erlotinib for lung cancer. *Respiration*. 2012;84(5):431–5.
 71. Rennoll V, McLane I, Emmanouilidou D, West J, Elhilali M. Electronic stethoscope filtering mimics the perceived sound characteristics of acoustic stethoscope. *IEEE J Biomed Health Inform*. 2021;25(5):1542–9.
 72. Gairola S, Tom F, Kwatra N, Jain M. RespireNet: a deep neural network for accurately detecting abnormal lung sounds in limited data setting. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Mexico; 2021. p. 527–30.
 73. Pavlosky A, Glauche J, Chambers S, Al-Alawi M, Yanev K, Loubani T.

- Validation of an effective, low cost, free/open access 3D-printed stethoscope. *PLoS One*. 2018;13(3):e0193087.
74. Tosi J, Taffoni F, Santacatterina M, Sannino R, Formica D. Performance evaluation of Bluetooth Low Energy: a systematic review. *Sensors (Basel)*. 2017;17(12):2898.
 75. Memon S, Soothar KK, Memon KA, Magsi AH, Laghari AA, Abbas M, ul Ain N. The design of wireless portable electrocardiograph monitoring system based on ZigBee. *EAI Endorsed Trans Scalable Inf Syst*. 2020;7(28):e6.
 76. Wang J, Huang D, Fan S, Han K, Jeon G, Rodrigues JJ. PSDCE: physiological signal-based double chaotic encryption for instantaneous E-healthcare services. *Future Gener Comput Syst*. 2023;141:116–28.
 77. Kim Y, Hyon Y, Jung SS, Lee S, Yoo G, Chung C, et al. Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning. *Sci Rep*. 2021;11(1):17186.
 78. Grooby E, Sitaula C, Tan K, Zhou L, King A, Ramanathan A, et al. Prediction of neonatal respiratory distress in term babies at birth from digital stethoscope recorded chest sounds. In: 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Glasgow, Scotland, United Kingdom; 2022. p. 4996–9.
 79. 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(11):1450–5.
 80. Mayorga P, Druzgalski C, Morelos R, Gonzalez O, Vidales J. Acoustics based assessment of respiratory diseases using GMM classification. In: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology. Buenos Aires, Argentina; 2010. p. 6312–6.
 81. Kahya YP, Guler EC, Sahin S. Respiratory disease diagnosis using lung sounds. In: Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 'Magnificent Milestones and Emerging Opportunities in Medical Engineering' (Cat. No. 97CH36136), Chicago, IL, USA; 1997;5:2051–3.
 82. Cinyol F, Baysal U, Köksal D, Babaoğlu E, Ulaşlı SS. Incorporating support vector machine to the classification of respiratory sounds by convolutional neural network. *Biomed Signal Process Control*. 2023;79:104093.
 83. Gemmeke JF, Ellis DP, Freedman D, Jansen A, Lawrence W, Moore RC, et al. Audio set: an ontology and human-labeled dataset for audio events. In: 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). New Orleans, LA, USA; 2017. p. 776–80.
 84. Rocha BM, Filos D, Mendes L, Serbes G, Ulukaya S, Kahya YP, et al. An open access database for the evaluation of respiratory sound classification algorithms. *Physiol Meas*. 2019;40(3):035001.
 85. Fraiwan M, Fraiwan L, Khassawneh B, Ibrani A. A dataset of lung sounds recorded from the chest wall using an electronic stethoscope. *Data Brief*. 2021;35:106913.
 86. Hsu FS, Huang SR, Huang CW, Huang CJ, Cheng YR, Chen CC, et al. Benchmarking of eight recurrent neural network variants for breath phase and adventitious sound detection on a self-developed open-access lung sound database-HF_Lung_V1. *PLoS One*. 2021;16(7):e0254134.
 87. Hsu FS, Huang SR, Huang CW, Cheng YR, Chen CC, Hsiao J, et al. An update on a progressively expanded database for automated lung sound analysis. *arXiv*. 2021. <https://arxiv.org/abs/2102.04062>.
 88. Altan G, Kutlu Y, Garbí Y, Pekmezci AÖ, Nural S. Multimedia respiratory database (RespiratoryDatabase@TR): auscultation sounds and chest X-rays. *Nat Eng Sci*. 2017;2(3):59–72.
 89. World Health Organization. World health statistics 2017: monitoring health for the SDGs, sustainable development goals. https://api.semanticscholar.org/CorpusID:203489275?utm_source=wikipedia. Accessed 8 May 2018.
 90. Guide P, Copd T. Global initiative for chronic obstructive lung a guide for health care professionals global initiative for chronic obstructive disease. *Glob Initiative Chronic Obstr Lung Dis*. 2010;22(4):1–30.
 91. Altan G, Kutlu Y, Hessenberg elm autoencoder kernel for deep learning. *J Eng Technol Appl Sci*. 2018;3(2):141–51.
 92. Roy A, Satija U. A novel melspectrogram snippet representation learning framework for severity detection of chronic obstructive pulmonary diseases. *IEEE Trans Instrum Meas*. 2023;72:1–11.
 93. Emmanouilidou D, McCollum ED, Park DE, Elhilali M. Computerized lung sound screening for pediatric auscultation in noisy field environments. *IEEE Trans Biomed Eng*. 2018;65(7):1564–74.
 94. Meng F, Wang Y, Shi Y, Zhao H. A kind of integrated serial algorithms for noise reduction and characteristics expanding in respiratory sound. *Int J Biol Sci*. 2019;15(9):1921.
 95. Haider NS, Behera AK. Respiratory sound denoising using sparsityassisted signal smoothing algorithm. *Biocybern Biomed Eng*. 2022;42(2):481–93.
 96. Singh D, Singh BK, Behera AK. Comparative study of different iir filter for denoising lung sound. In: 2021 6th International Conference for Convergence in Technology (I2CT). Maharashtra, India; 2021. p. 1–3.
 97. Pouyani MF, Vali M, Ghasemi MA. Lung sound signal denoising using discrete wavelet transform and artificial neural network. *Biomed Signal Process Control*. 2022;72:103329.
 98. Singh D, Singh BK, Behera AK. Comparative analysis of lung sound denoising technique. In: 2020 First International Conference on Power, Control and Computing Technologies (ICPC2T). Raipur, India; 2020. p. 406–10.
 99. Syahputra M, Situmeang S, Rahmat R, Budiarto R. Noise reduction in breath sound files using wavelet transform based filter. In: IOP Conference Series: Materials Science and Engineering. Semarang, Indonesia; 2017;190:012040.
 100. Sangeetha B, Periyasamy R. Performance metrics analysis of adaptive threshold empirical mode decomposition denoising method for suppression of noise in lung sounds. In: 2021 Seventh International Conference on Bio Signals, Images, and Instrumentation (ICBSII). Chennai, India; 2021. p. 1–6.
 101. Gupta S, Agrawal M, Deepak D. Gammatonegram based triple classification of lung sounds using deep convolutional neural network with transfer learning. *Biomed Signal Process Control*. 2021;70:102947.
 102. Meng F, Wang Y, Shi Y, Cai M, Yang L, Shen D. A new type of wavelet de-noising algorithm for lung sound signals. In: 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). Madrid, Spain; 2018. p. 2544–8.
 103. Haider NS. Respiratory sound denoising using empirical mode decomposition, hurst analysis and spectral subtraction. *Biomed Signal Process Control*. 2021;64:102313.
 104. Nersisyan R, Noel MM. Heart sound and lung sound separation algorithms: a review. *J Med Eng Technol*. 2017;41(1):13–21.
 105. Khan TEA, Vijayakumar P. Separating heart sound from lung

- sound using labVIEW. *Int J Comput Electr Eng.* 2010;2(3):524–33.
106. Ayari F, Ksouri M, Alouani AT. Lung sound extraction from mixed lung and heart sounds fastica algorithm. In: 2012 16th IEEE Mediterranean Electrotechnical Conference. Yasmine Hammamet, Tunisia; 2012. p. 339–42.
 107. Lin C, Hasting E. Blind source separation of heart and lung sounds based on nonnegative matrix factorization. In: 2013 International Symposium on Intelligent Signal Processing and Communication Systems. Naha, Japan; 2013. p. 731–6.
 108. Mondal A, Banerjee P, Somkuwar A. Enhancement of lung sounds based on empirical mode decomposition and Fourier transform algorithm. *Comput Methods Programs Biomed.* 2017;139:119–36.
 109. Grooby E, Sitaula C, Fattahi D, Sameni R, Tan K, Zhou L, et al. Noisy neonatal chest sound separation for high-quality heart and lung sounds. *IEEE J Biomed Health Inform.* 2023;27(6):2635–46.
 110. Grooby E, He J, Fattahi D, Zhou L, King A, Ramanathan A, et al. A new non-negative matrix co-factorisation approach for noisy neonatal chest sound separation. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Mexico; 2021. p. 5668–73.
 111. Li T, Tang H, Qiu T, Park Y. Heart sound cancellation from lung sound record using cyclostationarity. *Med Eng Phys.* 2013;35(12):1831–6.
 112. Tsai KH, Wang WC, Cheng CH, Tsai CY, Wang JK, Lin TH, et al. Blind monaural source separation on heart and lung sounds based on periodic-coded deep autoencoder. *IEEE J Biomed Health Inform.* 2020;24(11):3203–14.
 113. Ghaderi F, Mohseni HR, Sanei S. Localizing heart sounds in respiratory signals using singular spectrum analysis. *IEEE Trans Biomed Eng.* 2011;58(12):3360–7.
 114. Kim Y, Hyon Y, Lee S, Woo SD, Ha T, Chung C. The coming era of a new auscultation system for analyzing respiratory sounds. *BMC Pulm Med.* 2022;22(1):119.
 115. Bahoura M, Pelletier C. Respiratory sounds classification using cepstral analysis and Gaussian mixture models. In: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. San Francisco, CA, USA; 2004. p. 9–12.
 116. Haider NS, Singh BK, Periyasamy R, Behera AK. Respiratory sound based classification of chronic obstructive pulmonary disease: a risk stratification approach in machine learning paradigm. *J Med Syst.* 2019;43(8):255.
 117. Tocchetto MA, Bazanella AS, Guimaraes L, Fragoso J, Parraga A. An embedded classifier of lung sounds based on the wavelet packet transform and ANN. *IFAC Proc.* 2014;47(3):2975–80.
 118. 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(7):473–82.
 119. Lozano M, Fiz JA, Jané R. Automatic differentiation of normal and continuous adventitious respiratory sounds using ensemble empirical mode decomposition and instantaneous frequency. *IEEE J Biomed Health Inform.* 2016;20(2):486–97.
 120. Datta S, Choudhury AD, Deshpande P, Bhattacharya S, Pal A. Automated lung sound analysis for detecting pulmonary abnormalities. In: 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Jeju, Korea (South); 2017. p. 4594–8.
 121. Aykanat M, Kılıç Ö, Kurt B, Saryal S. Classification of lung sounds using convolutional neural networks. *EURASIP J Image Video Process.* 2017;2017(1):65.
 122. Messner E, Fediuk M, Swatek P, Scheidl S, Smolle-Jüttner FM, Olschewski H, et al. Multi-channel lung sound classification with convolutional recurrent neural networks. *Comput Biol Med.* 2020;122:103831.
 123. Tariq Z, Shah SK, Lee Y. Lung disease classification using deep convolutional neural network. In: 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). San Diego, CA, USA; 2019. p. 732–5.
 124. Pham L, Phan H, Palaniappan R, Mertins A, McLoughlin I. CNN-MoE based framework for classification of respiratory anomalies and lung disease detection. *IEEE J Biomed Health Inform.* 2021;25(8):2938–47.
 125. Fraiwan M, Fraiwan L, Alkhodari M, Hassanin O. Recognition of pulmonary diseases from lung sounds using convolutional neural networks and long short-term memory. *J Ambient Intell Humaniz Comput.* 2022;13(10):4759–71.
 126. Serbes G, Sakar CO, Kahya YP, Aydin N. Pulmonary crackle detection using time–frequency and time-scale analysis. *Digit Signal Process.* 2013;23(3):1012–21.
 127. Messner E, Fediuk M, Swatek P, Scheidl S, Smolle-Jüttner FM, et al. Crackle and breathing phase detection in lung sounds with deep bidirectional gated recurrent neural networks. In: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Honolulu, HI, USA; 2018. p. 356–9.
 128. Li J, Wang C, Chen J, Zhang H, Dai Y, Wang L, et al. Explainable CNN with fuzzy tree regularization for respiratory sound analysis. *IEEE Trans Fuzzy Syst.* 2022;30(6):1516–28.
 129. Choi Y, Lee H. Interpretation of lung disease classification with light attention connected module. *Biomed Signal Process Control.* 2023;84:104695.
 130. Yu S, Ding Y, Qian K, Hu B, Li W, Schuller BW. A glance-and-gaze network for respiratory sound classification. In: ICASSP 2022–2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Singapore, Singapore; 2022. p. 9007–11.
 131. Nguyen T, Pernkopf F. Lung sound classification using snapshot ensemble of convolutional neural networks. In: 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Montreal, QC, Canada; 2020. p. 760-3.
 132. Sengupta N, Sahidullah M, Saha G. Lung sound classification using cepstral-based statistical features. *Comput Biol Med.* 2016;75:118–29.
 133. Grzywalski T, Piecuch M, Szajek M, Bręborowicz A, Hafke-Dys H, Kociński J, et al. Practical implementation of artificial intelligence algorithms in pulmonary auscultation examination. *Eur J Pediatr.* 2019;178(6):883–90.
 134. Pham L, Ngo D, Tran K, Hoang T, Schindler A, McLoughlin I. An ensemble of deep learning frameworks for predicting respiratory anomalies. In: 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Glasgow, Scotland, United Kingdom; 2022. p. 4595–8.
 135. Zhao Z, Gong Z, Niu M, Ma J, Wang H, Zhang Z, et al. Automatic respiratory sound classification via multi-branch temporal convolutional network. In: ICASSP 2022–2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Singapore, Singapore; 2022. p. 9102–6.
 136. Rocha BM, Pessoa D, Marques A, Carvalho P, Paiva RP. Automatic

- classification of adventitious respiratory sounds: a (un)solved problem? *Sensors (Basel)*. 2020;21(1):57.
137. Petmezias G, Cheimariotis GA, Stefanopoulos L, Rocha B, Paiva RP, Katsaggelos AK, et al. Automated lung sound classification using a hybrid CNN-LSTM network and focal loss function. *Sensors (Basel)*. 2022;22(3):1232.
 138. Mondal A, Bhattacharya P, Saha G. Detection of lungs status using morphological complexities of respiratory sounds. *Sci World J*. 2014;2014:182938.
 139. García-Ordás MT, Benítez-Andrades JA, García-Rodríguez I, Benavides C, Alaiz-Moretón H. Detecting respiratory pathologies using convolutional neural networks and variational autoencoders for unbalancing data. *Sensors*. 2020;20(4):1214.
 140. Shuvo SB, Ali SN, Swapnil SI, Hasan T, Bhuiyan MIH. A lightweight CNN model for detecting respiratory diseases from lung auscultation sounds using EMD-CWT-based hybrid scalogram. *IEEE J Biomed Health Inform*. 2021;25(7):2595–603.
 141. Shi L, Zhang Y, Zhang J. Lung sound recognition method based on wavelet feature enhancement and time-frequency synchronous modeling. *IEEE J Biomed Health Inform*. 2023;27(1):308–18.
 142. Kwon AM, Kang K. A temporal dependency feature in lower dimension for lung sound signal classification. *Sci Rep*. 2022;12:7889.
 143. Altan G, Kutlu Y, Gökçen A. Chronic obstructive pulmonary disease severity analysis using deep learning on multi-channel lung sounds. *Turk J Elec Eng Co*. 2020;28(5):2979–96.
 144. Yu H, Zhao J, Liu D, Chen Z, Sun J, Zhao X. Multi-channel lung sounds intelligent diagnosis of chronic obstructive pulmonary disease. *BMC Pulm Med*. 2021;21(1):1–13.
 145. Pham L, Phan H, Schindler A, King R, Mertins A, McLoughlin I. Inception-based network and multi-spectrogram ensemble applied to predict respiratory anomalies and lung diseases. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Mexico; 2021. p. 253–6.
 146. Fernandes T, Rocha BM, Pessoa D, de Carvalho P, Paiva RP. Classification of adventitious respiratory sound events: A stratified analysis. In: 2022 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI). Ioannina, Greece; 2022. p. 1–5.
 147. Kochetov K, Putin E, Balashov M, Filchenkov A, Shalyto A. Noise masking recurrent neural network for respiratory sound classification. In: Artificial Neural Networks and Machine Learning–ICANN 2018. Cham: Springer International Publishing; 2018. p. 208–17.
 148. Ma Y, Xu X, Yu Q, Zhang Y, Li Y, Zhao J, et al. LungBRN: a smart digital stethoscope for detecting respiratory disease using bi-ResNet deep learning algorithm. In: 2019 IEEE Biomedical Circuits and Systems Conference (BioCAS). Nara, Japan; 2019. p. 1–4.
 149. Hsiao CH, Lin TW, Lin CW, Hsu FS, Lin FYS, Chen CW, et al. Breathing sound segmentation and detection using transfer learning techniques on an attention-based encoder-decoder architecture. In: 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Montreal, QC, Canada; 2020. p. 754–9.
 150. Kevat A, Kalirajah A, Roseby R. Artificial intelligence accuracy in detecting pathological breath sounds in children using digital stethoscopes. *Respir Res*. 2020;21(1):1–6.
 151. Jayalakshmy S, Sudha GF. Scalogram based prediction model for respiratory disorders using optimized convolutional neural networks. *Artif Intell Med*. 2020;103:101809.
 152. Ngo D, Pham L, Nguyen A, Phan B, Tran K, Nguyen T. Deep learning framework applied for predicting anomaly of respiratory sounds. In: 2021 International Symposium on Electrical and Electronics Engineering (ISEE). Ho Chi Minh, Vietnam; 2021. p. 42–7.
 153. Becker K, Scheffer C, Blanckenberg M, Diacon A. Analysis of adventitious lung sounds originating from pulmonary tuberculosis. In: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Osaka, Japan; 2013. p. 4334–7.
 154. Altan G, Kutlu Y, Pekmezci AÖ, Yayık A. Diagnosis of chronic obstructive pulmonary disease using deep extreme learning machines with lu autoencoder kernel. In: 7th International Conference on Advanced Technologies (ICAT'18). Antalya; 2018. p. 618–22.
 155. Altan G, Kutlu Y, Allahverdi N. Deep learning on computerized analysis of chronic obstructive pulmonary disease. *IEEE J Biomed Health Inform*. 2020;24(5):1344–50.
 156. Monaco A, Amoroso N, Bellantuono L, Pantaleo E, Tangaro S, Bellotti R. Multi-time-scale features for accurate respiratory sound classification. *Appl Sci*. 2020;10(23):8606.
 157. Brunese L, Mercaldo F, Reginelli A, Santone A. A neural network-based method for respiratory sound analysis and lung disease detection. *Appl Sci*. 2022;12(8):3877.
 158. Morillo DS, León Jiménez A, Moreno SA. Computer-aided diagnosis of pneumonia in patients with chronic obstructive pulmonary disease. *J Am Med Inform Assoc*. 2013;20(e1):e111–7.
 159. Nguyen T, Pernkopf F, Kosmider M. Acoustic scene classification for mismatched recording devices using heated-up softmax and spectrum correction. In: ICASSP 2020–2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Barcelona, Spain; 2020. p. 126–30.
 160. Fernando T, Sridharan S, Denman S, Ghaemmaghami H, Fookes C. Robust and interpretable temporal convolution network for event detection in lung sound recordings. *IEEE J Biomed Health Inform*. 2022;26(7):2898–908.
 161. Selvaraju RR, Cogswell M, Das A, Vedantam R, Parikh D, Batra D. Grad-CAM: visual explanations from deep networks via gradient-based localization. In: Proceedings of the IEEE International Conference on Computer Vision. Venice, Italy; 2017. p. 618–26.
 162. Altan G. DeepOCT: An explainable deep learning architecture to analyze macular edema on oct images. *Eng Sci Technol Int J*. 2022;34:101091.
 163. Mishra S, Sturm BL, Dixon S. Local interpretable model-agnostic explanations for music content analysis. In: ISMIR. 2017. p. 537–43.
 164. Ganin Y, Ustinova E, Ajakan H, Germain P, Larochelle H, Laviolette F, et al. Domain-adversarial training of neural networks. *J Mach Learn Res*. 2016;17:1–35.
 165. Tzeng E, Hoffman J, Saenko K, Darrell T. Adversarial discriminative domain adaptation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Honolulu, HI, USA; 2017. p. 7167–76.
 166. Wang Y, Yao Q, Kwok JT, Ni LM. Generalizing from a few examples: a survey on few-shot learning. *ACM Comput Surv*. 2020;53(3):63.
 167. Pons J, Serrà J, Serra X. Training neural audio classifiers with few data. In: ICASSP 2019–2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Brighton, UK; 2019. p. 16–20.

168. Wolters P, Careaga C, Hutchinson B, Phillips L. A study of few-shot audio classification. arXiv. 2020. <https://arxiv.org/abs/2012.01573>.
169. Snell J, Swersky K, Zemel R. Prototypical networks for few-shot learning. arXiv. 2017. <https://arxiv.org/abs/1703.05175>.
170. Li T, Cao P, Yuan Y, Fan L, Yang Y, Feris RS, et al. Targeted supervised contrastive learning for long-tailed recognition. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. New Orleans, LA, USA; 2022. p. 6908–28.
171. Gou J, Yu B, Maybank SJ, Tao D. Knowledge distillation: a survey. *Int J Comput Vis*. 2021;129(6):1789–819.
172. Ding W, Huang Z, Huang Z, Tian L, Wang H, Feng S. Designing efficient accelerator of depthwise separable convolutional neural network on FPGA. *J Syst Archit*. 2019;97:278–86.
173. Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, et al. MobileNets: efficient convolutional neural networks for mobile vision applications. arXiv. 2017. <https://arxiv.org/abs/1704.04861>.
174. Giannakopoulos T. pyAudioAnalysis: an open-source python library for audio signal analysis. *PLoS ONE*. 2015;10(12):e0144610.
175. Huang D, Wang L, Lu H, Wang W. A contrastive embedding-based domain adaptation method for lung sound recognition in children community-acquired pneumonia. In: ICASSP 2023–2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Rhodes, Greece; 2023. p. 1–5.

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