bioengineering

Supplementary Materials

Machine Learning for Automated Classification of Abnormal Lung Sounds Obtained from Public Databases: A Systematic Review

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Table S1. List of included studies main characteristics. Sorted by author.

Author, Year	Classifier (method)	Feature Extraction (method)	Database(s)	Performance Metrics	Categories	Classification Classes
Acharya, 2020 [57]	CNN + RNN(Bi-LSTM)	Mel-frequency Spectrogram	ICBHI 2017	Accuracy: * Sens: 48.63 Spec: 84.14	Adventitious sounds	Normal vs Wheeze vs Crackle vs Crackle and Wheeze
Alqudah, 2022 [58]	CNN + RNN(LSTM)	Convolutional Neural Networks	(1) ICBHI 2017, (2) KAUH database	Non-augmented dataset: Accuracy: 99.37 Sens: 98.5 Spec: 99.87 Augmented dataset: Accuracy: 99.53 Sens: 98.80 Spec: 99.92	Diseases	Healthy vs Asthma vs Fibrosis vs COPD vs BRON vs HF vs HF+COPD vs HF + Fibrosis vs Pleural effusion vs Pneumonia
Altan, 2020 [59]	k-NN, DT, SVM, DBN	Hilbert-Huang Transform	RespiratoryDatabase@TR	k-NN: Accuracy: 83.5 Sens: 79.33 Spec: 87.67 DT: Accuracy: 84.83 Sens: 87.67	Diseases	Healthy vs COPD

				Spec: 82.00 SVM: Accuracy: 89.62 Sens: 90.67 Spec: 88.59 DBN: Accuracy: 93.67 Sens: 91.00 Spec: 96.33		
Bahoura, 2009 [35]	GMM, MLP	Fourier Transform; Linear Predictive Coding; Cepstral Analysis; Wavelet Transform	(1) Bahoura 1999 (2) R.A.L.E. Lung Sounds, (3) ASTRA database, and (4) Others (non-specified)	GMM: Accuracy: * Sens: 97.20 Spec: 94.20	Adventitious sounds	Normal vs Wheeze
Bahoura, 2018 [60]	MLP	Mel-Frequency Cepstral Coefficients	(1) Bahoura 1999 (2) R.A.L.E. Lung Sounds, (3) ASTRA database, and (4) Others (non-specified)	XSG: Accuracy: 86.05 Sens: 81.52 Spec: 88.51 MATLAB: Accuracy: 86.07 Sens: 81.71 Spec: 88.43	Adventitious sounds	Normal vs Wheeze
Bardou, 2018 [61]	CNN (Ensemble model)	Mel-Frequency Cepstral Coefficients	R.A.L.E. Lung Sounds	Augmented + ensemble: Accuracy: 95.56 Sens: * Spec: *	Adventitious sounds	Normal vs Coarse crackle vs Fine crackle vs Monophonic wheeze vs Polyphonic wheeze vs Squawk vs Stridor
Basu, 2020 [62]	NN	Mel-Frequency Cepstral Coefficients	ICBHI 2017	Accuracy: 95.67 Sens: 95.65 Spec: *	Diseases	Healthy vs Bronchiolitis vs Bronchiectasis vs Pneumonia vs URTI vs COPD
Boujelben, 2018 [93]	SVM	Mel-Frequency Cepstral Coefficients	(1) Bahoura 1999 (2) R.A.L.E. Lung Sounds, (3) ASTRA database, and (4) Others (non-specified)	Default XSG: Accuracy: 93.72 Sens: 89.72 Spec: 96.06 Optimized XSG: Accuracy: 93.49 Sens: 89.36 Spec: 96.06 MATLAB: Accuracy: 93.59 Sens: 89.72 Spec: 96.06	Adventitious sounds	Normal vs Wheeze

Brunese, 2022 [63]	k-NN, SVM, NN, LR	Mel-Frequency Cepstral Coefficients; Root Mean Square; Chromagram; Spectral Centroid; Spectral Roll-off; Zero Crossing Rate	ICBHI 2017	Task 1: k-NN: Accuracy: * Sens: 99.7 Spec: 96.5 SVM: Accuracy: * Sens: 100 Spec: 96.6 NN: Accuracy: * Sens: 98.8 Spec: 97.9 LR: Accuracy: * Sens: 98.2 Spec: 97.6 Task 2: k-NN: Accuracy: * Sens: 90.80 Spec: 88.30 SVM: Accuracy: * Sens: 90.70 Spec: 89.00 NN: Accuracy: * Sens: 93.10 Spec: 91.70 LR: Accuracy: * Sens: 90.40 Spec: 88.60	Diseases	Task 1: Healthy vs non-Healthy Task 2: Asthma vs Bronchiectasis vs Bronchiolitis vs COPD vs Pneumonia vs LRTI vs URTI
Chen, 2019 [64]	CNN (Residual Network)	Optimized S-Transform	ICBHI 2017	OST (Optimized S control)-ResNet: Accuracy: 98.79 Sens: 96.27 Spec: 100	Adventitious sounds	Normal vs Wheeze vs Crackle vs Wheeze and Crackle

				ST-ResNet: Accuracy: 97.79 Sens: 93.17 Spec: 100 STFT-ResNet: Accuracy: 93.98 Sens: 86.96 Spec: 97.33		
Chen, 2019 [65]	SVM, ELM, k-NN	Enhanced Generalized S-Transform	(1) ICBHI 2017, (2) R.A.L.E. Lung Sounds	Accuracy: 99.52 Sens: 100 Spec: 99.27	Adventitious sounds	Normal vs Wheeze
Datta, 2017 [37]	SVM	Welch Method (Spectral Features); Spectrogram Features; Discrete Wavelet Transform; Mel-Frequency Cepstral Coefficients	(1) R.A.L.E. Lung Sounds, (2) Steven Lehrer Sound Repository (CD) (3) Healthy sounds were self-recorded	Overlapping: Accuracy: 85.00 Sens: * Spec: * Non-overlapping: Accuracy: 80.00 Sens: * Spec: *	Adventitious sounds	Normal vs Abnormal (Wheeze, Crackle, Squawks, Stridor, Grunt, Squeak, Pleural rub)
Demir, 2020 [67]	CNN (LDA + RSE)	Convolutional Neural Networks	ICBHI 2017	Accuracy: 71.15 Sens: 61.00 Spec: 86.00	Adventitious sounds	Normal vs Wheeze vs Crackle vs Crackle and Wheeze
Demir, 2020 [66]	CNN, SVM	Short-time Fourier Transform	ICBHI 2017	Deep feature + SVM: Accuracy: 65.50 Sens: 53.00 Spec: 83.00 Transfer learning + Softmax: Accuracy: 63.09 Sens: * Spec: *	Adventitious sounds	Normal vs Wheeze vs Crackle vs Crackle and Wheeze
D. Perna, 2018 [68]	CNN	Mel-Frequency Cepstral Coefficients	ICBHI 2017	Task 1: Accuracy: 83.00 Sens: * Spec: * Task 2: Accuracy: 82.00 Sens: * Spec: *	Diseases	Task 1: Healthy vs Unhealthy Task 2: Healthy vs Chronic disease vs non-Chronic disease

Fraiwan, 2022 [69]	CNN + RNN (BDLSTM)	Convolutional Neural Networks	(1) ICBHI 2017 (only included 110 patients), (2) KAUH database	CNN only: Accuracy: 99.04 Sens: 93.02 Spec: 99.33 BDLSTM only: Accuracy: 98.16 Sens: 90.06 Spec: 98.61 CNN + RNN (BDLSTM): Accuracy: 99.62 Sens: 98.43 Spec: 99.69	Diseases	Normal vs Asthma vs Pneumonia vs Bronchiectasis vs COPD vs Heart failure
Gairola, 2017 [70]	CNN	Mel-frequency Spectrogram	ICBHI 2017	Task 1: Accuracy: 77.00 Sens: 73.10 Spec: 80.90 Task 2: Accuracy: 68.50 Sens: 53.70 Spec: 83.30	Adventitious sounds	Task 1: Normal vs Abnormal Task 2: Normal vs Wheeze vs Crackle vs Crackle and Wheeze
Garcia-Ordas, 2020 [71]	CNN	Mel-frequency Spectrogram	ICBHI 2017	Task 1: Accuracy: * Sens: 98.80 Spec: 98.60 Task 2: Accuracy: * Sens: 98.50 Spec: 99.00	Diseases	Task 1: Healthy vs Chronic disease vs non-Chronic disease Task 2: Healthy vs Bronchiolitis vs Bronchiectasis vs Pneumonia vs URTI vs COPD
G. Chambres, 2018 [102]	Boosted DT	Mel-Frequency Cepstral Coefficients	ICBHI 2017	Accuracy: 49.43 Sens: 20.81 Spec: 78.05	Adventitious sounds	Normal vs Wheeze vs Crackle vs Crackle and Wheeze
Hazra, 2020 [72]	CNN	Mel-Frequency Cepstral Coefficients	ICBHI 2017	Accuracy: 92.39 Sens: 50.83 Spec: *	Diseases	Healthy vs Bronchiolitis vs Bronchiectasis vs Pneumonia vs URTI vs COPD
Jaber, 2020 [109]	RF	Mel-Frequency Cepstral Coefficients	R.A.L.E. Lung Sounds	Accuracy: 99.04 Sens: 98.70 Spec: 99.49	Adventitious sounds	Normal vs Coarse crackle vs Fine crackle vs Monophonic wheeze vs Polyphonic wheeze vs Squawk vs Stridor
Jakovljevic, 2018 [113]	HMM	Mel-Frequency Cepstral Coefficients	ICBHI 2017	Accuracy: * Sens: 42.32 Spec: 59.69	Adventitious sounds	Normal vs Wheeze vs Crackle vs Crackle and Wheeze

Jung, 2021 [73]	DS-CNN	Mel-Frequency Cepstral Coefficients; Short-time Fourie Transform	Hsiao 2020	Accuracy: 85.74 Sens: 86.25 Spec: 86.75	Adventitious sounds	Normal vs Wheeze vs Crackle vs Unknown
Kochetov, 2018 [74]	NM-RNN	Mel-Frequency Cepstral Coefficients	ICBHI 2017	Accuracy: * Sens: 58.40 Spec: 73.00	Adventitious sounds	Normal vs Wheeze vs Crackle vs Crackle and Wheeze
Kok, 2019 [103]	DT	Mel-Frequency Cepstral Coefficients; Discrete Wavelet Transform; Time Domain Features	ICBHI 2017	Accuracy: 87.1 Sens: 86.80 Spec: 93.60	Adventitious sounds	Task 1: Normal vs abnormal Task 2: Normal vs Wheeze vs Crackle vs Crackle and Wheeze
Li, 2022 [75]	Explainable CNN (based on fuzzy DT)	Mel-frequency Spectrogram	ICBHI 2017	Task 1: Accuracy: * Sens: 61.00 Spec: 82.00 Task 2: Accuracy: * Sens: 98.00 Spec: 92.00	Both adventitious sounds and diseases	Task 1: Crackle vs Normal vs Wheeze Task 2: COPD vs Healthy vs Pneumonia
Li, 2021 [76]	CNN (ResNet+Attention-augmented convolution)	Dual tunable Q-factor Wavelet Transform; Short-time Fourier Transform	ICBHI 2017	Accuracy: * Sens: 36.36 Spec: 71.44	Adventitious sounds	Normal vs Wheeze vs Crackle vs Crackle and Wheeze
Lu, 2008 [34]	GMM	Wavelet Packet Transform	(1) ASTRA database, (2) R.A.L.E. Lung Sounds	Accuracy: * Sens: 92.90 Spec: 94.40	Adventitious sounds	Normal vs Crackle vs Wheeze
Minami, 2019 [77]	CNN	Short-Time Fourier Transform; Wavelet Transform	ICBHI 2017	Accuracy: * Sens: 28.00 Spec: 81.00	Diseases	Bronchiectasis vs pneumonia vs bronchiolitis vs COPD vs URTI vs normal
Monaco, 2020 [78]	MLP, SVM, DNN, RF	Multi-time Scale Feature Extraction	ICBHI 2017	MLP: Accuracy: 85.00 Sens: * Spec: *	Adventitious sounds	Normal vs Crackle vs Wheeze vs Crackle and Wheeze

				RF: Accuracy: 84.00 Sens: * Spec: * DNN: Accuracy: 82.00 Sens: * Spec: * SVM: Accuracy: 81.00 Sens: * Spec: *		
Mukherjee, 2021 [79]	MLP	Linear Predictive Cepstral Coefficient	ICBHI 2017	Accuracy: 99.22 Sens: 99.17 Spec: 99.26	Diseases	Healthy vs non-Healthy
Naqvi, 2020 [106]	QDA	Mel-Frequency Cepstral Coefficients; Gammatone Cepstral Coefficients; Time Domain Features; Spectral Domain Features	ICBHI 2017	Accuracy: 99.80 Sens: * Spec: *	Diseases	Healthy, COPD, Pneumonia
Naves, 2016 [39]	k-NN, Naive Bayes	Higher-order Statistics	Steven Lehrer Sound Repository 2002 (CD)	Accuracy: 94.60 Sens: * Spec: *	Adventitious sounds	Normal vs coarse crackle vs Fine crackle vs Monophonic wheeze vs Polyphonic wheeze
Ngo, 2021 [80]	C-DNN + autoencoder	Short-time Fourier Transform, Gammatone	ICBHI 2017	Accuracy: * Sens: 30.00 Spec: 69.00	Adventitious sounds	Normal vs Crackle vs Wheeze vs Crackle and Wheeze
Nguyen, 2020 [81]	CNN, SE	Fast Fourier Transform	ICBHI 2017	Task 1: CNN: Accuracy: * Sens: 69.10 Spec: 86.10 SE: Accuracy: * Sens: 69.40 Spec: 87.30 Task 2:	Adventitious sounds	Task 1: Normal vs Crackle vs Wheeze vs Crackle and Wheeze Task 2: Normal vs Abnormal

				CNN: Accuracy: * Sens: 80.40 Spec: 86.10 SE: Accuracy: * Sens: 80.10 Spec: 87.30		
Ntalampiras, 2020 [114]	DAG-HMM	Discrete Wavelet Transform	ICBHI 2017	Accuracy: 50.10 Sens: * Spec: *	Adventitious sounds	Normal vs Crackle vs Wheeze vs Crackle and Wheeze
Ntalampiras, 2020 [111]	HMM + GMM	Mel-Frequency Cepstral Coefficients; Discrete Wavelet Transform	ICBHI 2017	Accuracy: 66.70 Sens: * Spec: *	Adventitious sounds	Normal vs Abnormal
Oletic, 2014 [104]	DT	Short-time Fourier Transform	(1) R.A.L.E. Lung Sounds, (2) Stethographics Lung Sound Samples, (3) Mediscuss Respiratory Sounds, (4) 3M Littmann Lung Soundsw Library, (5) East Tennessee State University Breath Sounds	Accuracy: 92.96 Sens: 96.92 Spec: 91.21	Adventitious sounds	Normal vs Wheeze
Oletic, 2018 [115]	HMM	CS-recovered Short-time Fourier Transform	(1) R.A.L.E. Lung Sounds, (2) Stethographics Lung Sound Samples, (3) Mediscuss Respiratory Sounds, (4) 3M Littmann Lung Soundsw Library, (5) East Tennessee State University Breath Sounds	Accuracy: 94.91 Sens: 89.34 Spec: 96.28	Adventitious sounds	Normal vs Wheeze
Oweis, 2015 [38]	ANN, ANFIS	Fast Fourier Transform	(1) Williams 2009 (CD), (2) Steven Lehrer	ANN: Accuracy: 98.60 Sens: 97.80	Adventitious sounds	Bronchovesicular vs Normal bronchial vs Abnormal bronchial vs Crackle vs

			Sound Repository 2002 (CD)	Spec: 100 ANFIS: Accuracy: 66.40 Sens: 56.90 Spec: 70.40		Wheeze vs Stridor vs Normal bronchophony vs Bronchophony by consolidation vs Normal egophony vs Abnormal egophony
Palaniappan, 2014 [14]	SVM, k-NN	Mel-Frequency Cepstral Coefficients	R.A.L.E. Lung Sounds	SVM: Accuracy: 92.19 Sens: *, Spec: * k-NN: Accuracy: 98.26 Sens: * Spec: *	Diseases	Norma vs Airway obstruction vs Parenchymal pathology
Paraschiv, 2020 [82]	2D CNN	Mel-Frequency Cepstral Coefficients; Discrete Fourier Transform	ICBHI 2017	Accuracy: 90.21 Sens: * Spec: *	Diseases	Bronchiectasis vs Pneumonia vs Bronchiolitis vs COPD vs URTI vs Normal
Petmezas, 2022 [83]	CNN + RNN (LSTM)	Short-time Fourier Transform	ICBHI 2017	Accuracy: 76.39 Sens: 52.78 Spec: 84.26	Adventitious sounds	Normal vs Crackle vs Wheeze vs Crackle and Wheeze
Pham, 2021 [85]	CNN	Continuous Wavelet Transform	ICBHI 2017	Task 1: Accuracy: * Sens: 32.00 Spec: 73.00 Task 2: Accuracy: * Sens: 85.00 Spec: 88.00	Both adventitious sounds and diseases	Task 1: Normal vs Crackle vs Wheeze vs Crackle and Wheeze Task 2: Healthy vs Chronic disease (COPD, bronchiectasis, asthma) vs non-Chronic disease (URTI, LRTI, Pneumonia, Bronchiolitis)
Pham, 2021 [84]	C-DNN	Mel-frequency Spectrogram; Gammatone Filterbank Spectrogram; Stacked Mel-Frequency Cepstral Coefficients; Rectangular Constant Q Transform	ICBHI 2017	Task 1.1: Accuracy: * Sens: 68.00 Spec: 90.00 Task 1.2: Accuracy: * Sens: 78.00 Spec: 90.00 Task 2.1: Accuracy: * Sens: 95.00 Spec: 86.00 Task 2.2:	Both adventitious sounds and diseases	Task 1.1: Normal vs Crackle vs Wheeze vs Crackle and Wheeze Task 1.2: Normal vs Abnormal Task 2.1: Healthy vs Chronic disease (COPD, bronchiectasis, asthma) vs non-Chronic disease (URTI, LRTI, Pneumonia, Bronchiolitis) Task 2.2: Healthy vs Unhealthy

				Accuracy: * Sens: 98.00 Spec: 86.00		
Pham Thi Viet, 2022 [86]	CNN + Ensemble learning	Continuous Wavelet Transform	ICBHI 2017	Task 1: Accuracy: * Sens: 83.10 Spec: 86.40 Task 2: Accuracy: * Sens: 75.10 Spec: 84.20	Adventitious sounds	Task 1: Normal vs Abnormal Task 2: Normal vs Crackle vs Wheeze vs Crackle and Wheeze
Porieva, 2021 [107]	QDA	Fast Fourier Transform; Multilevel Wavelet Transform; Mel-Frequency Cepstral Coefficients	CORA database	Accuracy: 93.2 Sens: * Spec: *	Diseases	Normal vs Bronchitis vs COPD
Pramono, 2019 [119]	LR	Mel-Frequency Cepstral Coefficients; Tonality Index; Linear Predictive Coding	(1) R.A.L.E. Lung Sounds, (2) Pulmonary Breath Sounds ETSU 2002, (3) 3M Littmann Lung Sounds Library, (4) Stethographics Lung Sound Samples	Accuracy: * Sens: 83.86 Spec: 81.19	Adventitious sounds	Normal vs Wheeze
Rocha, 2020 [87]	LDA, SVM, RUSBoost (Type of DT), CNN	Short-term Fourier Transform	ICBHI 2017	LDA: Accuracy: 84.20 Sens: * Spec: * SVM: Accuracy: 89.70 Sens: * Spec: * RUSBoost: Accuracy: 92.30 Sens: * Spec: * CNN: Accuracy: 96.90 Sens: * Spec: *	Adventitious sounds	Crackle vs Wheeze vs Others

Sen, 2014 [94]	LIBSVM	Vector Autoregression	Bogazici University Lung Acoustics Laboratory	Task 1: Accuracy: * Sens: 85.00 Spec: 85.00 Task 2: Accuracy: * Sens: 75.00 Spec: *	Diseases	Task 1: Healthy vs Pathologic Task 2: Healthy vs Bronchiectasis vs Interstitial pulmonary disease
Serbes, 2018 [95]	SVM	Short-time Fourier Transform; Non-linear Resonance Based Wavelet Decomposition	ICBHI 2017	Accuracy: 57.88 Sens: 55.29 Spec: 83.25	Adventitious sounds	Normal vs crackle vs wheeze vs crackle and wheeze
Shuvo, 2020 [88]	Lightweight CNN	Empirical Mode Decomposition; Continuous Wavelet Transform	ICBHI 2017	Task 1: Accuracy: 98.92 Sens: 98.90 Spec: 100 Task 2: Accuracy: 98.70 Sens: 98.60 Spec: 100	Diseases	Task 1: Healthy vs Chronic disease (COPD, Bronchiectasis, Asthma) vs non-Chronic disease (URTI, LRTI, Pneumonia, Bronchiolitis) Task 2: Healthy vs Bronchiectasis vs Bronchiolitis vs COPD vs Pneumonia vs URTI
Sosa, 2015 [97]	SVM	Short-time Fourier Transform; Wavelet Packet Transform; Mel-Frequency Cepstral Coefficients	R.A.L.E. Lung Sounds	Accuracy: * Sens: 81.50 Spec: 82.60	Adventitious sounds	Normal vs Wheeze
Stasiakiewicz, 2021 [96]	SVM	Continuous Wavelet Transform	(1) ICBHI 2017, (2) Self-recorded	Accuracy: 98.00 Sens: 97.80 Spec: 98.20	Diseases	Healthy vs Pneumonia vs Pulmonary fibrosis vs Heart failure vs COPD
Tariq, 2019 [89]	2D CNN	Mel-frequency Spectrogram	ICBHI 2017	Accuracy: 97.00 Sens: * Spec: *	Diseases	Healthy vs Asthma vs COPD vs Bronchiectasis vs Pneumonia vs LRTI vs URTI
Tasar, 2022 [98]	k-NN, SVM, DT	Tunable Q Factor Wavelet; Iterative Neighborhood	ICBHI 2017	Task 1: k-NN: Accuracy: 99.45 Sens: 99.52 Spec: 98.78	Diseases	Task 1: Healthy vs Bronchiolitis vs COPD vs Bronchiectasis vs Pneumonia vs LRTI vs URTI Task 2: COPD vs Pneumonia vs Asthma

		Component Analysis		SVM: Accuracy: 98.41 Sens: 96.97 Spec: 99.01 DT: Accuracy: 83.70 Sens: 77.76 Spec: 78.91 Task 2: k-NN: Accuracy: 99.31 Sens: 99.57 Spec: 99.46 SVM: Accuracy: 97.87 Sens: 98.55 Spec: 98.48 DT: Accuracy: 96.66 Sens: 94.35 Spec: 97.19 Task 3: k-NN: Accuracy: 99.19 Sens: 99.01 Spec: 98.77 SVM: Accuracy: 97.80 Sens: 96.63 Spec: 98.19 DT: Accuracy: 86.41 Sens: 82.06 Spec: 82.40		Task 3: Healthy vs Asthma vs COPD vs Bronchiectasis vs Bronchiolitis vs Pneumonia vs LRTI vs URTI
Tocchetto, 2014 [36]	ANN	Wavelet Packet Transform	Steven Lehrer Sound Repository (CD)	Accuracy: 99.26 Sens: * Spec: *	Adventitious sounds	Normal vs Wheeze vs Crackle
Tripathy, 2022 [117]	LGBM	Empirical Wavelet Transform	KAUH database	Accuracy: 84.76 Sens: 91.12 Spec: 82.96	Diseases	Healthy vs asthma vs COPD vs Pneumonia

Vidhya, 2022 [99]	GB, SVM, k-NN	Mel-Frequency Cepstral Coefficients	ICBHI 2017	GB: Accuracy: 97.00 Sens: * Spec: * SVM: Accuracy: 69.40 Sens: * Spec: * k-NN: Accuracy: 90.23 Sens: * Spec: *	Diseases	Healthy vs Pneumonia
Yang, 2020 [90]	CNN (ResNet)	Short-time Fourier Transform	ICBHI 2017	Accuracy: * Sens: 17.80 Spec: 81.20	Adventitious sounds	Normal vs Crackle vs Wheeze vs Crackle and Wheeze
Yi Ma, 2019 [91]	Bi-ResNet NN	Short-time Fourier Transform; Wavelet Packet Transform	ICBHI 2017	Accuracy: 67.44 Sens: 58.54 Spec: 80.06	Adventitious sounds	Normal vs Crackle vs Wheeze vs Crackle and Wheeze
Zulfiqar, 2021 [18]	AlexNet, InceptionNet, ResNet	Fourier Transform	(1) R.A.L.E. Lung Sounds, (2) Thinklabs database, (3) Easy Auscultation database (4) Others	AlexNet: Accuracy: 100 Sens: 100 Spec: * InceptionNet: Accuracy: 95.00 Sens: 95.00 Spec: * ResNet: Accuracy: 95.00 Sens: 93.00 Spec: * LeNet: Accuracy: 89.00 Sens: 90.00 Spec: *	Adventitious sounds	Coarse crackle vs. Fine crackle vs. Pleural rub vs. Rhonchi vs. Squawk vs. Stridor vs. Wheeze

Legend: ANFIS: Adaptive Neuro-Fuzzy Interference Systems; BDLSTM: Bi-Directional Long Short-Term Memory Neural Network; DAG: Directed Acyclic Graph (type of CNN); DBN: Deep Belief Networks; DNN: Deep neural network; DS-CNN: Depthwise Separable Convolutional Neural Network; DT: Decision Tree; ELM: Extreme Learning Machine; GMM: Gaussian Mixture Models; HMM: Hidden Markov Model; k-NN: k-Nearest Neighbor; LDA: Linear Discriminant Analysis; LGBM: Light Gradient Boosting Machine; LR: Logistic Regression; MLP: Multi-Layer Perceptron; NM-RNN: Noise-Masking Recurrent Neural Network; QD: Quadratic Discriminant Analysis (type of Discriminant Analysis); RF: Random Forest; RSE: Random Subspace Ensembles; RUSBoost: Random Undersampling Boosted Trees; SE: Snapshot Ensemble (type of CNN); SVM: Support Vector Machine; XSG: Xilinx System Generator

*Not provided in the manuscript.

Table S2. Individual risk of bias assessment. Sorted in the same order as Table S1.

Author, Year	Patient Selection	Index Test	Reference Standard	Flow and timing
Acharya, 2020 [57]	High	Low	High	Low
Alqudah, 2022 [58]	High	Low	High	Low
Altan, 2020 [59]	High	Low	High	Low
Bahoura, 2009 [35]	High	Low	High	Unclear
Bahoura, 2018 [60]	High	Low	High	Unclear
Bardou, 2018 [61]	Unclear	Low	High	Unclear
Basu, 2020 [62]	High	Low	High	Low
Boujelben, 2018 [93]	High	Low	High	Unclear
Brunese, 2022 [63]	High	Low	High	Low
Chen, 2019 [64]	High	Low	High	Low
Chen, 2019 [65]	High	Low	High	Unclear
Datta, 2017 [37]	High	Low	High	High
Demir, 2020 [67]	High	Low	High	Low
Demir, 2020 [66]	High	Low	High	Low
D. Perna, 2018 [68]	High	Low	High	Low
Fraiwan, 2022 [69]	High	Low	High	Low
Gairola, 2017 [70]	High	Low	High	Low
Garcia-Ordas, 2020 [71]	High	Low	High	Low
G. Chambres, 2018 [102]	High	Low	High	Low
Hazra, 2020 [72]	High	Low	High	Low
Jaber, 2020 [109]	Unclear	Low	High	High
Jakovljevic, 2018 [113]	High	Low	High	Low
Jung, 2021 [73]	Unclear	Low	High	Low
Kochetov, 2018 [74]	High	Low	High	Low
Kok, 2019 [103]	High	Low	High	Low
Li, 2022 [75]	High	Low	High	Low
Li, 2021 [76]	High	Low	High	Low
Lu, 2008 [34]	High	Low	High	High
Minami, 2019 [77]	High	Low	High	Low
Monaco, 2020 [78]	High	Low	High	Low
Mukherjee, 2021 [79]	High	Low	High	Low
Naqvi, 2020 [106]	High	Low	High	Low
Naves, 2016 [39]	Unclear	Low	Unclear	Unclear

Ngo, 2021 [80]	High	Low	High	Low
Nguyen, 2020 [81]	High	Low	High	Low
Ntalampiras, 2020 [114]	High	Low	High	Low
Ntalampiras, 2020 [111]	High	Low	High	Low
Oletic, 2014 [104]	High	Low	High	High
Oletic, 2018 [115]	High	Low	High	High
Oweis, 2015 [38]	High	Low	Unclear	Unclear
Palaniappan, 2014 [14]	Unclear	Low	High	Unclear
Paraschiv, 2020 [82]	High	Low	High	Low
Petmezas, 2022 [83]	High	Low	High	Low
Pham, 2021 [85]	High	Low	High	Low
Pham, 2021 [84]	High	Low	High	Low
Pham Thi Viet, 2022 [86]	High	Low	High	Low
Porieva, 2021 [107]	Unclear	Low	Unclear	Unclear
Pramono, 2019 [119]	High	Low	High	Unclear
Rocha, 2020 [87]	High	Low	High	Low
Sen, 2014 [94]	Unclear	Low	High	High
Serbes, 2018 [95]	High	Low	High	Low
Shuvo, 2020 [88]	High	Low	High	High
Sosa, 2015 [97]	Unclear	Low	High	Unclear
Stasiakiewicz, 2021 [96]	High	Low	High	High
Tariq, 2019 [89]	High	Low	High	Low
Tasar, 2022 [98]	High	Low	High	Low
Tocchetto, 2014 [36]	Unclear	Low	Unclear	Unclear
Tripathy, 2022 [117]	Low	Low	High	Low
Vidhya, 2022 [99]	High	Low	High	Low
Yang, 2020 [90]	High	Low	High	Low
Yi Ma, 2019 [91]	High	Low	High	Low
Zulfiqar, 2021 [18]	High	Low	High	High

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Table S3. Individual applicability concerns assessment. Sorted in the same order as Table S1. 34

Author, Year	Patient Selection	Index Test	Reference Standard
Acharya, 2020 [57]	High	Low	High
Alqudah, 2022 [58]	High	Low	High
Altan, 2020 [59]	Low	Low	High
Bahoura, 2009 [35]	Uncertain	Low	High
Bahoura, 2018 [60]	Uncertain	Low	High
Bardou, 2018 [61]	Uncertain	Low	High

Basu, 2020 [62]	High	Low	High
Boujelben, 2018 [93]	Uncertain	Low	High
Brunese, 2022 [63]	High	Low	High
Chen, 2019 [64]	High	Low	High
Chen, 2019 [65]	High	Low	High
Datta, 2017 [37]	Uncertain	Low	High
Demir, 2020 [67]	High	Low	High
Demir, 2020 [66]	High	Low	High
D. Perna, 2018 [68]	High	Low	High
Fraiwan, 2022 [69]	High	Low	High
Gairola, 2017 [70]	High	Low	High
Garcia-Ordas, 2020 [71]	High	Low	High
G. Chambres, 2018 [102]	High	Low	High
Hazra, 2020 [72]	High	Low	High
Jaber, 2020 [109]	Uncertain	Low	High
Jakovljevic, 2018 [113]	High	Low	High
Jung, 2021 [73]	Low	Low	High
Kochetov, 2018 [74]	High	Low	High
Kok, 2019 [103]	High	Low	High
Li, 2022 [75]	High	Low	High
Li, 2021 [76]	High	Low	High
Lu, 2008 [34]	Uncertain	Low	High
Minami, 2019 [77]	High	Low	High
Monaco, 2020 [78]	High	Low	High
Mukherjee, 2021 [79]	High	Low	High
Naqvi, 2020 [106]	High	Low	High
Naves, 2016 [39]	Uncertain	Low	High
Ngo, 2021 [80]	High	Low	High
Nguyen, 2020 [81]	High	Low	High
Ntalampiras, 2020 [114]	High	Low	High
Ntalampiras, 2020 [111]	High	Low	High
Oletic, 2014 [104]	Uncertain	Low	High
Oletic, 2018 [115]	Uncertain	Low	High
Oweis, 2015 [38]	Uncertain	Low	High
Palaniappan, 2014 [14]	Uncertain	Low	High
Paraschiv, 2020 [82]	High	Low	High
Petmezas, 2022 [83]	High	Low	High
Pham, 2021 [85]	High	Low	High
Pham, 2021 [84]	High	Low	High
Pham Thi Viet, 2022 [86]	High	Low	High
Porieva, 2021 [107]	Uncertain	Low	High
Pramono, 2019 [119]	Uncertain	Low	High

Rocha, 2020 [87]	High	Low	High
Sen, 2014 [94]	Uncertain	Low	High
Serbes, 2018 [95]	High	Low	High
Shuvo, 2020 [88]	High	Low	High
Sosa, 2015 [97]	Uncertain	Low	High
Stasiakiewicz, 2021 [96]	High	Low	High
Tariq, 2019 [89]	High	Low	High
Tasar, 2022 [98]	High	Low	High
Tocchetto, 2014 [36]	Uncertain	Low	High
Tripathy, 2022 [117]	High	Low	High
Vidhya, 2022 [99]	High	Low	High
Yang, 2020 [90]	High	Low	High
Yi Ma, 2019 [91]	High	Low	High
Zulfiqar, 2021 [18]	Uncertain	Low	High

Search strategy:

Cochrane Central Register of Controlled Trials (CCTR) via Ovid (1991+)):

(((auscultat* or stethoscope* or ((lung* or breath* or respirat* or pulmonary) adj2 sound*)).ab,hw,ti. AND (remote* or tele* or bio-tele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or smart-phone* or mobile-app* or virtual*).ab,hw,ti. AND ((remote* or tele* or biotele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*).ti,kw. or ((auscultat* or stethoscope* or ((lung* or breath* or respirat* or pulmonary) adj2 sound*)) adj4 (remote* or tele* or biotele* or ehealth or e-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*)).ab,kw,ti.) or (teleauscultat* or digiscope*).ab,hw,ti.) AND (airway or asthma* or bronch* or cardiopulmo-nary or chest or COPD or diaphragm or lung* or mediastinal or pleur* or pneumo* or pulmonary or thora* or trach*).ab,hw,ti.) NOT ((canine* or dog or dogs or feline* or hamster* or lamb or lambs or sheep or mice or mouse or murine or monkey* or pig* or porcine or primate* or rabbit* or rat or rats or rodent* or horse* or equine* or veterinar*).ti,hw. OR (fetal or fetus or newborn* or neonat* or infant* or toddler* or child* or adolesc* or teen* or youth or school* or pediatric* or paediatric*).ti.)

Embase via Ovid (1974+):

((exp auscultation/ or exp abnormal respiratory sound/ or (auscultat* or stethoscope* or ((lung* or breath* or respirat* or pulmo-nary) adj2 sound*)).ab,kw,ti.) AND (exp telecommunication/ or videoconferencing/ or wireless communication/ or exp telemetry/ or exp amplifier/ or smartphone/ or exp mobile application/ or (remote* or tele* or biotele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or smart-phone* or mobile-app* or vir-tual*).ab,kw,ti.) AND (exp *telecommunication/ or *videoconferencing/ or *wireless communication/ or exp *telemetry/ or *smartphone/ or exp *mobile application/ or exp *amplifier/ or exp *auscultation/ or (remote* or tele* or biotele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*).ti,kw. or ((auscultat* or stethoscope* or ((lung* or breath* or respirat* or pulmonary) adj2 sound*)) adj4 (remote* or tele* or biotele* or ehealth or e-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*)).ab,kw,ti,tw. or (teleauscultat* or digiscope*).ab,kw,ti.) AND (exp respiratory tract disease/ or exp respiratory tract disease assessment/ or (airway or asthma* or bronch* or cardiopulmonary or chest or COPD or diaphragm or lung* or mediastinal or pleur* or pneumo* or pulmonary or thora* or trach*).ab,kw,ti,tw.)) NOT ((exp animal/ or exp juvenile animal/ or adult animal/ or animal cell/ or animal tissue/ or nonhuman/ or animal experiment/ or animal model/) not exp human/ or (canine* or dog or dogs or feline* or hamster* or lamb or lambs or sheep or mice or mouse or murine or monkey* or pig* or porcine or primate* or rabbit* or rat or rats or rodent* or horse* or equine* or veterinar*).ti,kw,dq,jx. OR (exp juvenile/ not adult/)) Limit to English, 1990+

MEDLINE via Ovid (1946+ and Epub Ahead of Print, In-Process & Other Non-Indexed Citations and Ovid MEDLINE(R) Daily):

((exp Auscultation/ or Respiratory Sounds/ or (auscultat* or stethoscope* or ((lung* or breath* or respirat* or pulmonary) adj2 sound*)).ab,kf,ti.) AND (exp Telecommunications/ or Amplifiers, Electronic/ or Smartphone/ or Mobile Applications/ or (remote* or tele* or biotele* or ehealth or e-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or smart-phone* or mobile-app* or virtual*).ab,kw,ti.) AND (exp *Telecommunications/ or *Amplifiers, Electronic/ or *Smartphone/ or *Mobile Applications/ or (remote* or tele* or biotele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*).ti,kw. or ((auscultat* or stethoscope* or ((lung* or breath* or respirat* or pulmonary) adj2 sound*)) adj4 (remote* or tele* or biotele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*)).ab,kf,ti,tw. or (teleauscultat* or digiscope*).ab,kw,ti.) AND (exp Respiratory Tract Diseases/ or (airway or asthma* or bronch* or cardiopulmonary or chest or COPD or diaphragm or lung* or mediastinal or pleur* or pneumo* or pulmonary or thora* or trach*).ab,kw,ti,tw.)) NOT ((exp Animals/ or Models, Animal/ or Disease Models, Animal/) not Humans/ or (canine* or dog or dogs or feline* or hamster* or lamb or lambs or sheep or mice or mouse or murine or monkey* or pig* or porcine or primate* or rabbit* or rat or rats or rodent* or horse* or equine* or veterinar*).ti,kw,jw. OR (exp Infant/ or exp CHILD/) not exp ADULT/)) Limit to English, 1990+

Scopus via Elsevier (1970+):

(((TITLE-ABS-KEY (auscultat* OR stethoscope*) OR TITLE-ABS-KEY ((lung* OR breath* OR respirat* OR pulmonary) W/2 sound*))) AND (TITLE-ABS-KEY (remote* OR tele* OR biotele* OR ehealth OR e-health OR mhealth OR m-health OR computeri* OR digit* OR electr* OR wireless* OR visual* OR automat* OR smartphone* OR smart-phone* OR mobile-app* OR virtual*)) AND ((TITLE (remote* OR tele* OR biotele* OR ehealth OR e-health OR mhealth OR m-health OR computeri* OR digit* OR electr* OR wireless* OR visual* OR automat* OR smartphone* OR phone* OR mobile-app* OR virtual*) OR KEY (remote* OR tele* OR biotele* OR ehealth OR e-health OR mhealth OR m-health OR computeri* OR digit* OR electr* OR wireless* OR visual* OR automat* OR smartphone* OR phone* OR mobile-app* OR virtual*) OR TITLE-ABS-KEY (teleauscultat* OR digiscope*) OR TITLE-ABS-KEY ((auscultat* OR stethoscope* OR ((lung* OR breath* OR respirat* OR pulmonary) W/2 sound*)) W/4 (remote* OR tele* OR biotele* OR ehealth OR e-health OR computeri* OR digit* OR electr* OR wireless* OR visual* OR automat* OR smartphone* OR phone* OR mobile-app* OR virtual*)))) AND (TITLE-ABS-KEY (airway OR asthma* OR bronch* OR cardiopulmonary OR chest OR copd OR diaphragm OR lung* OR mediastinal OR pleur* OR pneumo* OR pulmonary OR thora* OR trach*))) AND NOT (TITLE (canine* OR dog OR dogs OR feline* OR hamster* OR lamb OR lambs OR sheep OR mice OR mouse OR murine OR monkey* OR pig* OR porcine OR primate* OR rabbit* OR rat OR rats OR rodent* OR horse* OR equine* OR veterinar* OR fetal OR fetus OR newborn* OR neonat* OR infant* OR toddler* OR child* OR adolesc* OR teen* OR youth OR school* OR pediatric* OR paediatric*) OR SUBJAREA (vete)) AND (LIMIT-TO (SRCTYPE,"j")) AND (LIMIT-TO (DOCTYPE,"ar") OR

LIMIT-TO (DOCTYPE,"cp") OR LIMIT-TO (DOCTYPE,"re") OR LIMIT-TO (DOCTYPE,"le") OR LIMIT-TO (DOCTYPE,"no") OR LIMIT-TO (DOCTYPE,"sh") OR LIMIT-TO (DOCTYPE,"ed") OR LIMIT-TO (DOCTYPE,"dp")) AND (LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2020) OR LIMIT-TO (PUBYEAR,2019) OR LIMIT-TO (PUBYEAR,2018) OR LIMIT-TO (PUBYEAR,2017) OR LIMIT-TO (PUBYEAR,2016) OR LIMIT-TO (PUBYEAR,2015) OR LIMIT-TO (PUBYEAR,2014) OR LIMIT-TO (PUBYEAR,2013) OR LIMIT-TO (PUBYEAR,2012) OR LIMIT-TO (PUBYEAR,2011) OR LIMIT-TO (PUBYEAR,2010) OR LIMIT-TO (PUBYEAR,2009) OR LIMIT-TO (PUBYEAR,2008) OR LIMIT-TO (PUBYEAR,2007) OR LIMIT-TO (PUBYEAR,2006) OR LIMIT-TO (PUBYEAR,2005) OR LIMIT-TO (PUBYEAR,2004) OR LIMIT-TO (PUBYEAR,2003) OR LIMIT-TO (PUBYEAR,2002) OR LIMIT-TO (PUBYEAR,2001) OR LIMIT-TO (PUBYEAR,2000) OR LIMIT-TO (PUBYEAR,1999) OR LIMIT-TO (PUBYEAR,1998) OR LIMIT-TO (PUBYEAR,1997) OR LIMIT-TO (PUBYEAR,1996) OR LIMIT-TO (PUBYEAR,1995) OR LIMIT-TO (PUBYEAR,1994) OR LIMIT-TO (PUBYEAR,1993) OR LIMIT-TO (PUBYEAR,1992) OR LIMIT-TO (PUBYEAR,1991) OR LIMIT-TO (PUBYEAR,1990)) AND (LIMIT-TO (LANGUAGE,"English")) AND (LIMIT-TO (EXACTKEYWORD,"Lung Auscultation") OR LIMIT-TO (EXACTKEYWORD,"Auscultation"))

Web of Science Core Collection via Clarivate Analytics (1975+):

((TS=(auscultat* or stethoscope* or ((lung* or breath* or respirat* or pulmonary) NEAR/2 sound*)) AND TS=(remote* or tele* or biotele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or smart-phone* or mobile-app* or virtual*) AND (TITLE=(remote* or tele* or biotele* or ehealth or e-health or mhealth or m-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*) OR TS=((auscultat* or stethoscope* or lung-sound* or breath-sound* or respiratory-sound* or respiration-sound* or pulmonary-sound*) NEAR/4 (remote* or tele* or biotele* or ehealth or e-health or computeri* or digit* or electr* or wireless* or visual* or automat* or smartphone* or phone* or mobile-app* or virtual*)) OR TS=breathing-sound*) OR TS=(teleauscultat* or digiscope*) AND (TS=(airway or asthma* or bronch* or cardiopulmonary or chest or COPD or diaphragm or lung* or mediastinal or pleur* or pneumo* or pulmonary or thora* or trach*)) NOT (TI=(canine* or dog or dogs or feline* or hamster* or lamb or lambs or sheep or mice or mouse or murine or monkey* or pig* or porcine or primate* or rabbit* or rat or rats or rodent* or horse* or equine* or veterinar* or fetal or fetus or newborn* or neonat* or infant* or toddler* or child* or adolesc* or teen* or youth or school* or pediatric* or paediatric*) OR SU=veterin) Limit to English, 1990+, exclude meeting abstracts, book chapters