

## **APPENDICES:**

# **Deep Learning for Respiratory Sound Analysis: A Systematic Review and Meta-Analysis (2019–2024)**

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**APPENDIX A**  
**DETAILED PER-STUDY SUMMARY (2019–2024)**

For transparency and reproducibility, the complete per-study summary table is provided in this appendix. The table reports the dataset used in each study, task definition, model family, main reported performance measure, and available uncertainty information. Due to its size, the table is presented in landscape format for readability.

## **APPENDIX B**

### **SUPPLEMENTAL PROTOCOL PACKAGE**

The following protocol materials are provided to enhance transparency and reproducibility:

- Full database search strings for all sources (PubMed, IEEE Xplore, ScienceDirect, and Scopus).
- Screening checklist and study eligibility decision form.
- Standardized data-extraction template (variables, operational definitions, and coding rules).
- Meta-analytic specification sheet (effect computation rules and handling of multiple outcomes).

Availability: The full review protocol package is provided in the Supplementary Material.

**Table VI.** Condensed summary of studies (2019–2024)

Study (Year)	Dataset	Task	Family	Effect (Acc/AUC/Score)	95% CI / SE
Yu et al., 2025 [1]	ICBHI17 (6898 cycles)	4c (N/Cr/Wh/Both)	bi-ResNet	Score 50.16% (1of 69.30%)	—
Johari et al., 2019 [2]	Clinical (43)	Bin (N vs Cr)	MFCC/LPCC+Stats	90–100%	—
Nabi et al., 2019 [3]	Clinical wheeze (55)	3c severity	ENS/KNN/SVM	PPR 100/92/94%	—
Chen et al., 2019 [4]	Noisy resp.	3c (Wh/Cr/N)	ResNet (OST)	98.79%	—
Neili et al., 2020[5]	Breath sound signals	Classification	ELM + KNN	—	±0.004
Srivastava et al., 2021 [6]	ICBHI17	Bin	CNN	99.20%	±0.5
Chen et al., 2024 [7]	Review dataset	Review	Review Deep learning	—	—
Aulia, 2021 [8]	Lung sound dataset	Classification	EMD + GLDM	—	±0.004
Fraivan et al., 2021 [9]	ICBHI	Bin	CNN	98.20%	—
Shuvo et al., 2020 [10]	RALE	Multi	CNN	83.78%	—
Hariri and Narin, 2021 [11]	Cough dataset (COVID-19)	Bin	Deep Learning	—	—
Mukherjee et al., 2021 [12]	Respiratory sounds	Screening classification	ML/DL	—	±0.83
Kim et al., 2021 [13]	Clinical dataset	Multi	CNN	85–86%	—
Satea et al., 2022 [14]	6k files	Multi	CNN	—	—
Jothi et al., 2022 [15]	Sleep apnea dataset	Detection	ML	—	—
Song & Han, 2023 [16]	Respiratory dataset	Sound Classification	Contrastive learning	—	—
Shi et al., 2023 [17]	Clinical dataset	Classification	DL	—	—
Ali et al., 2023 [18]	ICBHI17 (920/126)	Bin/4c	ANN/VGGish/OpenL3	72–81%	—
Krishnan et al., 2023 [19]	ICBHI17+Heart	11c (lung+heart)	CNN+BDF	99.97%	Reported
Dubey et al., 2023 [20]	RALE (372 ev)	3c (Wh/Cr/N)	SVM/LSTM(+BO)	95.70%	—
Lal, 2023 [21]	ICBHI17	Bin (H vs COPD)	TL (VGGish+BiGRU)	94% (F1=0.94)	—
Prabhakar & Won, 2023 [22]	ICBHI17	2c/3c/4c	Hybrid (HISET)	95.39/90.61/89.27%	—
Aptekarev et al., 2023 [23]	Resp. DB (1371)	Bin (S/H; Asthma)	DenseNet201 (TL)	87% / 87%	—
Choi & Lee, 2023 [24]	Clinical (1021 seg)	6c	VGGish+Attn	92.56% (F1 92.29%)	—
Ali et al., 2023 [25]	Hosp.+ICBHI17	4c (Asth/COPD/Bx/N)	LDA/kNN/DT/RF	99.72% (RF)	—
Dar et al., 2023 [26]	Resp. DB	Bin (N vs Abn)	DRN+Fr-WCSO	94.8%	—
Chudasama et al., 2023 [27]	ICBHI17+Coswara	8c (mix)	RF/SVM/kNN/XGB+CNN	90.9% (ICBHI)	—
Zhang et al., 2023 [28]	ICBHI17	6c	CNN/LSTM/BLSTM	98.82% (LSTM)	—
Jaffery et al., 2023 [29]	ICBHI17 (subset)	3c (N/Bx/Bt)	DWT+MFCC+kNN	99.3%	—
Yang et al., 2023 [30]	ICBHI17	4c (N/Cr/Wh/Both)	BLNet (Res+GoogLeNet+Attn)	Score 72.72%	—
Ren et al., 2023 [31]	ICBHI17	4c (N/Cr/Wh/Both)	Self-Expl. NN	UAR 43.7%	—
Kalaiyaranan and Sridhar, 2023 [32]	Tromsø (24k rec)	Bin (Wh?/Cr?)	InceptionV3	AUC 0.88	95% CI 0.84–0.92
Fava et al., 2024 [33]	CTD–ILD	Bin (ILD vs non-ILD)	DNN	97% (AUC 0.99)	±2% (5f)
Zhang et al., 2024 [34]	Lung-sound (6c)	6c	Dual-Ch. CNN–LSTM	99.01%	—
Trivedi and Degadwala, 2024 [35]	EIT-labeled + RSD	Regr (airflow)	CNN+BiLSTM (ens)	Corr 0.770; RMSE 0.170	±SD
Nadkarni et al., 2024 [36]	ICBHI17 (8c)	8c	Ensemble (CNN+XGB)	97.57% (AUC 0.994)	—
Aljaddouh et al., 2024 [37]	KAUH (5c)	5c (N/Ast/Pn/COPD/Fib)	ViT (+RMS/EBU)	91.04% (WA)	—
Hakki and Serbes, 2024 [38]	ICBHI17 (aug)	Wheeze det.	CNN–BiLSTM	82–84%	—
Geetha and Benadict Raja, 2024 [39]	ICBHI17 (Kaggle)	Bin; 5c	CNN + metaheuristic	93.3% (bin); 75.0% (5c)	—
Khan et al., 2024 [40]	ICBHI17 (+aug)	8c (also 4/3/2c)	Parallel CAE + LSTM	94.16% (8c)	—
Sang et al., 2024 [41]	Wearable accel. (52)	Wheeze det. (bin)	2D CNN (mel)	AUC 0.986 (≈95%)	—
Xu et al., 2024 [42]	TB cough (456)	Bin (TB vs H)	Bi-LSTM+Conv2D	96.33%	—
Wu et al., 2024 [43]	ICBHI17	4c (N/Cr/Wh/Both)	Impr. Bi-ResNet	77.81% (F1 71.05%)	—
Wu et al., 2024 [44]	CoCross ICU (171)	ICU/90d outcome	VAE–ResNet50 + LSTM	AUC 0.759 / 0.752	—
Wang & Sun, 2024 [45]	ICBHI17	4c (N/Cr/Wh/Both)	CNN (spec.)	88.7% (F1 91.2%)	—
Mang et al., 2024 [46]	ICBHI17	2c (Wh/Cr); 4c	ViT + Cochleogram	67.9% (4c); 85.9%, 75.5%	—
Patel et al., 2024 [47]	RespDB@TR (42/504)	COPD severity (5c)	LSTM/CNN/MLP	87% (LSTM)	—
Wanasinghe et al., 2024 [48]	ICBHI17+Mendeley	10c	Light CNN (MFCC+Mel+Chroma)	91.04% (5f 89.2%)	—

Study (Year)	Dataset	Task	Family	Effect (Acc/AUC/Score)	95% CI / SE
Saeed et al., 2024 [49]	Clinical cough (RT-PCR)	Bin (COVID vs N)	RBF-Net (CNN-LSTM)	0.879 (unbiased)	—
Isangula & Haule, 2024 [50]	Tanzania (protocol)	Diagnostic triage	AI audio CDSS	—	—
Kim et al., 2025 [51]	ICBHI17 (920/126)	MTL: 4c sounds + 6c disease	MobileNet (SIMO-MTL)	74% (LS); 91% (LD)	—
Álvarez Casado et al., 2024 [52]	ICBHI17	Bin PvsH; COPD vs others; 4/6c	EMD+Spectral+MLP	BA 89%; 94%; 71.7%	—
Bhushan et al., 2024 [53]	ICBHI17 (920/6898/126)	4c (N/Cr/Wh/Both)	CNN-LSTM + Self-Attn	58.62% (Score 57.02%)	—

**Table VII.** Distribution of studies included in qualitative synthesis by Dataset, Architecture, and Task (N=98)

Dataset	Architecture	Task	Count
ICBHI 2017	CNN	Binary	12
ICBHI 2017	CNN	Multiclass	10
ICBHI 2017	CNN	Sound-level	6
ICBHI 2017	CNN	Severity	3
ICBHI 2017	RNN/LSTM	Binary	5
ICBHI 2017	RNN/LSTM	Multiclass	4
ICBHI 2017	RNN/LSTM	Sound-level	3
ICBHI 2017	RNN/LSTM	Severity	1
ICBHI 2017	Transformer/Hybrid	Binary	6
ICBHI 2017	Transformer/Hybrid	Multiclass	6
ICBHI 2017	Transformer/Hybrid	Sound-level	3
ICBHI 2017	Transformer/Hybrid	Severity	2
ICBHI 2017	Classical (SVM/RF)	Binary	3
ICBHI 2017	Classical (SVM/RF)	Multiclass	3
ICBHI 2017	Classical (SVM/RF)	Sound-level	2
ICBHI 2017	Classical (SVM/RF)	Severity	0
Clinical/Private	CNN	Binary	4
Clinical/Private	CNN	Multiclass	2
Clinical/Private	CNN	Sound-level	1
Clinical/Private	CNN	Severity	1
Clinical/Private	RNN/LSTM	Binary	2
Clinical/Private	RNN/LSTM	Multiclass	1
Clinical/Private	RNN/LSTM	Sound-level	1
Clinical/Private	RNN/LSTM	Severity	0
Clinical/Private	Transformer/Hybrid	Binary	2
Clinical/Private	Transformer/Hybrid	Multiclass	2
Clinical/Private	Transformer/Hybrid	Sound-level	1
Clinical/Private	Transformer/Hybrid	Severity	1
Clinical/Private	Classical (SVM/RF)	Binary	1
Clinical/Private	Classical (SVM/RF)	Multiclass	1
Clinical/Private	Classical (SVM/RF)	Sound-level	0
Clinical/Private	Classical (SVM/RF)	Severity	0
BRACETS	CNN	Binary	0
BRACETS	CNN	Multiclass	1
BRACETS	CNN	Sound-level	1
BRACETS	CNN	Severity	0
BRACETS	Transformer/Hybrid	Binary	0
BRACETS	Transformer/Hybrid	Multiclass	1
BRACETS	Transformer/Hybrid	Sound-level	0
BRACETS	Transformer/Hybrid	Severity	0
BRACETS	Classical (SVM/RF)	Binary	1
BRACETS	Classical (SVM/RF)	Multiclass	0
BRACETS	Classical (SVM/RF)	Sound-level	0
BRACETS	Classical (SVM/RF)	Severity	0
RSD	CNN	Binary	0
RSD	CNN	Multiclass	0
RSD	CNN	Sound-level	1
RSD	CNN	Severity	0
RSD	Transformer/Hybrid	Binary	0
RSD	Transformer/Hybrid	Multiclass	1
RSD	Transformer/Hybrid	Sound-level	0
RSD	Transformer/Hybrid	Severity	0
RSD	Classical (SVM/RF)	Binary	1
RSD	Classical (SVM/RF)	Multiclass	0
RSD	Classical (SVM/RF)	Sound-level	0
RSD	Classical (SVM/RF)	Severity	0
HF_Lung_V1	CNN	Binary	1
HF_Lung_V1	CNN	Multiclass	0
HF_Lung_V1	CNN	Sound-level	0
HF_Lung_V1	CNN	Severity	0
HF_Lung_V1	Transformer/Hybrid	Binary	0
HF_Lung_V1	Transformer/Hybrid	Multiclass	1
HF_Lung_V1	Transformer/Hybrid	Sound-level	0
HF_Lung_V1	Transformer/Hybrid	Severity	0

Note: This table reflects studies included in the qualitative synthesis (N = 98). The subset used for quantitative synthesis (N = 42) was further filtered based on the availability of comparable evaluation metrics.

**Table VIII.** Presents the complete characteristics of the 42 studies included in the quantitative synthesis, including dataset, task, model family, reported metrics, and validation-related methodological indicators.

Ref No.	Year	Task group	Eligible for primary accuracy meta-analysis?	Dataset	Sample size /recordings / subjects	Task	Model family	Native accuracy value used	AUC reported?	F1 reported?	Split type / validation design	External validation	Key note/ pooling status
[54]	2022	sound classification	Provisional Yes	ICBHI 2017 + multi-channel lung sound dataset	ICBHI: 920 recordings, 126 subjects, 6898 cycles	Adventitious lung sound classification + respiratory disease classification	Transfer learning / ResNet / co-tuning / StochNorm	— (score-based result; no clean native accuracy)	No	No	Official ICBHI 60/40 non-overlapping patients; other validation on private multi-channel set	No clear external validation	Primary ICBHI result score-based; descriptive/subgroup use
[55]	2022	sound / disease classification	Yes	ICBHI, Coswara breathing/speech/cough, combined datasets	Multi-dataset evaluation; D1 = ICBHI, D5 = ICBHI + Coswara	Lung abnormality and COVID-19 diagnosis from audio	Deep ensemble with A-CRNN, A-BiLSTM, A-BiGRU, CNN + PSO	0.9551 for D1; 0.9444 for D5	No	No	Subject-independent train-test split explicitly reported for D5; multiple datasets used	No true external validation in strict independent-clinical sense	Choose one task/dataset only if pooled
[56]	2025	wheeze detection	Provisional Yes	Single-center pediatric dataset (Korea)	76 children; 103 wheeze + 184 non-wheeze sounds	Binary wheeze detection	Kernel SVM with multiple feature extractors	0.897	Yes	Yes	80/20 split with 5-fold CV and grid search on training	No	Useful for secondary subgroup; subject independence not fully resolved
[57]	2025	severity classification	Provisional Yes	Respiratory Database @TR + ICBHI	@TR: 42 patients, 504 recordings, 387 selected; ICBHI: 920 recordings, 877 selected	COPD severity classification	Classical ML + eigenspectral / SVD projection	0.756 (best SVC)	Yes	Yes	80/20 training/testing + 100 random stratified 5-fold stability analysis	No external validation	Severity subgroup, not sound-event primary pool
[34]	2024	sound / disease classification	Provisional Yes	ICBHI 2017	After removing classes: 917 samples; after augmentation/sampling: 5054 instances	6-class lung sound classification	Dual-channel CNN-LSTM	0.9901	No clear summary	Yes	Random split into train/validation/test after augmentation/sampling; 5-fold CV	No	High leakage risk due to augmentation + random split
[58]	2024	sound classification	Provisional Yes	ICBHI 2017	920 recordings, 126 patients, 6898 cycles; balanced to ~1200 samples shown in tables	4-class respiratory sound classification	Comparative ML: SVM, RF, KNN, NB, DNN	0.79 (Random Forest best)	No	No	Random splits 60/40, 80/20, 90/10 after preprocessing/balancing	No	Proceedings / unclear peer review; non-patient-wise splitting
[59]	2024	disease detection / multiclass condition identification	Provisional Yes	Respiratory sound database from Kaggle / 920 recordings from 126 patients	920 recordings, 126 patients; 70/30 train/test	Binary respiratory condition detection + multiclass condition identification	CNN optimized by metaheuristic s	0.933 binary; 0.750 multiclass	No clear summary	Yes	70/30 split on mel-spectrogram images; patient independence not clear	No	Task heterogeneity; use one binary accuracy if pooled
[33]	2024	disease detection	Provisional Yes	CTD-ILD + RA-ILD + Respiratory Database@TR	CTD-ILD: 84 patients/670 auscultations; RA-ILD: 137	Good/bad auscultation cleaning followed by ILD diagnosis	Signal cleaning + ML / DNN ensemble	0.97 on CTD-ILD cleaned by KNN	Yes	Yes	5-fold cross-validation; training/testing stated as distinct for	No clear external validation	Disease-detection subgroup, not sound-event primary pool

Ref No.	Year	Task group	Eligible for primary accuracy meta-analysis?	Dataset	Sample size /recordings / subjects	Task	Model family	Native accuracy value used	AUC reported?	F1 reported?	Split type / validation design	External validation	Key note/ pooling status
					patients/820 auscultations; @TR: 504 files						DNN		
[1]	2025	sound classification	Provisional Yes	ICBHI 2017	920 recordings, 126 subjects, 6898 cycles	4-class adventitious lung sound classification	Deep learning bi-ResNet with STFT + wavelet fusion	0.5279 official ICBHI; 0.6744 random 10-fold	No	No	Official ICBHI split plus separate random 10-fold evaluation	No	Use official split result only
[3]	2019	severity classification	Provisional Yes	Respiratory sound dataset (non-ICBHI)	Information insufficient from accessible source	Asthma severity classification	Feature-based ML (power features + classifier)	Accuracy reported but exact value not extractable	No	No	Information insufficient	No	Keep in subgroup / descriptive only
[4]	2019	sound classification	Provisional Yes	RALE database	Information insufficient from accessible source	Respiratory sound classification	SVM	Accuracy reported; exact extraction uncertain	No	No	Information insufficient	No	Needs source verification before pooling
[8]	2021	sound classification	Provisional Yes	ICBHI dataset	Information insufficient from accessible source	Lung sound classification	Boosted decision trees	Accuracy reported; exact extraction uncertain	No	No	Information insufficient	No	Needs split verification before pooling
[11]	2021	disease detection / severity classification	Provisional Yes	Clinically validated cough dataset (Spain + Mexico)	8380 cough samples (2339 positive, 6041 negative)	COVID-19 detection + severity classification	Deep learning (DeepCough)	– (AUC/F1-focused, no clean native accuracy)	Yes	Yes	10-fold cross-validation (stratified)	No clear external validation	AUC/F1 table, not accuracy primary pool
[13]	2021	sound classification	No	Clinical dataset (non-ICBHI)	1918 recordings / 871 subjects / 2840 raw sounds	Multi-class (normal/crackles/ wheezes/rhonchi)	CNN + transfer learning (VGG16)	0.865 binary; 0.857 multi-class	Yes	Yes	Random split + 5-fold CV (80/20)	No	Excluded from strict primary pool due possible leakage/non-patient-wise split
[18]	2023	wheeze detection / sound classification	No	ICBHI	126 patients / 920 recordings	Sound classification	CNN + ML embeddings (MusicANN/VGGish/OpenL3)	0.81 (max)	Unclear	No	5-fold CV (patient split unclear)	No	Excluded from strict primary pool
[19]	2023	disease detection	No	ICBHI + Yaseen	126 + 1000 records	Multi-class disease classification	CNN + Random Forest (BDF)	0.9994	No	Yes	Random 80/20 + 10-fold	No	Excluded from strict primary pool due augmentation leakage risk
[20]	2023	sound classification	Provisional Yes	RALE database	Approx. 372 sound instances (Normal 50, Wheeze 252, Crackle 70)	3-class adventitious sound classification	SVM / LSTM / LSTM + Bayesian Optimization	0.95699	No	Yes	5-fold setting mentioned; subject independence unclear	No	Keep in descriptive/subgroup analysis
[21]	2023	sound classification	Provisional Yes	Respiratory Sound Database from Kaggle / ICBHI-based	ICBHI described as 920 audio samples/126 subjects/6898 cycles; visible	Binary healthy vs COPD recognition	Transfer learning / VGGish + stacked BiGRU	No clean single final accuracy extractable with	No	Yes	15% validation split; patient-wise separation unclear	No	Relevant but not cleanly extractable for strict pooling

Ref No.	Year	Task group	Eligible for primary accuracy meta-analysis?	Dataset	Sample size /recordings / subjects	Task	Model family	Native accuracy value used	AUC reported?	F1 reported?	Split type / validation design	External validation	Key note/ pooling status
					experiment 36 healthy + 36 COPD files			confidence					
[22]	2023	sound classification	Provisional Yes	ICBHI dataset	920 recordings / 126 subjects / 6898 cycles mentioned in context	2-class, 3-class, and 4-class respiratory sound classification	Multiple hybrid pipelines	0.8927 (best 4-class)	No clear single summary	No clear single summary	Validation design not clearly captured	No	Methodologically heterogeneous; subgroup/descriptive use
[23]	2023	disease detection	No	Private asthma-focused respiratory sound database	1371 recordings total: 1238 patient + 133 healthy	Binary diagnosis: sick/healthy and asthmatic/non-asthmatic+healthy	DenseNet201 with transfer learning	0.87	No	No	50-record test groups + 5-fold CV on clips	No	Clip/block leakage concern; not strict primary pool
[24]	2023	disease detection	No	Single-center clinical respiratory sound dataset	126 respiratory sounds segmented into 1021 five-second samples	6-class lung disease classification	Improved VGGish + Light Attention	0.9256	No	Yes	5-fold CV on segmented samples; patient independence unclear	No	Strong descriptive study, not strict primary pool
[25]	2023	disease detection	No	Hospital-collected dataset + ICBHI dataset	Hospital dataset: 120 patients / 368 recordings; also evaluated on ICBHI	4-class pulmonary disease classification	Classical ML: LDA / k-NN / DT / RF	0.9972 (RF best)	Yes	Yes	10-fold CV + 20% holdout / 80–20 split	No clear true external validation	Very high accuracy; not strict primary pool
[26]	2023	disease detection	No	Respiratory sound database (not clearly specified)	Information insufficient from accessible text	Binary pulmonary abnormality detection	Fr-WCSO-based Deep Residual Network	0.948	No	No	Information insufficient	No	Dataset identity/validation not sufficient for strict pooling
[28]	2023	disease detection	No	Respiratory Sound Database / ICBHI respiratory audio files	920 recordings / 126 patients originally; after class filtering counts sum to 847	6-class pulmonary disease classification	CNN / LSTM / CNN-LSTM / CNN-BLSTM	0.9882 (best LSTM)	No	Yes	Random 80:20 split after over/under-sampling and class removal	No	Not strict primary pool
[30]	2023	sound classification	Provisional Yes	ICBHI 2017	920 recordings, 126 patients, 6898 cycles	4-class adventitious respiratory sound classification	BLNet with STFT + wavelet fusion + self-attention	0.7272 best random 8:2; official split score 0.5198	No	No	Official train-test split plus random 8:2 split	No	High risk if using random split result
[31]	2023	sound classification	No	ICBHI 2017	920 recordings, 126 subjects, 6898 cycles	4-class respiratory sound classification with interpretability focus	Self-explaining neural network	— (AS/UAR-based; no clean native accuracy)	No	No	Official ICBHI 60/40 split; training set further split 70/30	No	Keep in descriptive metric-specific analysis
[32]	2023	wheeze detection	No	Tromsø Study lung sound files + validation sets	Training: 24,198 files from 4,033 participants; validation A: 615; validation B: 120	Wheeze and crackle detection	Deep learning ensemble based on InceptionV3	—	Yes	Yes	5-fold development + two validation sets not used in training	Yes, independent validation sets used	Preprint + detection task; descriptive only

Ref No.	Year	Task group	Eligible for primary accuracy meta-analysis?	Dataset	Sample size /recordings / subjects	Task	Model family	Native accuracy value used	AUC reported?	F1 reported?	Split type / validation design	External validation	Key note/ pooling status
[36]	2024	disease detection / multiclass condition identification	Provisional Yes	ICBHI 2017 respiratory sound database	920 respiratory sounds	Respiratory disease classification from audio	Ensemble learning: MultiFeature CNN + XGBoost + soft voting	0.9757	Yes	No	Stratified 80/20 train-test split with augmentation; patient-wise independence unclear	No	arXiv / split clarity issue; sensitivity candidate
[37]	2024	disease detection / multiclass condition identification	Provisional Yes	Clinical lung sound dataset represented as spectrogram images	Original samples: 35/32/5/9/5 by class; augmented totals 370/407/75/188/84	5-class respiratory disease classification	Vision Transformer (ViT)	0.9104	No clear summary	No	Training design not sufficiently detailed; augmentation experiments reported	No clear external validation	Descriptive only unless full split details recovered
[38]	2024	wheeze detection	Provisional Yes	ICBHI-derived wheeze event data + synthetic data	ICBHI: 920 recordings/126 subjects; synthetic set: 1500 training + 200 testing audio files	Wheeze event detection / localization	CRNN family: CNN-LSTM/GRU/BiLSTM/BiGRU	0.84 (best accuracy)	No	Yes	70/30 split before synthetic generation; event-level labeling	No	Secondary wheeze subgroup; synthetic-data heavy
[40]	2024	disease detection / multiclass condition identification	Provisional Yes	ICBHI 2017	920 audio samples, 126 individuals, 6898 cycles	8-class disease, 4-class disease, and binary normal/abnormal classification	Hybrid deep learning with fused latent features + LSTM	0.9416 (8-class); 0.7961 (4-class); 0.8561 (binary)	No clear summary	Yes	Split design insufficiently captured from accessible text	No	Multiple tasks/settings; descriptive or subgroup only
[41]	2024	wheeze detection	No	Single-center wearable accelerometer patch dataset	52 patients with respiratory diseases	Wheeze detection from pulmonary-induced vibrations	Deep learning model vs deterministic time-frequency method	0.95	Yes	No clear summary	Test set evaluation on collected patient data; exact split not fully captured	No clear external validation	Biosignal patch task; not lung sound primary pool
[42]	2024	disease detection	No	Hospital-collected cough dataset	230 cough sounds from 70 TB patients and 226 from 74 healthy subjects	Pulmonary tuberculosis screening from cough sound	Feature fusion with Bi-LSTM / Bi-GRU and 2D convolution	0.9633	No	No	Split details not clearly captured	No	Cough subgroup only
[43]	2024	sound classification	Provisional Yes	ICBHI 2017	ICBHI 2017 used; full sample detail not restated in accessible text	Lung sound classification	Improved Bi-ResNet combining CNN and ResNet	0.7781	No	Yes	Data augmentation used; exact patient-wise split details unclear	No	Relevant but split details limited
[44]	2024	disease detection	No	CoCross ICU COVID-19 multimodal database	171 ICU patients; 3477 auscultations; plus CXRs and ICU variables	ICU mortality / 90-day mortality prediction	Multimodal deep learning fusion	0.761 ICU mortality; 0.743 90-day mortality	Yes	No clear summary	Longitudinal multimodal workflow	No clear external validation	Prognostic multimodal study; outside primary pool
[45]	2024	sound classification	Provisional Yes	ICBHI 2017	Augmented and balanced ICBHI dataset	Abnormal/normal lung sound classification parameter sensitivity study	CNN with spectrogram or MFCC under variable parameters	Accuracy emphasized but no clean single extracted value	No	No	Experimental comparison under variable parameters; split not fully captured	No	Methodological study, not clean comparable benchmark

Ref No.	Year	Task group	Eligible for primary accuracy meta-analysis?	Dataset	Sample size /recordings / subjects	Task	Model family	Native accuracy value used	AUC reported?	F1 reported?	Split type / validation design	External validation	Key note/ pooling status
[46]	2024	sound classification	Provisional Yes	ICBHI dataset	ICBHI dataset; exact sample detail not fully repeated in accessible text	Adventitious sound classification	Vision Transformer fed by cochleogram	Accuracy emphasized but no clean single extracted value	No clear summary	No clear summary	Split details insufficiently captured	No	Needs full text confirmation for strict pooling
[47]	2024	severity classification	No	RespiratoryDatabase@TR	504 wav files; 42 COPD patients; five severity classes	COPD severity classification	Multi-feature fusion with MLP, CNN, RNN, LSTM	0.87 best testing accuracy	No	No	Dataset balancing via SMOTE; exact subject-independent split not clearly captured	No	Severity subgroup only
[48]	2024	disease detection / multiclass condition identification	No	ICBHI 2017 + Fraiwan et al. Mendeley dataset	Combined ICBHI and multiclass Mendeley lung sound dataset	10-class lung disease classification	Lightweight CNN with stacked Mel/MFCC/C hromagram	0.9104	No clear summary	No clear summary	Combined-dataset classification; split not fully captured	No	Descriptive only
[60]	2024	cough detection	No	Accelerometer-based experimental dataset	23 participants; original 206 cough + 1011 non-cough; augmented to 2266 cough + 2022 non-cough	Cough vs non-cough detection	Deep learning best with SqueezeNet + wavelet scalograms	0.9221	No clear summary	No clear summary	1-second segmented samples with manual segmentation and augmentation	No	Accelerometer cough subgroup only
[49]	2024	disease detection	No	Clinically tagged proprietary cough dataset with RT-PCR COVID status	Initially 1094 positive and 3761 negative participants; after preprocessing 1022 positive and 2656 normal samples	COVID-19 diagnosis from cough audio under confounder-aware training	Bias-Free Network (RBF-Net)	0.841 gender-biased; 0.846 age-biased; 0.805 smoking-biased	No clear summary	No clear summary	Different intentionally biased training scenarios	No clear external validation	Cough COVID subgroup only
[53]	2024	sound classification	Provisional Yes	ICBHI'17 database	ICBHI'17 used; exact final sample count not restated in accessible snippet	4-class respiratory sound classification	Self-attention based hybrid CNN-LSTM	Accuracy not cleanly extractable from accessible snippet	No	No clear summary	Explicitly motivated as patient-independent; exact final split/accuracy needs full text	No	Needs full-text confirmation before strict pooling

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