

Review Article

Application of Deep Learning Algorithms in Lung Sound Classification: A Systematic Review Since 2015

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Abstract - The article systematically explored the application of deep learning for lung sound classification in three popular scientific databases – PubMed, ScienceDirect and IEEE Xplore, for articles published between 2015 and 2024. Using specific keywords combined with deep learning terms, we identified 1428 articles. Based on their titles, abstracts and content, 33 articles were deemed relevant and selected for review. The article's thorough analysis revealed that deep learning algorithms have outperformed traditional machine learning techniques in lung sound classification.

Keywords - Classification systems, Deep Learning, Lung sounds, Machine Learning, Systematic review.

1. Introduction

Auscultation is a method used by physicians to evaluate pulmonary conditions by listening to patients' breathing sounds through a stethoscope. During this process, the physician listens to the patient's chest and diagnoses based on the patient's medical history. Pulmonary diseases can generally be categorized into two main types based on sound characteristics: normal and adventitious sounds. However, distinguishing these sounds often requires precision that depends on the physician's training. An automatic breathing sound classification system could, therefore, be a valuable alternative.

Traditional machine learning algorithms for detecting anomalies in respiratory signals involve two steps: feature extraction and pattern classification. These methods have been used to differentiate between continuous adventitious sounds like wheezes and discontinuous sounds like crackles. Digital stethoscopes are commonly used for lung sound acquisition and save audio data for further analysis. Wheezes and crackles are clinically significant symptoms of pulmonary diseases. Wheezes, high-pitched continuous sounds, occur in the 200 Hz to 2 kHz frequency range and last longer than 250 ms. Crackles, shorter discontinuous sounds, are detected during inspiratory and expiratory cycles and last less than 100 ms. Normal lung sounds range from 37.5 Hz to 1 kHz.

Pulmonary diseases are the third leading cause of death globally, with acute lower respiratory tract infection, asthma, lung cancer, tuberculosis, and Chronic Obstructive Pulmonary Disease (COPD) being the most prevalent, according to the World Health Organization (WHO). Recent research has focused on developing automated systems for classifying abnormal lung sounds using feature extraction

techniques such as spectrograms, entropy, and Mel-Frequency Cepstral Coefficients (MFCC). Machine learning algorithms, including Hidden Markov Models (HMM), Gaussian Mixture Models (GMM), and logistic regression, have been employed for this purpose.

However, these methods face significant challenges. Most systems use binary classification to distinguish between crackles and wheezes, which is inadequate for multi-class classification. Additionally, the reliance on handcrafted features and the lack of freely available datasets hinder the evaluation and comparison of proposed algorithms. These limitations reduce the applicability of these methods in real-world scenarios.

Deep learning has emerged as a powerful solution, particularly when large datasets are available. Unlike traditional machine learning, deep learning does not require handcrafted feature extraction, as the model learns features directly from the data during training, as shown in Figure 1. This has made deep learning prominent in fields such as biomedical engineering.

Machine Learning (ML) and Deep Learning (DL) methods have been used for lung sound classification. However, to the best of our knowledge, few literature reviews have explored the application of machine learning algorithms in lung sound classification. Furthermore, the use of deep learning for lung sound classification has not been thoroughly studied, and a related research agenda has not been defined. Therefore, this systematic review aims to fill this gap by exploring the recent literature describing the use of DL to classify lung sounds. In this context, we identified several future research directions that could guide researchers when conducting future work. These include



exploring the most promising research goals, investigating the effectiveness of transfer learning, and utilizing large datasets in research. Using both 1D raw audio data and 2D time-frequency images in lung sound classification using deep learning algorithms presents significant opportunities for improving the early detection and diagnosis of respiratory diseases. By identifying the most effective

techniques and evaluating the results of various studies, this review could help streamline the field, enabling researchers to build upon previous work and develop more robust and effective models for lung sound classification. Ultimately, this could lead to improved patient outcomes and a reduced burden of respiratory diseases on global health.

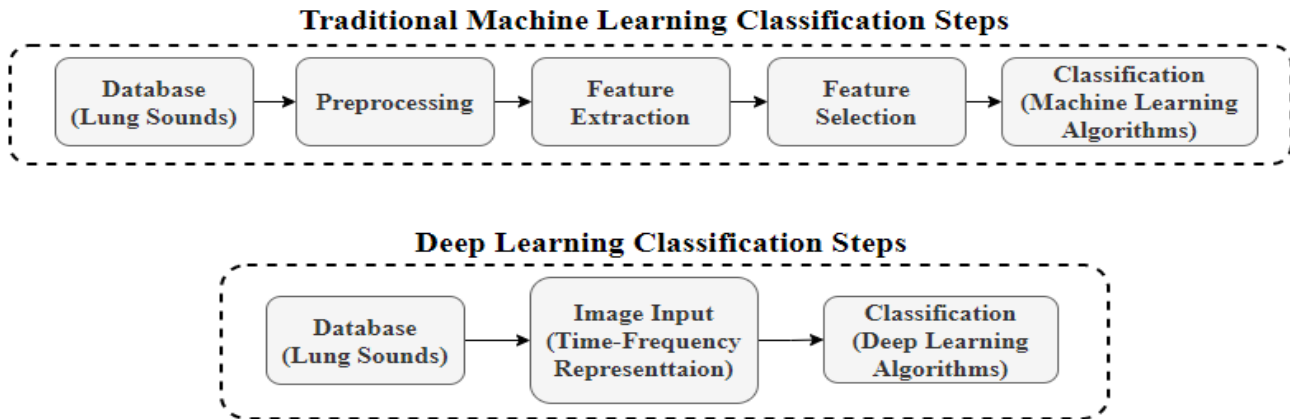


Fig. 1 Differences among traditional classification methods based on machine learning algorithms and deep learning algorithms

The main objectives of this review paper and its novelty which set it apart from other similar works in the literature are the following – 1) We evaluate various techniques for classifying lung sounds, not images of the lung (such as x-rays); 2) Lung sound classification is typically processed as either a one-dimensional audio signal or a two-dimensional image (time-frequency representation), 3) Our focus is specifically on lung sounds related to breathing, and we do not consider other sounds from the lungs, such as coughing, and 4) Our review specifically examines deep learning techniques for lung sound classification, rather than other machine learning approaches. The remainder of this manuscript is organized as follows – Section 2 provides a detailed description of the characteristics of lung sounds, the stethoscope used for recording them, and the available databases. Section 3 describes our search methodology, the process we used for selecting studies, and the data analysis presented in our review. Section 4 outlines the results of our study. We then discuss our findings and report on future work in Section 5. Finally, in Section 6, we present our conclusion.

2. Background on Lung Sounds

During the phases of respiration (inspiration and expiration), lung sounds are produced by airflow within the pulmonary system and can be heard over the chest wall. These sounds, characterized by their non-linear and non-stationary nature, pose challenges for clinicians in identifying abnormal and adventitious respiratory sounds, thereby complicating accurate diagnoses. Table 1 delineates the characteristics and types of lung sounds, correlating each type of respiratory pathology with specific breath sounds [39]. Lung sounds exhibit dominant frequencies ranging from 150 to 2000 Hz, while heart sounds predominantly fall below 150 Hz, enabling their differentiation. A variety of stethoscopes, including the Welch Allyn Meditron Master

Elite Electronic Stethoscope, the 3M Littmann 3200 Electronic Stethoscope, the AKG C417L Microphone, and the 3M Littmann Classic II SE Stethoscope, are commercially available and employed for recording lung sounds. These devices are adept at capturing lung sound recordings and filtering out heart sounds, facilitating the processing and analysis of computerized lung signals. The development of the Computerized Respiratory Sound Analysis (CORSA) [37] standard has established guidelines for sensor placement, enhancing the quality of recorded patient sound data. The advent of electronic stethoscopes has significantly improved the collection of high-fidelity lung sound data from both healthy and diseased individuals, leading to the creation of extensive databases. These datasets are crucial for developing automated classification systems utilizing deep learning algorithms to identify pulmonary diseases.

Currently, two prominent databases are widely utilized in research, especially for deep learning applications – the International Conference on Biomedical Health Informatics (ICBHI) database [34], which is freely accessible, and the Respiration Acoustics Laboratory Environment (R.A.L.E.) repository [38], available commercially. Despite the availability of the R.A.L.E. database, recent studies predominantly employ the ICBHI dataset due to its public accessibility. The ICBHI database is notably unbalanced and contains a high noise level, presenting a challenging dataset for validating deep learning models under difficult conditions. In 2021, Fraiwan et al. [35] contributed lung sound data recorded from the chest wall to a publicly accessible database, further enriching resources available for respiratory sound analysis research. This comprehensive review underscores the importance of high-quality lung sound recordings and the role of electronic stethoscopes and standardized databases in advancing pulmonary diagnostics through deep learning algorithms.

Table 1. Characteristics of lung sounds

Lung sound types	Sub-types of lung sound	Symptom	Dominant frequency range	Duration	Related Disease	Sensor location	Breath sound
Normal	Tracheal	/	/	/	/	/	High Pitch
	Vesicular	/	/	/	/	/	Low Pitch
	Bronchial	/	/	/	/	/	High Pitch
	Bronchovesicular	/	/	/	/	/	Low Pitch
Abnormal	Decreased normal lung sound	/	/	/	/	/	/
	Bronchial sounds	/	/	/	/	/	/
Adventitious	Continuous	Wheeze	400 Hz or more	> 250 ms	Asthma	Over the lungs/trachea and most of the chest wall	High Pitch
		Rhonchi	200 Hz or less	> 250 ms	COPD	Over the lungs/trachea and most of the chest wall	Low Pitch
	Discontinuous	Crackles	200 to 2000 Hz	Coarse Crackles < 100 ms Fine Crackles < 100 ms	Pneumonia Pulmonary fibrosis CHF IPF	Anterior and posterior chest wall for coarse crackles Posterior lung base for fine crackles	Low Pitch for coarse crackles High Pitch for fine crackles

3. Materials and Methods

We systematically conducted a comprehensive literature search of the PubMed, ScienceDirect, and IEEE Xplore databases to identify journal articles on lung sound classification using deep learning published between 2015 and 2023. Conferences, books, letters, and clinical reports were excluded from this review. We screened the results based on predefined inclusion and exclusion criteria.

An initial selection process involved checking research titles to identify studies relevant to lung sound classification using deep learning. This step helped remove unreliable and duplicate articles. Research articles with unclear methodologies were also excluded. As depicted in Figure 2, our search strategy identified 1428 articles. After individual eligibility screening, 1335 articles were excluded because

they were unrelated, duplicates, or lacked sufficient information.

Additionally, 66 articles were removed after reviewing their titles and abstracts, as they did not align with the scope of our review. These excluded articles either evaluated pulmonary pathologies without including lung sound classification, discussed respiratory sounds without performing lung sound analysis, did not evaluate pulmonary pathologies or lung sound classification, or were review articles. Further screening removed studies with unclear methodologies or those not focusing on the biomedical field and not using deep learning. The final stage identified 27 original research articles for this systematic review. An additional 6 articles, identified from other resources using similar eligibility criteria, provided supporting information on lung sound classification using deep learning.

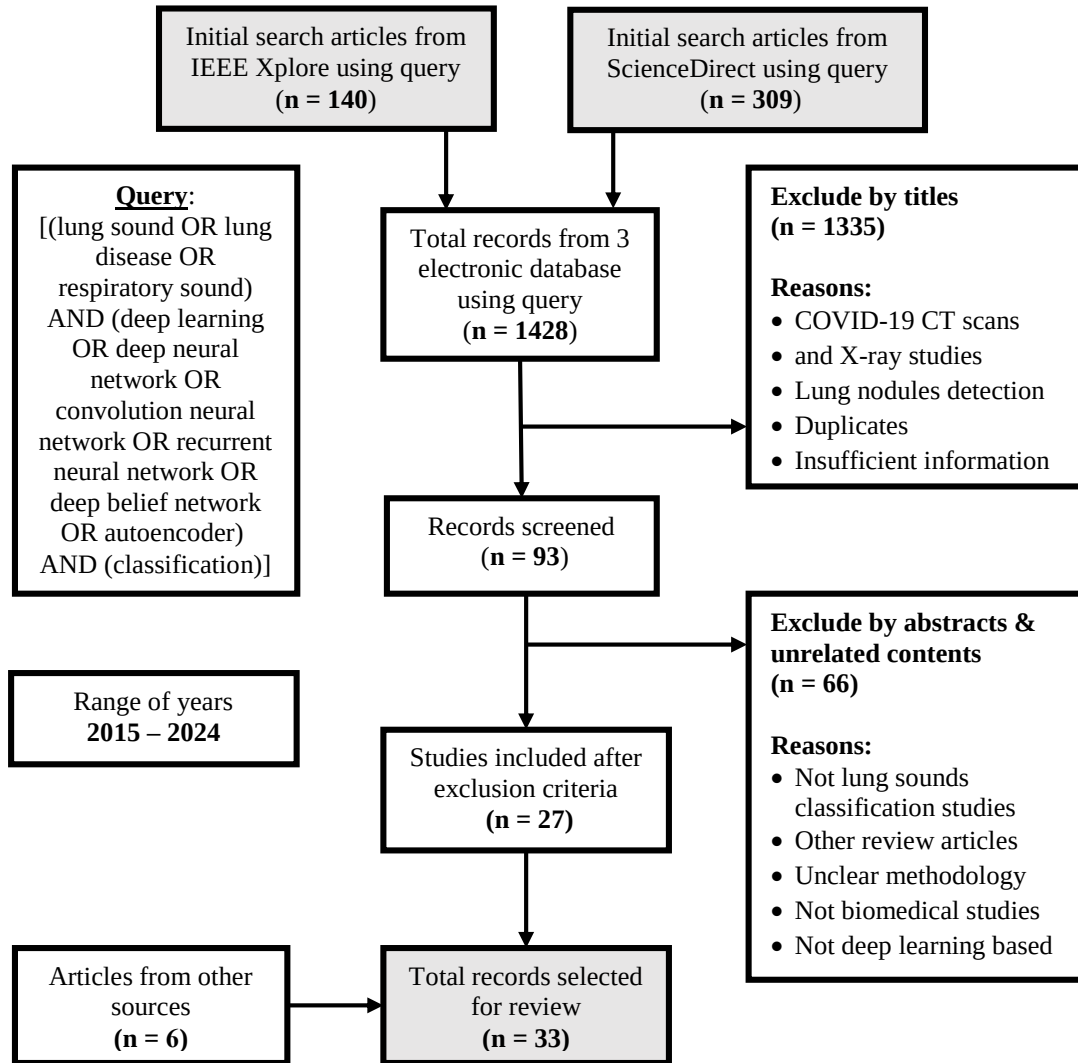


Fig. 2 Summary of the search process on lung sound classification from the literature

4. Results

The retrieved articles were sourced from three distinct databases, with the majority being published within the last three years. This trend highlights the increasing significance and interest in applying deep learning to lung sound classification. The reviewed papers, as summarized in Table 2, can be broadly categorized based on the type of input data used for deep learning networks: 1D input data (raw audio signals) and 2D input data (time-frequency images).

4.1. Raw Audio Signals (1D Input Data)

Fraiwani et al. in [1] explored the use of deep learning architectures, specifically Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory units (BDLSTM), to recognize pulmonary diseases from respiratory sounds. Their study utilized data from 213 patients, with 103 patients' data collected by the authors and 110 patients' data from the ICBHI database. To eliminate noise and artefacts, the dataset underwent preprocessing steps such as z-score normalization, displacement artefact removal, and wavelet smoothing. Evaluation metrics included accuracy, F1-score, Cohen's kappa, sensitivity,

specificity, and precision, with the CNN + BDLSTM model achieving an accuracy of 99.62% and a precision of 98.85%. Despite these high-performance metrics, the study noted that preprocessing, although common in traditional machine learning, might not be suitable for clinical applications where real-time, raw data analysis is required, such as telemedicine during the COVID-19 pandemic.

Khodabakhshi et al. [2] 2017 introduced a dynamic modelling method for lung sound characterization using an Adaptive Recurrent Neural Network (ARNN) based on fuzzy functions, evaluated with Recurrent Quantification Analysis (RQA). Their study classified healthy, COPD, and asthma conditions, achieving a 91% accuracy using the fuzzy functions ARNN with RQA features. However, the study was limited by a small sample size (27 COPD patients, 31 asthma patients, and 25 healthy individuals), highlighting the need for data augmentation and further validation before clinical application.

Altan et al. in [3, 4] quantified lung sounds in 3D space using deep learning models with data from the

RespiratoryDatabase@TR, which included 12 channels of lung sounds. Their approach requires validation with diverse datasets to confirm its clinical applicability.

These studies collectively emphasize that while preprocessing aids in classification accuracy, it contradicts the objective of deep learning to learn from raw, unprocessed data, which is essential for real-world clinical applications. Jayalakshmy et al. [5] examined using RNN-based stacked BiLSTM and Gammatone Cepstral Coefficients (GTCC) for lung sound classification. They used Empirical Mode Decomposition (EMD) to process respiratory signals from the ICBHI and R.A.L.E. databases. Their method, Stacked BiLSTM-IMF 3 with GTCC, achieved a specificity of 0.88 and a sensitivity of 0.78. The study used a 70/30 train/test split but lacked a validation set, which is crucial for model training and evaluation in deep learning.

A related study [6] evaluated three different deep learning models: CNN, LSTM, and a hybrid CNN-LSTM, applied to raw lung auscultation sounds without preprocessing. This study used data augmentation techniques to enhance model accuracy and utilized a large dataset from two online sources, classifying 11 categories of lung sounds, including ten diseases and healthy sounds. The findings demonstrated the potential for real-time classification of pulmonary diseases using deep learning on unprocessed data, a significant contribution to the field. However, further research is necessary to validate these methods across different datasets and real-time applications, which could ultimately provide valuable tools for clinicians in diagnosing and treating pulmonary diseases. In summary, these studies highlight the potential of deep learning models for pulmonary disease classification from respiratory sounds. Despite the high accuracy achieved through preprocessing, the ultimate goal is to develop models capable of handling raw data for real-time applications, especially in telemedicine and other clinical settings. Further research and validation across diverse datasets are essential to realize the full potential of these deep learning approaches in practical, clinical scenarios.

4.2. Time-Frequency Images (2D Input Data)

Aykanat et al. [7] designed an electronic stethoscope, introducing a Convolutional Neural Network (CNN) instead of traditional machine learning techniques such as Support Vector Machines (SVM). They validated their CNN model using data collected with their device. However, this validation is insufficient for such systems; different CNN deep learning-based models should be tested with various datasets to accurately assess their device's effectiveness. Additionally, there is no information on the hyperparameters tuning for CNN configurations or the optimization algorithm used. The article also lacks details on positive predictive value, negative predictive value, the Area Under the Receiver Operating Curve (AUROC), and the confusion matrix. However, the authors did not compare their results with existing works to highlight the system's advantages.

Bardou et al. [8] compared CNN with traditional methods like SVM, kNN, and GMM for lung sound classification using a 70/30 train/test data partition. However, they did not mention any data validation. The dataset should be split into three sets: training, validation, and testing, using the validation data to stop model training and testing data for evaluation. The study did not use other texture features like LPQ and BISIF or time-frequency representations. Jácome et al. [9] demonstrated Breathing Phase Detection (BPD) using CNN-based deep learning from respiratory sound recordings. Their approach should be validated with larger databases like the ICBHI challenge database. The method used in the detection process was not applied to other time-frequency representations to test its effectiveness. Chen et al. [10] introduced a modified time-frequency representation called Stockwell transform (S-transform) for lung sound classification using ResNets and Optimized S-Transform (OST). The accuracy reached 98.79%, with sensitivity and specificity at 96.27% and 100%, respectively. However, the wheeze + crackles class was not included, and the model's generalization during the learning process was not described.

Shi et al. [11] improved lung sound recognition using a VGGish-BiGRU system, discussing the effects of heart sounds, different time-frequency analyses, transfer learning, and retraining methods. However, the study did not report results from different epochs for assessing model learning. Demir et al. [12] used 6898 respiratory cycles from the ICBHI 2017 database for lung sound classification with a CNN and SVM. Their first method achieved 65.5% accuracy, while the second method achieved 63.09%. The use of transfer learning and SVM for deep learning is not novel, and the main contributions were not clarified. Acharya et al. [13] presented a hybrid CNN-RNN model for classifying breathing cycles using the ICBHI dataset. They did not report hyperparameters such as batch size, optimization algorithm, learning rate values, or the number of epochs. They plan to develop an embedded implementation for telemedicine, which might require a lightweight CNN model.

Rocha et al. [14] used the ICBHI dataset to introduce an automatic lung sound classification method. They employed Linear Discriminant Analysis (LDA), SVM, boosted trees, and CNNs for model learning. The best results were achieved with a dual input CNN, but further discussion was not provided. García-Ordás et al. [15] addressed data imbalance using variational autoencoders for data augmentation with the ICBHI dataset. The accuracy was not reported, and further evaluation without preprocessing techniques was suggested. Shuvo et al. [16] presented a lightweight CNN architecture for classifying respiratory diseases using a hybrid scalogram time-frequency representation. The study achieved high accuracy but noted that long computation times could be a bottleneck for real-time implementation. Demir et al. [17] introduced a parallel pooling CNN-based model for lung sound classification. They achieved 71.15% accuracy but should report the number of epochs and use different time-

frequency representations for further validation. Messner et al. [18] used a convolutional RNN for multi-channel lung sound classification. Data augmentation was necessary due to a small dataset, and a large number of data samples were needed for training and testing. Jayalakshmy et al. [19] used a pretrained CNN-based model AlexNet with EMD and scalogram representations for lung sound classification. They achieved 83.78% accuracy but should validate their system against the ICBHI database for a more reliable comparison.

Pham et al. [20] used various time-frequency representations for lung sound classification with a deep learning C-DNN model. They introduced a mixture of expert techniques to enhance performance but did not compare it with other well-established representations. Sharan et al. [21] used different time-frequency representations for CNNs to classify lung sounds in children with pertussis. They achieved 90.48% accuracy but should use data collected according to the CORSA standard and report confusion matrices. Jung et al. [22] investigated three features for a DS-CNN model-based lung sound classification, reporting accuracy for STFT and MFCC. However, they did not provide information on hyperparameters. Jayalakshmy et al. [23] used deep learning for respiratory signal classification with the ICBHI dataset, Thinklabs Lung Sounds Library, and R.A.L.E. respiratory data. They achieved high accuracy but should report 95% confidence intervals for performance metrics.

Kim et al. [24] developed an automatic breath sound classification system using CNN-based deep learning. They achieved 86.5% accuracy and an AUC of 0.93 but should clarify their research aim and visualize learned features on the Mel-spectrogram. In [25], the authors introduced a preprocessing technique using Variational Mode Decomposition (VMD) for denoising respiratory signals and generating gammatonegram images for classification using deep convolution neural networks. They achieved high performance but should compare VMD with other

techniques like Empirical Mode Decomposition (EMD) and test other Intrinsic Mode Functions (IMFs). In [26], the authors used cochleograms to enhance CNN models in respiratory adventitious sound classification. However, they did not compare cochleograms with other time-frequency representations to validate effectiveness. The authors in [27] made a comparison with several time-frequency representations as input data. They showed that different standard CNN architectures produce different experimental results for the various types of input data representation. The authors used the ICBHI database as the input data source in that work.

The study in [28] utilized CNN and SVM for multi-class respiratory sound classification. The authors should compare their approach with techniques like gammatonegram and scalogram for a more comprehensive evaluation. The authors in [29] introduced a hybrid CNN-RNN model for classifying lung sounds into normal, crackle, wheeze, and both categories. They should evaluate the CNN model's performance before combining it with RNN and conduct further experiments for validation. In [30], normal and abnormal respiratory sounds were collected by specialists and classified using a dense, lightweight CNN-bidirectional GRU model. Future work should explore eXplainable Artificial Intelligence (XAI) to understand correlations between diseases and symptoms. In [31], a hybrid neural model with focal loss function addressed data imbalance, using CNN and LSTM networks for lung sound classification. The authors should compare their standard time-frequency representation with others like scalograms and gammatonegram. The work in [32] classified abnormal respiratory sounds using CNN and artificial noise addition. The authors used five different networks with various settings and achieved a best performance of 100%. The research in [33] proposed a new preprocessing technique and CNN architecture for lung sound diagnosis. They should isolate and analyse the effects of each stage separately before combining them to establish a baseline performance.

Table 2. Summary of findings on lung sound classification from selected literature

REF	YEAR	DL TYPE	DATABASE	NO. OF CLASSES	1D / 2D DATA	RESULTS
[1]	2021	1D CNN + BDLSTM	Self-collected dataset + ICBHI dataset	6	1D raw data	Accuracy 99.62% Precision 98.85%
[2]	2017	Attractor RNN (ARNN)	Self-collected dataset	3	1D raw data	Accuracy 91%
[3]	2018	Deep Belief Networks (DBN)	Self-collected dataset	2	1D raw data	Accuracy 93.67% Sensitivity 91% Specificity 96.33%
[4]	2019	Deep Belief Networks (DBN)	Self-collected dataset	2	1D raw data	Accuracy 95.84% Sensitivity 93.34% Specificity 93.65%
[5]	2021	RNN-based stacked	ICBHI dataset	4	1D raw data	Sensitivity 0.78

		BiLSTM				Specificity 0.88
[6]	2022	CNN-LSTM	KAUH + ICBHI	8	1D raw data	99.6%, 99.8%, 82.4%, and 99.4% for datasets 1, 2, 3, and 4 (w/o data augmentation) 100%, 99.8%, 98.0%, and 99.5% for datasets 1, 2, 3, and 4 (with data augmentation)
[7]	2017	CNN	Self-collected dataset	78	Spectrogram (STFT)	healthy vs. pathological 86% rale, rhonchus, and normal 76% singular respiratory 80% all audio types 62%
[8]	2018	CNN	RALE database	7	Spectrogram (STFT)	Accuracy 95.56%
[9]	2019	CNN	Self-collected dataset	2	Spectrogram (STFT)	Sensitivity of 97% Specificity of 84%
[10]	2019	ResNet	ICBHI Database	3	OST-spectrogram	Accuracy 98.79% Sensitivity 96.27% Specificity 100%
[11]	2019	VGGish-BiGRU	Self-collected dataset	3	Mel-spectrogram	Asthma 83.33% Pneumonia 86.75% Normal 91.94%
[12]	2020	VGG16 + SVM	ICBHI Database	4	Spectrogram (STFT)	Accuracy of 65.5% for the first Method Accuracy of 63.09% for the second method
[13]	2020	CNN-RNN	ICBHI Database	4	Spectrogram (STFT)	66.31% of the 4 classes on overall data 71.81% of the 4 classes on patient-specific data
[14]	2021	CNN	ICBHI Database	3	Spectrogram Mel-spectrogram	3 class fixed durations tasks, best classifier accuracy 96.9% 3 class variable durations tasks, best classifier accuracy 81.8%
[15]	2020	CNN & Variational Autoencoders	ICBHI Database	3, 6	Mel-spectrogram	0.993 F-Score in 3 class 0.990 F-Score in 6 class
[16]	2020	CNN	ICBHI Database	6	Scalogram (STFT)	99.20% for ternary chronic classification 99.05% for six-class pathological classification
[17]	2020	CNN	ICBHI Database	4	Spectrogram (STFT)	Accuracy 71.15.%
[18]	2020	GRNNs & CNN	Self-collected dataset	2	Spectrogram (STFT)	F1-score 92%
[19]	2020	AlexNet	RALE database	4	Scalogram (STFT)	Accuracy 83.%
[20]	2021	CNN-MoE	ICBHI Database	8	4 Spectrogram types	Sensitivity 99%
[21]	2021	2D CNN	Dataset constructed from YouTube	5	Mel-spectrogram Wavelet scalogram Cochleogram	Accuracy 90.48%
[22]	2021	Depthwise Separable CNN (DS-CNN)	Self-collected dataset	4	Spectrogram (STFT)	Accuracy 85.74%
[23]	2021	cGAN	ICBHI dataset	4	Scalogram Spectrogram	Accuracy 92.68%
[24]	2021	VGG16 & CNN	Self-collected dataset	4	Mel-spectrogram	Accuracy 86.50%
[25]	2021	CNN	Self-collected dataset	3	Gammatonegram	Accuracy 98.8% Precision 97.7% Sensitivity 100% Specificity 97.6%
[26]	2023	CNN	ICBHI Database	4	Cochleogram	85.1% in wheezes

						73.8% of crackles
[27]	2022	CNN	ICBHI Database	4	Scalogram Spectrogram Mel-spectrogram Gammatonegram	Gammatonegram and scalogram produced the best classification results
[28]	2023	CNN + SVM	Self-collected dataset	3	Spectrogram (STFT)	Accuracy 83%
[29]	2021	CNN + RNN	ICBHI Database	4	Spectrogram (STFT)	Sensitivity 0.63 Specificity 0.83 Average score 0.73 Harmonic score 0.72
[30]	2022	CNN and BiGRU	Self-collected dataset	6	Mel-spectrogram	Accuracy of 92.3% Sensitivity of 92.1% Specificity of 98.5% F1-score of 91.9%
[31]	2022	CNN-LSTM	ICBHI Database	4	Spectrogram (STFT)	60/40 split - Sensitivity 47.37%, Specificity 82.46%, F1-Score 64.92%, Accuracy 73.69% 10 Fold CV - Sensitivity 52.78%, Specificity 84.26%, F1-Score 68.52%, Accuracy 76.39% LOO CV - Sensitivity 60.29%, Accuracy 74.57%
[32]	2021	ANA + CNN	Datasets from multiple internet sources	7	Spectrum analysis	VGG-B1 = 0.95%, VGG-B3 = 0.95%, VGG Drop = 0.95%, VGG-V1 = 0.84%, VGG-V2 = 0.84%, AlexNet = 100%, InceptionNet = 0.95%, ResNet = 0.95%, LeNet5 = 0.89%
[33]	2022	CNN	ICBHI Database	8	Mel-spectrogram	Recall of 0.991, F1 score of 0.993 and precision of 0.994

5. Discussion

We systematically analysed 33 articles that explore the application of deep learning to lung sound classification. The studies reviewed not only contribute to the field of lung sound analysis but are also significant across various health domains. Deep learning, a prominent technique in artificial intelligence, is particularly prevalent in the biomedical field. The majority of studies included in this work were conducted within the last two years, indicating that technology-based deep learning is a recent research hotspot. Current lung sound applications, including eHealth embedded system diagnosis, require improvements, especially for diagnosing lung conditions. Digital lung sound recordings, widely collected by electronic stethoscope systems and uploaded to cloud repositories, are expected to see increased efficiency in healthcare applications due to the rapid development of the Internet and 5G networks, which will enhance data variability and volume, particularly in pulmonary care.

The increasing availability of data is well-suited for deep learning algorithms. Currently, we find two publicly available databases [34, 35]. These data, coupled with tools like TensorFlow Lite, can be used to deploy deep learning applications on inference systems such as smartphones for real-time diagnosis and classification of pulmonary pathologies. To integrate deep learning technologies into healthcare, several initiatives in artificial intelligence aim to

enhance model functionality and transparency. For instance, the Shapley Additive Explanations (SHAP) framework demonstrates how input data features contribute to the final output, which has been validated by many healthcare applications.

Spirometry, a fundamental measure of pulmonary function, plays a crucial role in diagnosing conditions like asthma and COPD early. These conditions have similar symptoms, making differential diagnosis challenging. Traditionally, a spirometer, which uses a threshold for the forced air applied by the patient, helps determine the condition. Developing an automatic pulmonary disease classification system using deep learning on lung sound signals could offer an alternative strategy for earlier diagnosis and serve as a validated tool alongside spirometry. Current studies focus on diagnosing and classifying various pulmonary diseases, but no previous study has developed an automatic system to distinguish between asthma and COPD. For example, Trivedy et al. [36] developed an automatic disease classification system using a CNN for a smartphone-enabled spirometer, achieving an accuracy of 98.98%. Future research should focus on classifying lung sounds from asthma and COPD to aid doctors in early diagnosis, even those not well-trained.

Deep learning technologies have shown advantages over traditional machine learning algorithms. Designing a

real-time lung sound classification system must consider real-world hospital settings, where background noise, patient movement, and conversation are common. The literature review reveals that researchers typically perform preprocessing steps, facilitating deep learning-based classification and improving accuracy.

However, deploying these algorithms on Single-Board Computers (SBCs) for real-time use may reduce accuracy in actual diagnoses. To address this, exploring the direct use of raw audio recordings with deep learning algorithms without preprocessing could reveal the true power of deep learning and aid in developing SBC-based hardware systems for hospital use. Nearly all reviewed studies (99%) utilized the ICBHI challenge database, employing preprocessing steps like slicing, resampling, and feature extraction. No study has examined classifying ICBHI audio data without these steps, indicating a need for further evaluation to ensure the robustness and effectiveness of deep learning methods. Researchers should address challenges such as noise and artefact inclusion in input data and feature selection difficulties.

The review also highlighted that transfer learning often used models pretrained on ImageNet, which may not be suitable for time-frequency representations of lung sounds. Future research should explore transfer learning using lung sound spectrogram data to improve accuracy and reliability, enhancing deep learning performance in clinical diagnosis and treatment. There is a critical need to collect and share diverse lung sound datasets, such as those for asthma, COPD, and lung cancer, to support related research. This

would facilitate the development of accurate diagnostic tools such as and improve the reproducibility and comparability of research findings. Despite challenges like background noise and patient movement in real-world settings, deep learning models trained on large, diverse datasets can identify complex patterns in lung sounds. Future research should focus on developing robust deep learning models, possibly using generative models for data augmentation and techniques to handle missing or imbalanced data.

6. Conclusion

This manuscript systematically summarizes and reviews various deep-learning studies on lung sound classification. The relevant research has been evaluated based on the data, algorithms, and models utilized. The studies are assessed for using deep learning algorithms in lung sound classification, focusing on their capabilities to distinguish various time-frequency inputs. While applying deep learning in lung sound classification has shown promising performance, certain challenges and limitations remain unresolved.

The review's contributions are twofold – (1) it highlights the limitations of current studies and identifies future research opportunities, and (2) it provides a systematic and comprehensive review of deep learning studies on lung sound classification. Further research is needed to explore the potential of deep learning in enhancing the diagnosis and management of respiratory diseases in clinical settings. This review can serve as a valuable reference for future research in this field.

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