Artificial intelligence framework for multi-stage lung disease detection with audio signals

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ABSTRACT

Automated diagnostic systems are increasingly pivotal in advancing the accuracy and efficiency of medical diagnostics. Due to abnormal changes in human life and pollution, lung disease and cancer cases increasing in huge number. Identification and prediction of lung diseases may help to increase the human life span. This study introduces a robust framework for automatic lung disease detection using respiratory sound signals. The methodology brings together a series of activities like preprocessing, feature extraction, selection, and classification to improve diagnostic accuracy. The adaptive empirical stockwell-transform (AEST) is used to enhance the quality of the signal, whereby extracting and refining features, mainly Mel-frequency cepstral coefficients (MFCC), and Mel-spectrograms, are used. The scalable convolutional geyser network (SCGN) helps to mitigate challenges posed by imbalanced datasets, redundant features, and overfitting, ensuring reliable classification of the features. The model is validated when using the International Conference on Biomedical and Health Informatics (ICBHI) dataset, which validates the performance indicators of the model (F1-score 0.94, accuracy 0.95, precision 0.93, recall 0.94). This is shown superior performance compared to other existing models and demonstrates the framework's ability to diagnose a serviceable and reliable medical diagnosis; which indicates the strengths of combining advances in signal processing and scalable deep learning (DL) in healthcare applications.

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1. INTRODUCTION

This research is focused on the use of a respiratory audio dataset for a computer-assisted classification of chronic lung diseases, such as bronchitis, pneumonia, and asthma [1]. A common problem with any medical diagnosis using deep learning (DL) methods is the lack of annotated datasets and background noise in the audio recordings [2] which can result in poor DL model training and performance. DL has been used to analyze respiration sounds to diagnose lung disease via X-rays [3], [4]. Acoustical signal analysis and machine learning in these samples highlights the growing importance of applied machine learning to predict and monitor the management of respiratory diseases efficiently [5], [6]. To tackle these problems, this study proposes to leverage the VGGish network, which has been pre-trained using a large dataset of audio known as audio set, and combines it with a neural network known as a bidirectional gated recurrent unit (BiGRU) [7], [8]. When training the model, VGGish parameters will be frozen in order to preserve pretraining for knowledge, while the BiGRU layers will be finetuned with lung sound data. This study intends to create better detection of respiratory disease [9] of lung sounds. The design addresses several issues associated with imbalanced data in a medical application, and may improve classic detection of different lung conditions [10]. This study proposes a new automated classification method for pulmonary disease detection from signals extracted from lung sounds which uses empirical wavelet transform and state-of-the-art feature extraction [11]. This approach employed several classifiers, including the use of light gradient boosting machine (LGBM), which leads applicable high detection across disease classification, such as asthma, pneumonia, and chronic obstructive pulmonary disease (COPD) [12].

Technical contributions: i) developed a novel preprocessing method (adaptive empirical stockwell-transform (AEST)) to enhance respiratory sound signals. ii) utilized Mel-frequency cepstral coefficients (MFCC) and Mel-spectrograms for effective feature extraction and selection. iii) introduced scalable convolutional geyser network (SCGN) for accurate lung disease classification. iv) ensured robust, scalable performance with real-world applicability using International Conference on Biomedical and Health Informatics (ICBHI) dataset.

2. LITERATURE REVIEW

Various simulation tools and research works have previously existed in the literature that is based on the artificial intelligence (AI) framework for multi-stage lung disease detection with audio signals [13]–[15]. It incorporates lung cancer with computed tomography (CT) images enhancement, extraction of features, categorization using region of interest (ROI), and recurrent neural network (RNN)-long short-term memory (LSTM) DL model [16]. The proposed method achieves high accuracy, outperforming existing approaches in disease detection.

It is shown a multichannel DL method for using chest X-rays to identify lung conditions like pneumonia and tuberculosis [17]–[19]. The method fuses feature from EfficientNetB0, B1, and B2 models, processes them through fully connected layers, and classifies diseases using a stacked ensemble learning classifier. Wiley *et al.* [20] have proposed DL architecture that classifies lung conditions and normal X-rays pulmonary edema. Wang *et al.* [21] have proposed a new framework that divides continuous recordings into discrete events for lung sound lung texture classification event detection like inhalation, crackles, and rhonchi utilizing a temporal convolutional network (TCN) combined with a fusion strategy.

3. PROPOSED METHODOLOGY

Figure 1 represented the proposed methodology for automatic lung disease detection involves four key stages: preprocessing, feature extraction, feature selection, and classification. Respiratory sound signals are preprocessed using the AEST, followed by the extraction of MFCC and Mel-spectrograms. The selected features are then classified using a SCGN, which addresses challenges like imbalanced datasets and ensures accurate results. SCGN used for classification and geyser inspired optimization algorithm (GOA) used. The dataset used for experimentation is ICBHI.

3.1. Dataset exploration

The lung sound classification with multi features [22] includes lung sound recordings for pulmonary diseases, lasting 10 to 90 seconds and sampled at different frequencies. The ICBHI dataset is widely recognized as one of the datasets in the area of medical health information, especially used by people researching respiratory pulmonary sound analysis. It was originally created as part of the ICBHI 2017, to help advance the development of machine learning and classification for the diagnosis of breathing conditions. The dataset includes a variety of sound recordings collected from 128 patients with a range of different pulmonary conditions, such as COPD, asthma, bronchiectasis, and upper respiratory tract infections.

3.2. Signal preprocessing enhancement through AEST

Lung ultra sound spectroscopy [23] improves respiratory signal quality through adaptive windowing, which tweeks the window size but is still based on the local frequency content. This is a perfect methodology for non-stationary signals, since is permits variable frequency detection. The AEST is also superior to the short-time Fourier transform (STFT), as it provides a better time-frequency representation of representation.

It captures transient features and is resistant to noise. This adaptability is crucial for analyzing complex respiratory sounds. By using lung sound signals diseases may be classified and predicted. Variations in lung sounds may depend on the health conditions and age of the patients. The Gaussian window s[(i(t)] can be represented as signal consideration with respect to the initial time period i(t) is shown in (1).

$$s[(i(t)] = \int_{-\infty}^{\infty} I(\alpha + t)e^{-\frac{2\pi^2 x^2}{f^2}} e^{iwt} dt \tag{1}$$

Where ‘$I(\alpha + t)$’ is the time-shifted signal, ‘f’ is the frequency index, ‘α’ is the shifting of the signal with respect to the time period ‘t’, ‘x’ is a positive variable to identify the signal differences according to the time slots to identify the lung disease severity in patients, ‘w’ is the wavelength of the generated signal with respect to the initial time period ‘i(t)’ and the term ‘$e^{-\frac{2\pi^2 x^2}{f^2}}$’ represents the frequency-dependent Gaussian window.

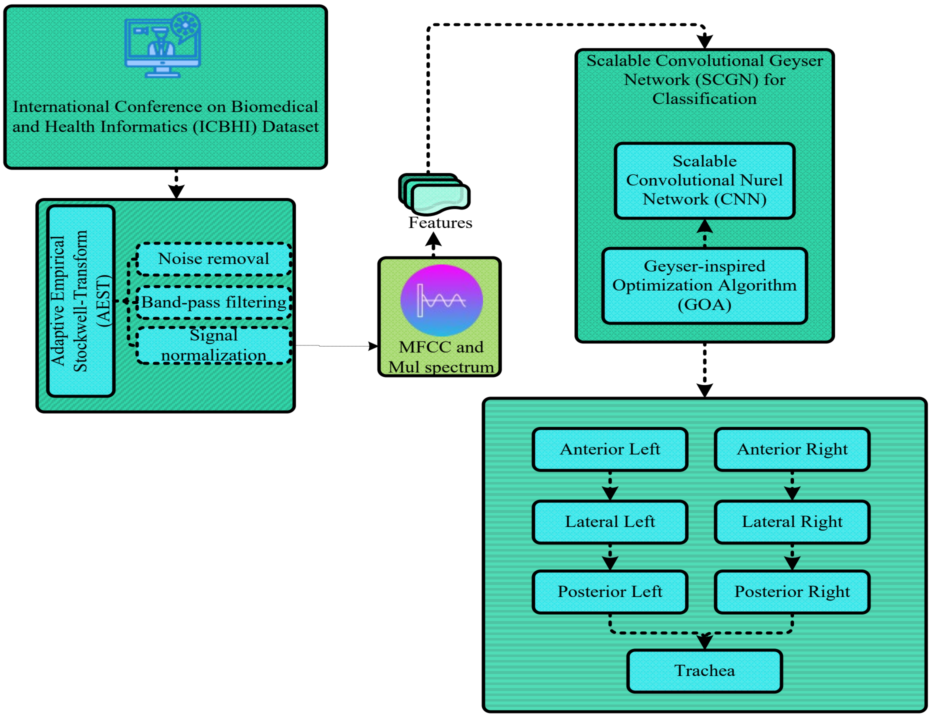


Figure 1. Overall proposed methodology schematic representation

3.3. MFCC and Mel-spectrum for audio signal feature extraction

The process begins with extracting audio from a video file. Once the audio is extracted, MFCC is computed using a library like librosa. Mel-spectrograms capture temporal changes in pitch and other audio properties, allowing the model to be resilient to noise [24]. The signal variations with respect to the time period are shown in (2).

$$T_{combine} = concentrate(T_{mfcc}, T_{mel}) \tag{2}$$

Where, ‘$T_{combine}$’ denotes the Combined signals, ‘concentrate’ represents to connect two pictures along their height, ‘T_{mfcc}’ denotes the MFCC features and ‘T_{mel}’ denotes the Mel spectrum. All features extracted from the cluster kernel Reed-Xiaoli (CKRX) model.

3.4. SCGN for optimized classification

The SCGN is an optimized DL [25] architecture designed for efficient and accurate classification of respiratory sound signals. SCGN has been designed as an ideal architecture for high-dimensional datasets where classification is a primary goal. SCGN enables efficient computational performance via its use of scalable convolutional layer(s), which allow for systematic hierarchical analysis of input data. Furthermore, SCGN employs a dynamic scaling method to determine the amount of depth and complexity to use for specific classification problem solving. SCGN leverages geyser-type activation functions as a means of mitigating both vanishing gradients and gradient propagation issues when constructing deep networks.

3.4.1. Scalable convolutional neural network

The enhancement of the audio signal that's targeted for future aspects, such as recognizing the prevalent features in a sample of audio, is a method of improving the audio signal through AEST preprocessing. Feature extraction uses Mel-spectrograms and MFCC to extract relevant features of the audio/sound sample to reach a point where you can classify the feature and classify the sample with SCGN which has been proven to be effective for classification of lung diseases. The architecture of the SCGN is defined by the activation function of the exponential linear unit (ELU). It is defined in (3).

$$ELU(x) = \begin{cases} x \; if \; x > 0 \\ e^x - 1 \; if \; x \leq 0 \end{cases} \tag{3}$$

Where 'x' is is a positive variable to identify the signal differences according to the time slots to identify the lung disease severity in patients.

The output is the same as the input for positive values of 'x'. The output is calculated by term '$e^x - 1$' for non-positive values of 'x', where the exponential function 'e^x' is used on the input. The classification of audio signals from lung disease through the use of an output layer identifies those audio signals as trachea (Tc), posterior left (Pl), and many other categories. The inclusion of this layer will help to reduce the problem of imbalanced datasets and training instability. The architecture presented in the implementation can effectively classify the complex medical audio signals of lung diseases accurately.

3.5. Geyser-inspired optimization algorithm

The GOA is a natural analogue for optimization that takes its inspiration from how geysers behave when they erupt and uses those principles to identify optimal solutions. The GOA uses the periodic behavior and riskiness of geyser eruptions to solve difficult problems by taking advantage of the way pressure builds up in a geyser before releasing that pressure. The way the GOA mimics the cyclical building-up-and-release of pressure in geysers also gives it the ability to continuously escape from local optima, using continuous processes to help it explore the entire global space. The GOA is designed to incorporate randomness, which allows it to avoid falling into local optima repeatedly and to explore the width of the global solution space. The cyclical character of the GOA process also ensures that there will be a balance between the time spent learning about the optimal solution and the time spent exploiting the optimal solution in the optimization process.

4. RESULTS AND DISCUSSION

The approach of detecting lung impairment utilizes AEST-extending audio, MFCC-based audio features, and a robust and scalable SCGN reinforced with ResNext. Testing was conducted using the ICBHI dataset, with phase-2 demonstrating reliable, scalable, accurate, and robust diagnostics. The SCGN was combined with the ResNext sliding double partial reinforcement network to address imbalanced datasets and unstable training, acting to create a framework that was both robust and reliable in classification output. System requirements included Python 3.12.7 and high computational capacity, and a stable model evaluation was established based upon system certification of 20 epochs, indicative of both the possible scalability alongside operational viability in appropriate medical diagnostic practice. Attention forward is now to the application of framework characteristics to either yield practical or efficient possibility within the medical diagnostic.

4.1. Feature extraction results of two audio files

Figure 2 might depict the features extracted from Figure 2(a) audio file 1 and Figure 2(b) audio file 2 (e.g., frequency, amplitude, or other spectral characteristics) from the two audio files. The x-axis for both graphs might depict time (or frequency), while the y-axis might depict magnitude (or other features). Figure 3 might depict the optimization process of fine-tuning a model's parameters to minimize errors or maximize performance. An optimization method could be a gradient descent method (there's many variants of gradient descent such as stochastic gradient descent, mini-batch gradient descent). This would iterate over the model, only updating the weights based on the gradient direction of the cost function. There are other optimizers that would utilize a notion of momentum which might smooth updates and help escape local minima during optimization "fine-tuning". There are also regularization parameters (e.g., weight decay) that can help prevent overfitting, and those would just cause the optimizer to also consider weight decay while optimizing the model. There will be graphs that depict the metrics during training that show metrics indicating the loss is decreasing, or the accuracy, for example, is increasing over each epoch of training.

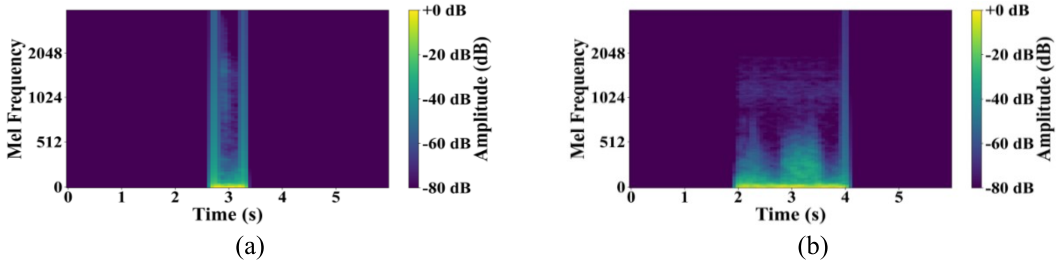


Figure 2. Extracted features in (a) audio file 1 and (b) audio file 2

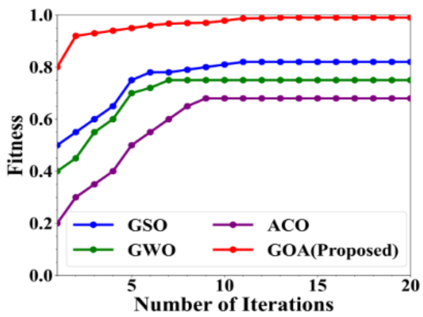


Figure 3. Comparison with existing optimization

Figure 4 gives a comparison of the SCGN model against the other models such as artificial neural network (ANN), deep learning convolutional neural network (DLCNN), and linear wave neurons (LWN). SCGN demonstrates very good performance according to the data shown: F1-score=0.94; accuracy=0.95; precision=0.93; and recall=0.94. The next best performer is the DLCNN model with an accuracy of 0.88 in all four metrics listed. The third best performer is the LWN model, which performed moderately at an accuracy of 0.82. The ANN model performed the worst, with an accuracy of 0.75, indicating that this model is not as effective as the other three. Figure 5 illustrates the results of training and validate comparison after 20 epochs. Figure 5(a) shows training accuracy=0.95; testing accuracy=0.97; this shows very good fit for both training and test data. Figure 5(b) shows training loss=0.91; testing loss=0.85 demonstrating very good generalization. Table 1 describes the frequency ranges and key characteristics of lung sounds recorded from different anatomical locations. Each site is associated with specific sound patterns, such as pitch, frequency, and an adventitious sound like wheezing or crackles.

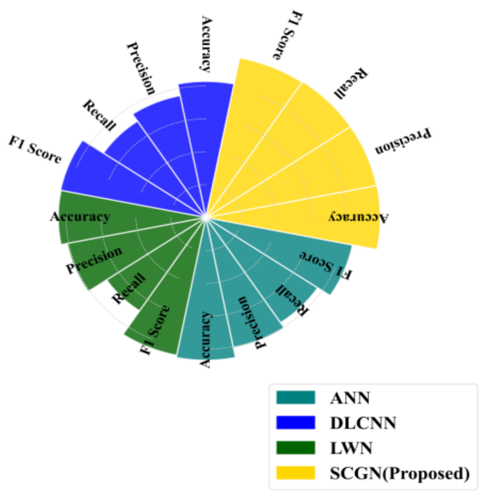
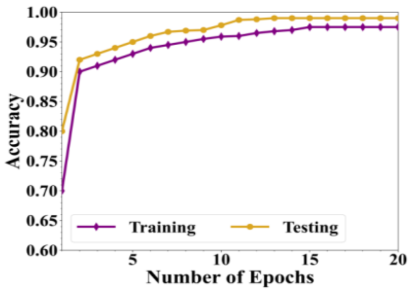
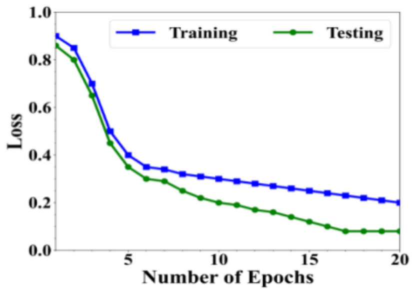


Figure 4. Existing network comparison



(a)



(b)

Figure 5. Training and validation through (a) accuracy curve and (b) loss curve

Table 1. Dataset classes identification with audio frequency

Classes	Frequency range (Hz)	Key characteristics
Anterior left (Al)	150-800	Lower amplitude, consistent inspiration/expiration cycle
Anterior right (Ar)	150-800	Balanced amplitude between inhale/exhale
Lateral left (Ll)	100-1,000	Higher frequency components, wheezing often detected
Lateral right (Lr)	100-1,000	Presence of crackles, variability in duration
Posterior left (Pl)	80-1,200	Lower pitch sounds, possible adventitious sounds
Posterior right (Pr)	80-1,200	Bronchial sound dominance, noise sensitivity
Trachea (Tc)	200-2,000	High-frequency components, turbulent airflow sounds

4.2. Evaluation metrics

Precision is an evaluation metric that measures the proportion of correctly identified positive instances out of all instances predicted as positive. Recall, also known as sensitivity or true positive rate, calculates the proportion of actual positive instances that were correctly identified by the model. The F-measure, or F1-score, is the harmonic mean of precision and recall, providing a single score that balances both metrics. Mean absolute error (MAE) measures the average magnitude of errors between predicted and actual values, without considering their direction. Root mean square error (RMSE) provides a measure of error that gives higher weight to large deviations due to its squaring of errors before averaging.

In Table 2, the evaluation matrixes highlight effectiveness of proposed lung disease detection model, with accuracy of 96.2% and area under the curve (AUC) of 0.98, indicates classification performance. With a low MAE of 0.08 and a low RMSE of 0.12, this model provides excellent accuracy. By achieving an F1-score that's greater than 96.1%, this AI model will prove to be highly successful in a practical context; thus, it has great application potential.

Table 2. Evaluation metrics

Number of folds	Metric	Lung disease detection model results
Fold 2	Accuracy (%)	96.2
Fold 4	Precision (%)	95.8
Fold 6	Recall (%)	96.5
Fold 8	F1-score (%)	96.1
Fold 10	MAE	0.08
Fold 12	RMSE	0.12
Fold 14	MAPE (%)	2.5
Fold 16	AUC	0.98

5. CONCLUSION

This research proposes a novel approach to AI-based multi-stage diagnosing methodology, detecting lung diseases with audio signals captured from respiratory sounds, using sophisticated signal processing capabilities, combined with advanced neural networks designed for easy scalability. The use of the AEST for the preprocessing phase of data input into the framework and the combination of MFCCs and Mel-spectrograms in the feature extraction phase has resulted in the enhancement of the ability to discriminate respiratory sounds. The SCGN, which was deployed with a geyser-like optimization strategy, has proven to be a very effective approach to many of the issues associated with the detection of lung disease, including noise, the non-stationary nature of the signal, the problems of dealing with an unbalanced dataset, and the instability of the training procedure. The experimental evaluation using the ICBHI dataset demonstrated high diagnostic performance, with accuracy, precision, recall, and F1-scores exceeding that achieved using traditional approaches such as ANN, LWN, and convolutional neural network (CNN). Additionally, the excellent training-validation behavior indicates considerable generalization ability for the proposed framework, indicating that it is ready to be deployed in a clinical setting. Overall, the results confirm that the combination of adaptive time-frequency analysis and scalable deep neural architectures represents an efficient pathway to an automated diagnosis of lung disease using audio analysis. Future work will involve integrating multimodal data to improve the accuracy of diagnosis and the number of patients covered, as well as the ability to implement the system in real time.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

DATA AVAILABILITY

The authors have confirmed that the data supporting the findings of this study are available within the article.

REFERENCES

[1] X. Zhang, B. Zhou, T. Osborn, B. Bartholmai, and S. Kalra, "Lung ultrasound surface wave elastography for assessing interstitial lung disease," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 5, pp. 1346–1352, May 2019, doi: 10.1109/ULTSYM.2016.7728512.

[2] B. Zhou, X. Yang, X. Zhang, W. J. Curran, and T. Liu, "Ultrasound elastography for lung disease assessment," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 67, no. 11, pp. 2249–2257, 2020, doi: 10.1109/TUFFC.2020.3026536.

[3] X. Zhang *et al.*, "Lung ultrasound surface wave elastography: a pilot clinical study," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 64, no. 9, pp. 1298–1304, Sep. 2017, doi: 10.1109/TUFFC.2017.2707981.

[4] X. Liu, L. Ma, L. Song, Y. Zhao, X. Zhao, and C. Zhou, "Recognizing common CT imaging signs of lung diseases through a new feature selection method based on fisher criterion and genetic optimization," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 2, pp. 635–647, Mar. 2015, doi: 10.1109/JBHI.2014.2327811.

[5] K. Taphorn *et al.*, "Direct differentiation of pathological changes in the human lung parenchyma with grating-based spectral X-ray dark-field radiography," *IEEE Transactions on Medical Imaging*, vol. 40, no. 6, pp. 1568–1578, Jun. 2021, doi: 10.1109/TMI.2021.3061253.
[6] G. Han *et al.*, "The LISS—a public database of common imaging signs of lung diseases for computer-aided detection and diagnosis research and medical education," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 2, pp. 648–656, Feb. 2015, doi: 10.1109/TBME.2014.2363131.
[7] N. R. Kolukula, P. N. Pothineni, V. M. K. Chinta, V. G. Boppana, R. P. Kalapala, and S. Duvvi, "Predictive analytics of heart disease presence with feature importance based on machine learning algorithms," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 32, no. 2, p. 1070, Nov. 2023, doi: 10.11591/ijeecs.v32.i2.pp1070-1077.
[8] R. K. Tripathy, S. Dash, A. Rath, G. Panda, and R. B. Pachori, "Automated detection of pulmonary diseases from lung sound signals using fixed-boundary-based empirical wavelet transform," *IEEE Sensors Letters*, vol. 6, no. 5, pp. 1–4, May 2022, doi: 10.1109/LSENS.2022.3167121.
[9] Q. Wei and Y. Hu, "A hybrid approach to segmentation of diseased lung lobes," *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 5, pp. 1696–1706, Sep. 2014, doi: 10.1109/JBHI.2014.2332955.
[10] A. Roy and U. Satija, "RDLINet: A novel lightweight inception network for respiratory disease classification using lung sounds," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–13, 2023, doi: 10.1109/TIM.2023.3292953.
[11] L. Pham, H. Phan, R. Palaniappan, A. Mertins, and I. McLoughlin, "CNN-MoE based framework for classification of respiratory anomalies and lung disease detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 8, pp. 2938–2947, Aug. 2021, doi: 10.1109/JBHI.2021.3064237.
[12] I. Sluimer, A. Schilham, M. Prokop, and B. van Ginneken, "Computer analysis of computed tomography scans of the lung: a survey," *IEEE Transactions on Medical Imaging*, vol. 25, no. 4, pp. 385–405, Apr. 2006, doi: 10.1109/TMI.2005.862753.
[13] G. D. O'Clock, Y. W. Lee, J. Lee, and W. J. Warwick, "A simulation tool to study high-frequency chest compression energy transfer mechanisms and waveforms for pulmonary disease applications," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 7, pp. 1539–1546, Jul. 2010, doi: 10.1109/TBME.2010.2041453.
[14] M. Ghita, C. Billiet, D. Copot, D. Verellen, and C. M. Ionescu, "Parameterisation of respiratory impedance in lung cancer patients from forced oscillation lung function test," *IEEE Transactions on Biomedical Engineering*, vol. 70, no. 5, pp. 1587–1598, May 2023, doi: 10.1109/TBME.2022.3222942.
[15] P. Yadav, N. Menon, V. Ravi, and S. Vishvanathan, "Lung-GANs: unsupervised representation learning for lung disease classification using chest CT and X-ray images," *IEEE Transactions on Engineering Management*, vol. 70, no. 8, pp. 2774–2786, 2023, doi: 10.1109/TEM.2021.3103334.
[16] S. Sun, C. Bauer, and R. Beichel, "Automated 3-D segmentation of lungs with lung cancer in CT data using a novel robust active shape model approach," *IEEE Transactions on Medical Imaging*, vol. 31, no. 2, pp. 449–460, Feb. 2012, doi: 10.1109/TMI.2011.2171357.
[17] T. Tan *et al.*, "Optimize transfer learning for lung diseases in bronchoscopy using a new concept: sequential fine-tuning," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 6, pp. 1–8, 2018, doi: 10.1109/JTEHM.2018.2865787.
[18] N. R. Kolukula, S. Puli, C. Babi, R. P. Kalapala, G. Ongole, and V. M. K. Chinta, "Processing of clinical notes for efficient diagnosis with feedback attention–based BiLSTM," *Medical & Biological Engineering & Computing*, vol. 62, no. 10, pp. 3193–3208, May 2024, doi: 10.1007/s11517-024-03126-8.
[19] S. Z. Y. Zaidi, M. U. Akram, A. Jameel, and N. S. Alghamdi, "Lung segmentation-based pulmonary disease classification using deep neural networks," *IEEE Access*, vol. 9, pp. 125202–125214, 2021, doi: 10.1109/ACCESS.2021.3110904.
[20] B. M. Wiley, B. Zhou, G. Pandompatam, J. Zhou, H. O. Kucuk, and X. Zhang, "Lung ultrasound surface wave elastography for assessing patients with pulmonary edema," *IEEE Transactions on Biomedical Engineering*, vol. 68, no. 11, pp. 3417–3423, Nov. 2021, doi: 10.1109/TBME.2021.3072891.
[21] Q. Wang, Y. Zheng, G. Yang, W. Jin, X. Chen, and Y. Yin, "Multiscale rotation-invariant convolutional neural networks for lung texture classification," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 1, pp. 184–195, Jan. 2018, doi: 10.1109/JBHI.2017.2685586.
[22] T. Wanasinghe, S. Bandara, S. Madusanka, D. Meedeniya, M. Bandara, and I. D. L. T. Díez, "Lung sound classification with multi-feature integration utilizing lightweight CNN model," *IEEE Access*, vol. 12, pp. 21262–21276, 2024, doi: 10.1109/ACCESS.2024.3361943.
[23] F. Mento, G. Soldati, R. Prediletto, M. Demi, and L. Demi, "Quantitative lung ultrasound spectroscopy applied to the diagnosis of pulmonary fibrosis: the first clinical study," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 67, no. 11, pp. 2265–2273, Nov. 2020, doi: 10.1109/TUFFC.2020.3012289.
[24] X. Zhang, D. Maddipatla, B. B. Narakathu, B. J. Bazuin, and M. Z. Atashbar, "Intelligent detection of adventitious sounds critical in diagnosing cardiovascular and cardiopulmonary diseases," *IEEE Access*, vol. 11, pp. 100029–100041, 2023, doi: 10.1109/ACCESS.2023.3313605.
[25] V. A. Binson, M. Subramoniam, Y. Sunny, and L. Mathew, "Prediction of pulmonary diseases with electronic nose using SVM and XGBoost," *IEEE Sensors Journal*, vol. 21, no. 18, pp. 20886–20895, Sep. 2021, doi: 10.1109/JSEN.2021.3100390.

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