Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI)
Vol. 8, No. 2, June 2022, pp. 318-325
ISSN: 2338-3070, DOI: 10.26555/jiteki.v8i2.24007

Lung Sounds Classification Based on Time Domain Features

Achmad Rizal, Istiqomah
School of Electrical Engineering, Telkom University, Bandung, Indonesia

ARTICLE INFO

Article history:

Received May 30, 2022
Revised July 10, 2022
Published July 28, 2022

Keywords:

Lung Sound;
Time-domain Feature;
Classifier

ABSTRACT

Signal complexity in lung sounds is assumed to be able to differentiate and classify characteristic lung sound between normal and abnormal in most cases. Previous research has employed a variety of modification approaches to obtain lung sound features. In contrast to earlier research, time-domain features were used to extract features in lung sound classification. Electromyogram (EMG) signal analysis frequently employs this time-domain characteristic. Time-domain features are MAV, SSI, Var, RMS, LOG, WL, AAC, DASDV, and AFB. The benefit of this method is that it allows for direct feature extraction without the requirement for transformation. Several classifiers were used to examine five different types of lung sound data. The highest accuracy was 93.9 percent, obtained Using the decision tree with 9 types of time-domain features. The proposed method could extract features from lung sounds as an alternative.

Corresponding Author:

Istiqomah, Telkom University, Jl. Telekomunikasi 1, Bandung 40257, Indonesia
Email: Istiqomah@telkomuniversity.ac.id

1. INTRODUCTION

Listening to lung sounds can determine the status of the lungs and respiratory tract. They have a distinct and distinctive pattern influenced by the respiratory process [1], [2]. A diagnostic instrument available to listen to abnormal lung sounds is the stethoscope. Advance technology nowadays makes it a possibility to convert lung sound into digital. Those data are analyzing that should be further explored [3]. During the inspiration and expiration phases, the airflow in the lungs creates the lung noises heard above the chest wall. Because these sounds are non-stationary and non-linear signals, physicians have difficulty detecting any abnormalities. Each lung sound is related to each lung disorder. The heart usually sounds have a dominant frequency of less than 150 Hz, whereas lung sounds have a dominating frequency of between 150 and 2000 Hz. Filtering the heart sounds from the lung sounds is easier because of the frequency difference [4].

Several scientists have worked to create a variety of algorithms for analyzing lung sounds automatically. Some research used CNN as a classifier [5]–[8]. Feature extraction has been included in the architecture layer of CNN. Therefore, architecture of CNN is essential to creating a good classifier. Another research classifies lung sound with machine learning [3], [9]–[15]. The result of the model classifier also depends on feature extra to obtain good accuracy. Therefore, the selection of feature extraction becomes essential to producing a good classifier. This study proposed the time-domain method as feature extraction [16]. The time-domain method produces lower computational costs and provides more information than the other domains [17]. In some applications, the time-domain method works well as feature extraction [18]–[25].

Several researchers developed a time-domain method for feature extraction in the classification of lung sounds. To categorize crackle and squeak lung sounds, Hadjileontiadis employed a gliding box and lacunarity [26]. Rizal et al. classified four categories of normal lung sounds using the LPC coefficient: tracheal, bronchial, bronchovesicular, and vesicular. The highest level of precision was 98.3 percent. The AR coefficient was used as a feature of three classes of lung sound in another article, and the accuracy was 66-88 percent [27]. Another method that directly measures the length of the signal in lung sounds is the measurement of crackle parameters, including initial deflection width (IDW) and largest deflection width (LDW). This method is used to identify crackles in lung sounds [28]. Electromyogram (EMG) analysis makes extensive use of time-domain characteristics. Direct measurements of EMG signal characteristics are frequently performed because EMG is examined directly from the change in signal shape rather than from frequency. This EMG signal's time-domain characteristic has never been utilized in lung sound signals.

The lung sounds were categorized using a time-domain characteristic for feature extraction in this study. The time-domain characteristics include Mean Absolute Value (MAV), Simple Square Integral (SSI), Variance (Var), Root Mean Square (RMS), Log Detector (LOG), Waveform Length (WL), Average Amplitude Change (AAC), Difference Absolute Standard Deviation Value (DASDV), and Amplitude of the First Burst (AFB) [16]. The findings of this study are expected to lead to suggestions for time-domain feature extraction algorithms that offer excellent accuracy in lung sound analysis and find which one time-domain feature impacts creating a good classifier.

2. MATERIAL AND METHODS

This section explains all proposed methods In this study. That elaborates general process from lung sound dataset until produce classification result. The system classifies data into five classification classes: Bronchial, Asthma, Crackle, Friction Rub, and Stridor. The next chapter presents the lung sound dataset, feature extraction, and classification used in this study.

2.1. Proposed Method

Fig. 1 is a picture of the method proposed in this study. There are 99 datasets of lung sound with 5 categories. Those data are preprocessed with amplitude normalization and the DC component elimination [10]. The next step, feature extraction, is done on data with the time domain feature. The following time-domain features were used in this study: Mean Absolute Value (MAV), Simple Square Integral (SSI), Variance (Var), Root Mean Square (RMS), Log Detector (LOG), Waveform Length (WL), Average Amplitude Change (AAC), Difference Absolute Standard Deviation Value (DASDV), and Amplitude of the First Burst (AFB) [16]. Several classifiers are used with N-Fold cross-validation for the validation method. For the training model of the classifier, Classification Learner is used in MATLAB.

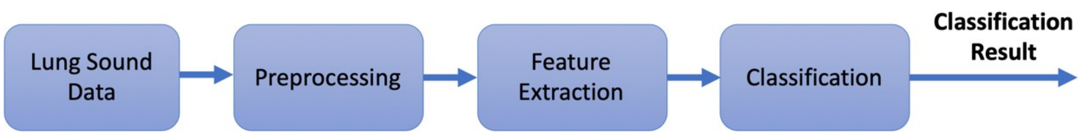


Fig. 1. Proposed Method

2.2. Lung Sound Datasets

Table 1 shows the lung sounds data used in this study, which includes 99 datasets divided into five categories: asthma, normal bronchial, crackle, friction rub, and stridor. Sounds are produced during inspiration and expiration in normal respiratory respiration, with the inspiration phase being louder [29]. The normal breathing sound frequency range is usually between 100 Hz and 1000 Hz. The frequency range for a wheezing sound is between 250 and 800 Hz [30][9]. The wheezing sound is created by airway restriction caused by bronchitis or chronic obstructive lung disease. Asthma is one example of a wheezing sound [31][32]. Crackles are non-musical, discontinuous respiratory sounds that occur more frequently during the inspiratory phase and are caused by the airway's opening and secretion [29][33]. Crackles are non-musical, discontinuous respiratory sounds that occur more frequently during the inspiratory phase and are caused by the airway's opening and secretion within the airway [3][11]. Friction rubs are non-musical, explosive, and usually biphasic sounds that are usually heard over the lung's basal parts and are related to pleural inflammation or malignancies [31]. Stridor is a type of loud wheezing that occurs when the upper respiratory airways (pharynx and larynx) and the upper part of the trachea become partially blocked owing to inflammation in the upper respiratory tract. It frequently happens during both inspiration and expiration. Due to the narrow supraglottic area, stridor is more common in newborns and babies, with a frequency range of up to 1000 Hz for the stridor components [29]. Detail number of each data is presented in Table 1.

2.3. Feature Extraction

Because time-domain features do not require any modifications and are calculated directly from raw time series, it is typically quick and easy to create [12]. Both medical and technical research and practice have extensively used time-domain properties. The signal's non-stationary attribute, which changes in statistical qualities with time, is a crucial drawback of features in this group. Time-domain features have become increasingly popular in medical and engineering research and practice. The signal's non-stationary quality, which changes statistical attributes with time, is a crucial drawback of features in this group. Furthermore, because their calculation relies on signal amplitude values, most of the interference acquired while recording becomes a disadvantage, especially for characteristics extracted from energy properties [12]. However, features in this group have been widely used due to their classification effectiveness in low-noise situations and lower computing complexity than features in the frequency and time-scale domains [12].

Table 1. Lung Sounds Data.

Data Classes	Amount of Data	Percentage
Bronchial	22	22.22%
Asthma	18	21.21%
Crackle	21	18.18%
Friction Rub	18	18.18%
Stridor	20	20.20%

The following time-domain features were used in this study: Mean Absolute Value (MAV), Simple Square Integral (SSI), Variance (Var), Root Mean Square (RMS), Log Detector (LOG), Waveform Length (WL), Average Amplitude Change (AAC), Difference Absolute Standard Deviation Value (DASDV), and Amplitude of the First Burst (AFB) [16]. The detail of each feature is resumed in Table 2.

Table 2. Features used in this paper

No	Name	Equation	Definition
1.	Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert X_i\rvert$	In a segment, the absolute value of the signal amplitude is averaged [16].
2.	Simple Square Integral (SSI)	$SSI = \sum_{i=1}^{N} x_i^2$	A sum of the signal amplitude's square values [16].
3.	Variance (VAR)	$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2$	The squared deviations from the mean's average [16].
4.	Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	Constant force and non-fatiguing contraction are related to an amplitude-modulated Gaussian random process [16].
5.	Waveform Length (WL)	$WL = \sum_{i=1}^{N-1}\lvert x_{i+1} - x_i\rvert$	A measure of the signal's complexity. It is defined as the total length of the signal's waveform over the time segment [16].
6.	Average Amplitude Change (AAC)	$ACC = \frac{1}{N}\sum_{i=1}^{N-1}\lvert x_{i+1} - x_i\rvert$	Almost identical to the WL feature, with the exception that the wavelength is averaged [16].
7.	Difference Absolute Standard Deviation Value (DASDV)	$DASDV = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\{x_{i+1} - x_i\}^2}$	The wavelength's standard deviation value [16].
8.	The amplitude of the First Burst (AFB)	$AFB = \sum_{i=0}^{N}\lvert x_i\rvert^2$	The initial maximum point is retrieved from the time function as a result [16].
9.	Log detector (LOG)	$LOG = e^{\frac{1}{N}\sum_{i=1}^{N} log(\lvert x_i\rvert)}$	The signal was changed based on the logarithm [16].

2.4. Classifier

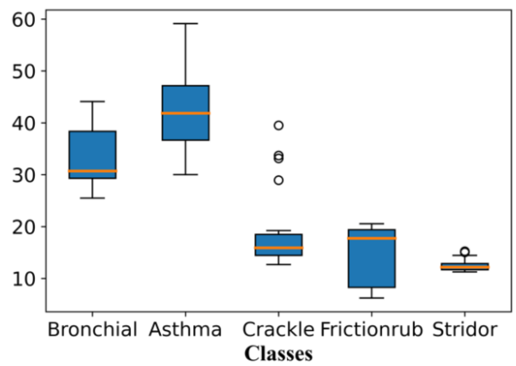
This research used several classifiers available in Classification Learner in MATLAB. The MATLAB Classification Learner toolbox can be used to train models that use supervised machine learning methods to categorize data [34]. A brief description of each classifier is presented in Table 3. This study used N-fold cross-validation (N-fold CV) with N = 3 to avoid overfitting. 3-fold CV means the lung sound data is split into three datasets, each used as test data and testing data in turn [35].

3. RESULTS AND DISCUSSION

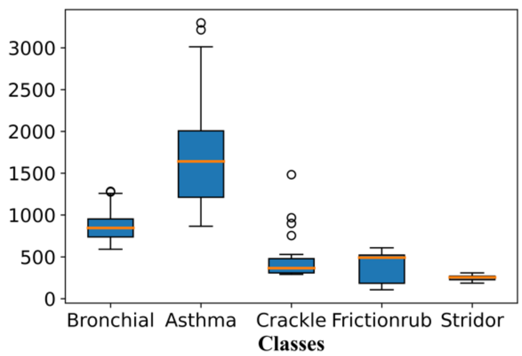
Fig. 2 and Fig. 3 show the boxplot of each feature for each lung sound class. Generally, the feature values from normal bronchial data and asthma have the highest and tend not to overlap with the other three classes. Meanwhile, crackle, friction rub, and stridor have relatively lower values and overlap each other. Feature values also range in the thousands (AFB, WL, SSI), in the tens (MAV, VAR, AAC), and in units (MS, DASDV). Meanwhile, the LOG value is very small, as shown in Fig. 3. The LOG value is very small because the signal is preprocessed, reducing the signal amplitude from -1 to 1. The values between overlapping features indicate that 100% accuracy will not be achieved, considering the features produced and not too different visually. The effect on accuracy will be seen in the accuracy test, especially for LOG, which has a very small value.

Table 3. Explanation of each classifier [36][37].

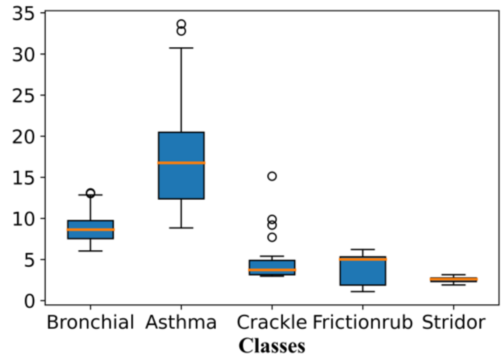
Classifier Types	Classification Description from Classification Learner Toolbox in MATLAB.
	Decision Trees
Fine tree	For a very flexible response function, there are many small leaves with hyperparameters are the minimum leaf size is 4, the maximum number of splitting is 100, and optimization is based on creating a split criterion based on Gini's diversity index.
Medium tree	For a less flexible response function, medium-sized leaves are provided with a hyperparameter are the minimum leaf size is 12, the maximum number of splitting is 20, and optimization is based on Gini's diversity index.
Coarse tree	For a coarse response function, a few large leaves with a hyperparameter with are minimum leaf size of 36, the maximum number of splits is four, and optimization based on Gini's diversity index is used.
	Nearest Neighbour Classifiers
Fine KNN	With the number of neighbours set to 1, it creates highly precise distinctions between classes.
Medium KNN	The number of neighbours set to 10 makes fewer distinctions than a Fine KNN.
Cosine KNN	The number of neighbours is set to 10, and the cosine distance measure is used.
Cubic KNN	The number of neighbours is set to 10, and the distance metric is cubic.
Weighted KNN	The number of neighbours is set to 10, and the distance weighting is used.
	Ensemble Classifiers
Bagged trees	It is a fine decision tree ensemble that's been bootstrapped. When dealing with huge datasets, it might be slow and memory intensive.
Subspace discriminant	Many predictors can be used, it is quick to fit and forecast, and it uses little memory, but the accuracy varies depending on the data. Using the Random Subspace technique, the model produces an ensemble of Discriminant classifiers.
Subspace KNN	Suitable for a wide range of predictions. Using the Random Subspace technique, the model produces an ensemble of nearest-neighbour classifiers.



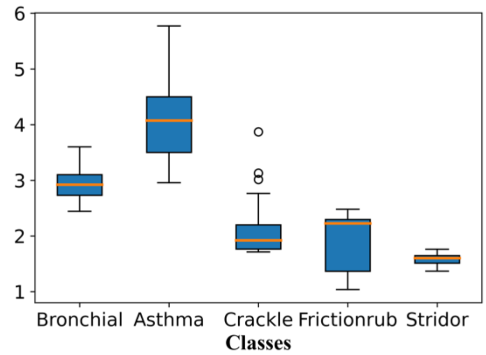
(a)



(b)



(c)



(d)

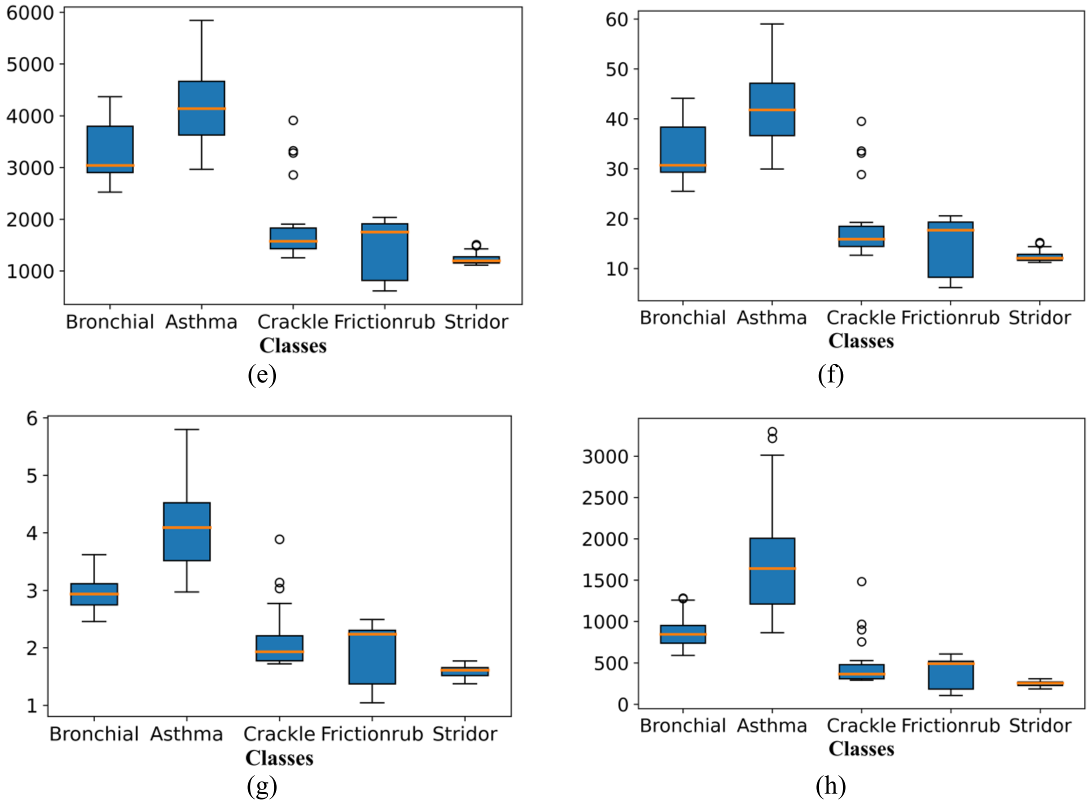


Fig. 2. (a) MAV (b) SSI (c) VAR (d) RMS (e)WL (f) AAC (g) DASDV (h) AFB

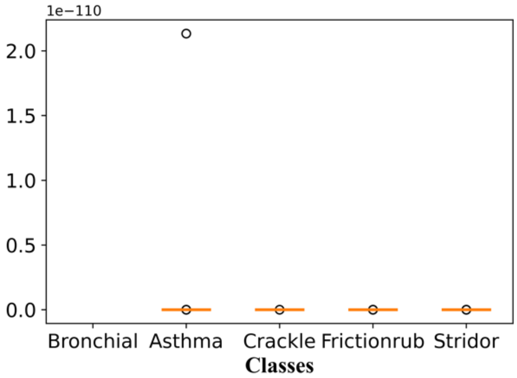


Fig. 3. Boxplot of LOG

Table 4 shows the accuracy obtained using several classifiers and nine feature extraction, and five classes. As seen in Table 4, the highest accuracy for each classifier is 93.9% for fine tree and medium tree. Eight features mean that LOG is not used as a feature, while nine features mean that LOG is used as a feature. These results indicate that even though the LOG value is relatively small, it significantly contributes to accuracy.

Table 5 shows a comparison of several similar studies. In previous research, gliding-box and Lacunarity were used to classify crackle and squawk; the accuracy is up to 100% [26]. Meanwhile, the highest accuracy of 98.33% was obtained using LPC in four normal lung sound classes [38]. The proposed method produces a promising accuracy considering that the accuracy is up to 93.9% for the five data classes. In general, the advantage of the proposed method is that feature calculations are carried out directly on the signal without the need for a transformation process. On the other hand, the proposed method is susceptible to noise, signal truncation, normalization, and processes that affect signal amplitude. The presence of noise will change several characteristics, such as WL, MAV, and others. Combination with other transformation methods is interesting to be explored in further research. This time-domain method can also analyze lung sounds for the covid-19 patient [40].

Table 4. Accuracy using Classification Learner in MATLAB.

Classifiers	Classifier Types	Accuracy using 8 features	Accuracy using 9 features
Decision Trees	Fine tree	76.8	93.9%
	Medium tree	76.8	93.9%
	Coarse tree	65.7	79.8%
K-Nearest Neighbour	Fine KNN	79.8	79.8%
	Medium KNN	67.7	64.6%
	Cosine KNN	63.6	66.7%
	Cubic KNN	66.7	66.7%
	Weighted KNN	78.8	78.8%
Ensemble Classifiers	Bagged trees	78.8	92.9%
	Subspace discriminant	58.6	62.6%
	Subspace KNN	77.8	77.8%

Table 5. Comparison with previous research using time-domain signal analysis

Ref	Data set	Method	Feature	*Classifier*	Accuracy (%)
[38]	4 normal class of lung sound	LPC	LPC coefficient	BP-NN	98.33
[26]	136 fine crackles, 94 coarse crackles, 133 squawk	Gliding box	Lacunarity	Discriminant analysis	99-100
[27]	18 COPD, 20 normal, 19 restrictive pulmonary diseases	AR modelling	AR coefficient of each segment	Multi-nominal, decision tree, parzen window	67-88
[28]	15 pulmonary fibrosis, 10 chronic bronchitis	*Crackle* parameter	initial deflection width (IDW), largest deflection width (LDW)	Fuzzy clustering	N.A Se=98.34 Sp=97.88%
[39]	56 normal, 56 patients	MFCC	HMM model of MFCC	Maximum likelihood	83
Proposed method	5 classes of lung sound	Time-domain feature	MAV, SSI, VAR, RMS, LOG, WL, AAC, DASDV, AFB	Decision tree	93.9%

4. CONCLUSION

This research described the classification of lung sounds based on the time domain. Five classes: asthma, bronchial, crackle, friction rub, and stridor data were used as the input data. Then, using Mean Absolute Value (MAV), Simple Square Integral (SSI), Variance (VAR), Root Mean Square (RMS), Log Detector (LOG), Waveform Length (WL), Average Amplitude Change (AAC), Difference Absolute Standard Deviation Value (DASDV), and Amplitude of the First Burst (AFB)., datasets extracted features based on time-domain classification. Then, the data is classified using the Classification Learner toolbox in MATLAB. The highest accuracy obtained is 93.9%, with the fine tree, medium tree, and bagged trees as classifiers. The proposed method is simple and is carried out directly on the signal without a transformation process. It is hoped that this method can improve its performance by combining it with other signal decomposition or transformation processes.

REFERENCES

[1] A. Rizal, R. Hidayat, and H. A. Nugroho, "Lung Sound Classification Using Hjorth Descriptor Measurement on Wavelet Sub-bands," *Jurnal of Information Processing Systems*, vol. 15, no. 5, pp. 2–14, 2019, https://doi.org/10.3745/JIPS.02.0116.

[2] Y. P. Kahya, E. C. Guler, and S. Sahin, "Respiratory disease diagnosis using lung sounds," *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, vol. 5, no. C, pp. 2051–2053, 1997, https://doi.org/10.48550/arXiv.1706.00005.

[3] M. Grønnesby, J. Carlos, A. Solis, E. Holsbø, H. Melbye, and L. A. Bongo, "Feature Extraction for Machine Learning Based Crackle Detection in Lung Sounds from a Health Survey," *arXiv preprint arXiv:1706.00005*, 2017, https://doi.org/10.1109/IEMBS.1997.758751

[4] R. Palaniappan, K. Sundaraj, and N. U. Ahamed, "Machine learning in lung sound analysis: A systematic review," *Biocybernetics and Biomedical Engineering*, vol. 33, no. 3, pp. 129–135, Jan. 2013, https://doi.org/10.1016/j.bbe.2013.07.001.

[5] D. Bardou, K. Zhang, and S. M. Ahmad, "Lung sounds classification using convolutional neural networks," *Artificial Intelligence in Medicine*, vol. 88, pp. 58–69, Jun. 2018, https://doi.org/10.1016/j.artmed.2018.04.008.

[6] M. Aykanat, Ö. Kılıç, B. Kurt, and S. Saryal, "Classification of lung sounds using convolutional neural networks," *Eurasip Journal on Image and Video Processing*, vol. 2017, no. 1, 2017, https://doi.org/10.1186/s13640-017-0213-2.

[7] S. B. Shuvo, S. N. Ali, S. I. Swapnil, T. Hasan, and M. I. H. Bhuiyan, "A Lightweight CNN Model for Detecting Respiratory Diseases from Lung Auscultation Sounds Using EMD-CWT-Based Hybrid Scalogram," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 7, pp. 2595–2603, Jul. 2021, https://doi.org/10.1109/JBHI.2020.3048006

[8] K. A. Babu and B. Ramkumar, "Automatic Recognition of Fundamental Heart Sound Segments from PCG Corrupted with Lung Sounds and Speech," *IEEE Access*, vol. 8, pp. 179983–179994, 2020, https://doi.org/10.1109/ACCESS.2020.3023044.

[9] Adnan Hassal Falah and Jondri, "Lung Sounds Classification Using Stacked Autoencoder and Support Vector Machine," in *2019 7th International Conference on Information and Communication Technology (ICoICT)*, 2019, pp. 1–5. https://doi.org/10.1109/ICoICT.2019.8835278.

[10] A. Rizal, R. Hidayat, and H. A. Nugroho, "Lung sound classification using hjorth descriptor measurement on wavelet sub-bands," *Journal of Information Processing Systems*, vol. 15, no. 5, pp. 1068–1081, 2019, https://doi.org/10.3745/JIPS.02.0116.

[11] M. Grønnesby, J. C. A. Solis, E. Holsbø, H. Melbye, and L. A. Bongo, "Machine Learning Based Crackle Detection in Lung Sounds," *arXiv*, pp. 1–13, 2017, https://doi.org/10.48550/arXiv.1706.00005.

[12] Shreyasi Datta, Anirban Dutta Choudhury, Parijat Deshpande, Sakyajit Bhattacharya, and Arpan Pal, "Automated Lung Sound Analysis for Detecting Pulmonary Abnormalities," in *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2017, https://doi.org/10.1109/EMBC.2017.8037879.

[13] A. Rizal, R. Hidayat, and H. A. Nugroho, "Pulmonary crackle feature extraction using tsallis entropy for automatic lung sound classification," *Proceedings of 2016 1st International Conference on Biomedical Engineering: Empowering Biomedical Technology for Better Future, IBIOMED 2016*, pp. 1–4, 2017, https://doi.org/10.1109/IBIOMED.2016.7869823.

[14] A. Rizal, R. Hidayat, and H. A. Nugroho, "Multilevel Wavelet Packet Entropy: A New Strategy for Lung Sound Feature Extraction Based on Wavelet Entropy," in *2017 International Conference on Robotics, Automation and Sciences (ICORAS)*, 2017, https://doi.org/10.1109/ICORAS.2017.8308048.

[15] R. Palaniappan, K. Sundaraj, and N. U. Ahamed, "Machine learning in lung sound analysis: A systematic review," *Biocybernetics and Biomedical Engineering*, vol. 33, no. 3, pp. 129–135, 2013, https://doi.org/10.1016/j.bbe.2013.07.001.

[16] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7420–7431, Jun. 2012, https://doi.org/10.1016/j.eswa.2012.01.102.

[17] C. Silveira, E. Brunton, R. Khushaba, and K. Nazarpour, "Evaluation of Time-Domain Features of Sensory ENG Signals," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018, https://doi.org/10.1109/EMBC.2018.8512798.

[18] R. Barioul, S. Fakhfakh, H. Derbel, and O. Kanoun, "Evaluation of EMG Signal Time Domain Features for Hand Gesture Distinction," in *2019 16th International Multi-Conference on Systems, Signals & Devices (SSD)*, 2019, https://doi.org/10.1109/SSD.2019.8893277.

[19] P. Mamta and S. V. A. V. Prasad, "EEG Feature Extraction Using Time Domain Analysis for Classifying Insomnia," in *Proceedings - 2020 IEEE India Council International Subsections Conference, INDISCON 2020*, Oct. 2020, https://doi.org/10.1109/INDISCON50162.2020.00053.

[20] Yogesh Paul, Vibha Goyal, and Ram Avtar Jaswal, "Comparative Analysis between SVM & KNN Classifier for EMG Signal Classification on Elementary Time Domain Features," in *4th IEEE International Conference on Signal Processing, Computing and Control (ISPCC 2k17)*, 2017, https://doi.org/10.1109/ISPCC.2017.8269670.

[21] M. Y. Chen and C. C. Huang, "Application of time-frequency analysis and back-propagation neural network in the lung sound signal recognition," in *Applied Mechanics and Materials*, 2012, https://doi.org/10.4028/www.scientific.net/AMM.190-191.927.

[22] S. A. Taplidou and L. J. Hadjileontiadis, "Wheeze detection based on time-frequency analysis of breath sounds," *Computers in Biology and Medicine*, vol. 37, no. 8, pp. 1073–1083, Aug. 2007, https://doi.org/10.1016/j.compbiomed.2006.09.007.

[23] G. Serbes, C. O. Sakar, Y. P. Kahya, and N. Aydin, "Pulmonary crackle detection using time-frequency and time-scale analysis," *Digital Signal Processing: A Review Journal*, vol. 23, no. 3, pp. 1012–1021, 2013, https://doi.org/10.1016/j.dsp.2012.12.009.

[24] Avik Bhattacharya, Anasua Sarkar, and Piyali Basak, "Time Domain Multi-Feature Extraction and Classification of Human Hand Movements Using Surface EMG," in *2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2017, https://doi.org/10.1109/ICACCS.2017.8014594.

[25] Mustafa Yazıcı and M. Ulutaş, "Classification of EEG Signals Using Time Domain Features," in *2015 23nd Signal Processing and Communications Applications Conference (SIU)*, 2015, https://doi.org/10.1109/SIU.2015.7130354.
[26] L. J. Hadjileontiadis, "A texture-based classification of crackles and squawks using lacunarity," *IEEE Trans Biomed Eng*, vol. 56, no. 3, pp. 718–32, Mar. 2009, https://doi.org/10.1109/TBME.2008.2011747.
[27] Y. P. Kahya, E. C. Guler, and B. Sankur, "Statistical Analysis of Lung Sound Data," in *Proceeding of The First Joint BME/EMBS Confrence,* 1999, https://doi.org/10.1109/IEMBS.1999.804168.
[28] F. Ayari, M. Ksouri, and A. Alouani, "A new scheme for automatic classification of pathologic lung sounds," *IJCSI International Journal of Computer Science (2012)*, https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.401.8794&rep=rep1&type=pdf.
[29] M. Y. Chen and C. C. Huang, "Application of time-frequency analysis and back-propagation neural network in the lung sound signal recognition," *Applied Mechanics and Materials*, 2012, https://doi.org/10.4028/www.scientific.net/AMM.190-191.927.
[30] A. Rizal, R. Hidayat, and H. A. Nugroho, "Signal Domain in Respiratory Sound Analysis : Methods, Application and Future Development," *Journal of Computer Science*, vol. 11, no. 10, pp. 1005–1016, 2015, https://doi.org/10.3844/jcssp.2015.1005.1016.
[31] A. Bohadana, G. Izbicki, and S. S. Kraman, "Fundamentals of lung auscultation.," *New England Journal of Medicine*, vol. 370, no. 8, pp. 744–51, Feb. 2014, https://doi.org/10.1056/NEJMra1302901.
[32] Y. Huang *et al.*, "The respiratory sound features of COVID-19 patients fill gaps between clinical data and screening methods," *MedRxiv*, 2020, https://doi.org/10.1101/2020.04.07.20051060.
[33] D. Bardou, K. Zhang, and S. M. Ahmad, "Lung sounds classification using convolutional neural networks," *Artificial Intelligence in Medicine*, vol. 88, pp. 58–69, 2018, https://doi.org/10.1016/j.artmed.2018.04.008.
[34] M. Z. Ali, M. N. S. K. Shabbir, X. Liang, Y. Zhang, and T. Hu, "Machine learning-based fault diagnosis for single- and multi-faults in induction motors using measured stator currents and vibration signals," in *IEEE Transactions on Industry Applications*, May 2019, https://doi.org/10.1109/TIA.2019.2895797.
[35] A. Géron, *Hands-on Machine Learning*, O'Reilly Media, Inc., 2017, https://books.google.co.id/books?id=HnetDwAAQBAJ.
[36] M. Z. Ali, M. N. S. K. Shabbir, X. Liang, Y. Zhang, and T. Hu, "Machine learning-based fault diagnosis for single- and multi-faults in induction motors using measured stator currents and vibration signals," *IEEE Transactions on Industry Applications*, vol. 55, no. 3, pp. 2378–2391, 2019, https://doi.org/10.1109/TIA.2019.2895797.
[37] T. Damrongsakmethee and V. E. Neagoe, "Principal component analysis and relieff cascaded with decision tree for credit scoring," *Advances in Intelligent Systems and Computing*, vol. 985, 2019, https://doi.org/10.1007/978-3-030-19810-7_9.
[38] A. Rizal, L. Anggraeni, and V. Suryani, "Pengenalan Suara Paru-Paru Normal Menggunakan LPC dan Jaringan Syaraf Tiruan Back-Propagation," in *Preceeding International Seminar on Electrical Power, Electronics Communication, Control, and Informatics (EECCIS 2006)*, 2006, https://achmadrizal.staff.telkomuniversity.ac.id/wp-content/uploads/sites/11/2014/06/fullpaper-klasifikasi-suara-paru-JST-BP.pdf.
[39] M. Yamashita, M. Himeshima, and S. Matsunaga, "Robust Classification between Normal and Abnormal Lung Sounds Using Adventitious-Sound and Heart-Sound Models," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2014, https://doi.org/10.1109/ICASSP.2014.6854437.
[40] Y. Huang *et al.*, "The respiratory sound features of COVID-19 patients fill gaps between clinical data and screening methods," *MedRxiv*, 2020, https://doi.org/10.1101/2020.04.07.20051060.

BIOGRAPHY OF AUTHORS

Achmad Rizal is a lecturer and researcher at the School of Electrical Engineering, Telkom University. Email: achmadrizal@telkomuniversity.ac.id

Istiqomah is a lecturer and researcher at the School of Electrical Engineering, Telkom University. Email: istiqomah@telkomuniversity.ac.id