ISSN: 1687-1006 p
ISSN: 2682-3640 e

The Egyptian International Journal of Engineering Sciences and Technology

Vol. 38 (2022) 54– 59

https://eijest.journals.ekb.eg/

EIJEST

The Egyptian International Journal of Engineering Sciences and Technology

Analysis of COVID-19 Heavy Cough Sounds Using Bark Wavelet Cepstral Coefficients

Mohamed. M.A.Gad*

Biomedical Engineering Dept.,MRI,Alexandria University, Alexandria, Egypt

A R T I C L E I N F O

Keywords:

COVID
MFCCs
MWCCs
BFCCs
BWCCs
DWT
DLNN
BILSTM

A B S T R A C T

Corona virus is known as COVID-19. It spreads all over the world as a pandemic. Until writing this paper, 164.5 million people worldwide are affected with this disease. Over 3.4 million people died due to that disease. Cough is one of the most common symptoms of that disease. The analysis of heavy cough sounds of COVID-19 is applied using machine learning algorithm. The dataset is from open source COSWARA dataset. The novelty of this paper is to use new feature extraction method which can distinguish between positive and healthy subjects of COVID-19 with high accuracy percent. Feature extraction from heavy cough sounds is applied by using new method which is called bark wavelet cepstral coefficients (BWCCs). This method is extracted from bark frequency cepstral coefficients (BFCCs) by replacing FFT step in the steps of calculating BFCCs with discrete wavelet transform step. The classification method is conducted using deep learning neural network (DLNN). The obtained accuracy percent using BWCCs is 98.25% which over performing BFCCs , mel frequency cepstral coefficients (MFCCs) or mel wavelet cepstral coefficients (MWCCs). So, BWCCs are the best way for feature extraction of heavy cough sounds of COVID-19.

1. Introduction

SARS-CoV-2 is a new virus which is the main cause of COVID-19. It first appears in Wuhan in china. WHO first knew of this new virus on 31 December 2019. Fever, dry cough, and fatigue are the most common symptoms of COVID-19. There are less common symptoms and may affect some patients include Loss of taste or smell, Nasal congestion, conjunctivitis (also known as red eyes), Sore throat, headache, muscle or joint pain, different types of skin rash, Nausea or vomiting, diarrhea, Chills or dizziness[1]. Many researches are conducted about analysis of cough sounds. R. J. Jaeger and his colleagues determine frequency of cough sounds [2]. K. A. Friend et al. found the characterization of cough sounds [3]. R. Jane et al. detect the snoring signals automatically in Obstructive Sleep Apnea Syndrome (OSAS)[4]. W. Thorpe et al. determine acoustic analysis of cough sounds[5]. K. Rosenberry et al. made analysis to the power of cough sounds [6]. A. Van Hirtum and his colleages determine the acoustic modeling of cough sounds [7]. Y. H. Hiewet al. determined digital signal processing of cough sounds [8]. S. Matos et al. detected cough sounds in continuous audio recording using hidden markov models in 2006 [9]. In 2007, S. Matos et al. monitored the frequency of cough sounds [10]. H. R. Tohidypour et al. compared between wavelet packet transform and bark wavelet & MFCC for recognition of speech signals[11].S. Huq and Z. Moussavi detected breath phases automatically using only tracheal sounds [12]. H. Chatrzarrin et al. differentiated between wet and dry cough sounds [13]. P. Moradshahi and his colleagues improved the performance of cough sound discriminator [14]. K. Kosasih et al. made analysis of cough sounds in pediatric patients [15]. V. Swarnkar et al. used automatic algorithm to classify wet and dry cough sounds [16]. Sarraf Shirazi and Z. Moussavi detected

*Corresponding author. Tel.: +2-01005090782
E-mail address: drmazmi@alexu.edu.eg

silence aspiration by breath[17]. T. Drugman et al. used sensors to detect cough automatically [18]. P. Moradshahi et al. distinguished between dry and cough sounds using microphone array [19]. U. R. Abeyratne et al. analyzed cough sounds for diagnosing pneumonia [20]. V. Swarnkar identified cough sounds automatically by neural network algorithm [21]. S. Le and W. Hu used Hilbert marginal spectrum to recognize cough sounds [22]. C. Lücioet et al. detected cough by internal sound analysis [23]. K. Kosasih et al. used wavelet transform for analyzing of cough sounds for diagnosing pneumonia [24]. J. Schröder et al. classified human cough sounds using features of spectro-temporal Gabor filterbank [25]. J. Amoh and K. Odame identified cough sounds by deep neural networks [26]. C. Infante et al. used cough sounds for diagnosing pulmonary disease [27]. Kiliç and Aykut Erdamar classified respiratory diseases automatically during sleep [28]. R. V. Sharan et al. diagnosis croup using cough sound recognition [29]. S. Khomsay et al. detected cough sounds using principal component analysis and deep learning [30]. C. R. Rodriguez and his colleagues analyzed spectrograms of coughing, sneezing and other respiratory sounds from infected people using deep learning technique [31]. A. Hassan et al. detected COVID-19 in infected people by analysis cough sounds, breathing sounds and voices of patients using recurrent neural networks [32]. M. B. Alsabek and his colleagues studied the sounds of COVID-19 using MFCC [33]. M.Z. Iqbal and M.F.I. Faiz analyzed cough sounds by mobile application [34]. J.A. Perez et al. detected cough sounds using empirical mode composition and deep learning [35]. K. Feng et al. identified COVID-19 by analysis cough sounds using MFCC and deep learning [36]. J. Vrindavanam and his colleagues classified cough sounds of COVID-19 by using machine learning [37]. P Mouawad et al. detected COVID-19 in cough sounds and recordings of vowel ‘ah’ of patients using recurrence dynamics and variable Markov model [38].They obtained accuracy percent of 97% and 99% of cough and ‘ah’ vowels respectively. In this paper BWCC is a new method applied on cough sounds and deep learning is used in the classification phase to distinguish between healthy and COVID heavy cough sounds.

2. Analysis Techniques

2.1 Wavelet Transform

Wavelet transform is suitable for signals of cough sounds because they are non stationary signals. Wavelet transform contain analysis in time domain and frequency domain so it is more applicable than Fourier transform which has frequency domain only. Wavelet transform is composed from groups of band-pass filters. Here, signals are divided into different bands. Lower and higher frequency components of the decomposed signal are calculated by low and high band pass filers. The obtained coefficients of details are deduced from the series of high pass filters. The obtained coefficients of approximation are deduced from the series of low pass filters. The used mother wavelet Daubechies (db4) because it looks like signals of cough sounds [39].

2.2 MFCCs

Feature of human speech is widely used by Mel-frequency Cepstral Coefficients (MFCCs) [40]. MFCCs can discriminate between redundant noise and energy of speech signal components and their frequencies. The Mel scale is logarithmic so is applicable for human perception of frequency. MFCCs are used for extracting features of cough sounds. Calculation of MFCCs contains pre-emphasizing, framing and windowing of the input signal. Then, Fast Fourier Transform (FFT) is computed. Then, these variables are transformed to Mel scale as shown in equation 1. After that, the obtained vectors are converted to log scale. Then, the redundant information is removed by discrete cosine transform (DCT). Finally, cepstral coefficients are obtained as shown in Fig.1.

$$Mel(f)=2595.log(1+f/700) \quad (1)$$

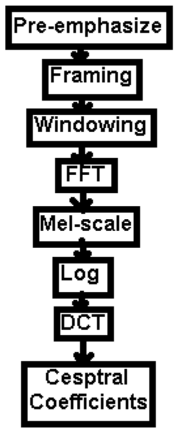

Fig1 MFCC

2.3 MWCCs

Mel-Wavelet Cepstral Coefficients MWCCs are new tool used to extract features of cough sounds. It contains pre-emphasizing, framing and windowing of the input signal. Then, discrete wavelet transform (DWT) is computed instead of using FFT. Then, these variables are transformed to Mel scale. After that, the obtained vectors are converted to log scale. Then, the redundant information is removed by discrete cosine transform (DCT). Finally, cepstral coefficients are obtained as shown in Fig.2

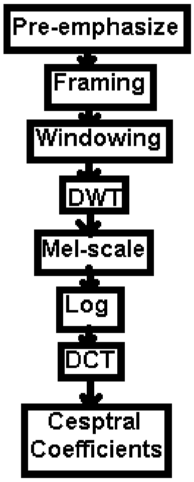

Fig.2 MWCC

2.4 BFCCs

Bark Frequency Cepstral Coefficients BFCCs are obtained by calculating pre-emphasizing, framing and windowing of the input signal. Then, FFT is computed. Then, these variables are transformed to bark scale as shown in equation 2. After that, the obtained vectors are converted to log scale. Then, the redundant information is removed by DCT. Finally, cepstral coefficients are obtained [41]. The steps of calculating BFCCs are shown in Fig.3.

$$Bark(f)=\{13.atan(0.76f/100)+3.5\} \quad (2)$$

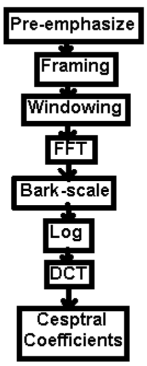

Fig.3 BFCC

2.5 BWCCs

Bark Wavelet Cepstral Coefficients BWCCs are new tools were made to extract features from heavy cough sounds. They are obtained by calculating pre-emphasizing, framing and windowing of the input signal. Then, DWT Transform is computed instead of FFT step in BFCC. Then, these variables are transformed to bark scale. After that, the obtained vectors are converted to log scale. Then, the redundant information is removed by DCT. Finally, cepstral coefficients are obtained. The steps of calculating BWCCs are shown in as shown in Fig.4.

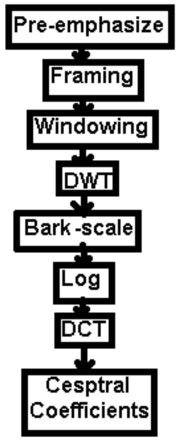

Fig.4 BWCC

3. Classification Method

Deep learning neural network is modern techniques of machine learning [42]. The learning algorithm is obtained by permitting the network to learn and select features from each hidden layer of neurons. Word “deep” is used to know that there is large number of hidden neurons in artificial neural network. The Recurrent Neural Network (RNN) is construction of deep learning. RNN can be considered as feed-forward recurrent network that means the network depend on the previous computations of the output. This operation is achieved by memory unit. There are two types of RNN are Long Short-Term Memory (LSTM) and the bidirectional LSTM (BILSTM). The process of learning of LSTM is long-term dependencies. The memory unit decomposed from three gates which are called input, output, and forget gate. These gates operate to control storing or forgetting information from the network. This information may be repeated for every input. Storing information and updating it is conducted by the input gate in the cell state. The used information is chosen by the output gate according to the cell state. Forget gate is used to remove the redundant information. The sequence of time in the forward direction is achieved by LSTM. The sequence of time in forward and backward directions is achieved by BILSTM.

4. Experiments & Results

Signals of cough sounds are selected from the open source site COSWARA [43]. These signals are sampled at 48000 Hz. Heavy cough sounds are selected. Heavy Cough sounds signals are divided into 2 classes: 1130 patients are healthy cough sounds (h), 200 patients are positive COVID cough sounds (p). 70% of this dataset is used for training. 30% of this dataset is used for testing. As shown in Fig.5 there is example of heavy cough sounds of healthy subject. As show in Fig.6 there is example of heavy cough sounds of positive COVID-19 subject.

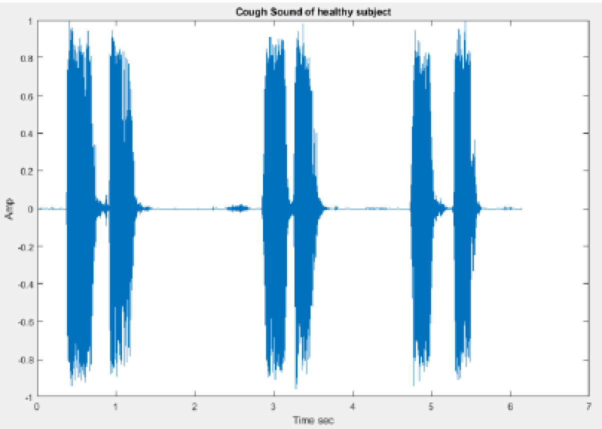

Fig.5 Cough Sound of healthy subject

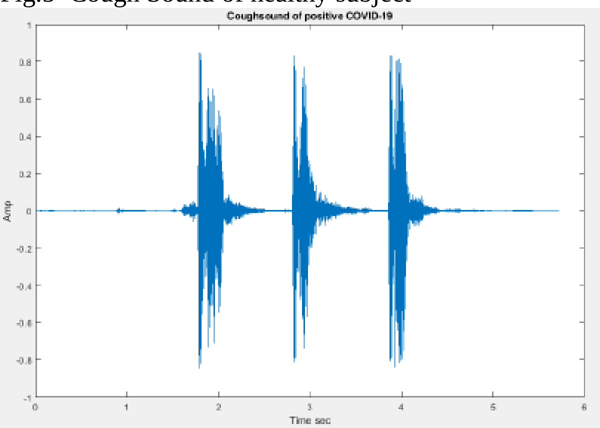

Fig.6 Cough Sound of COVID-19 subject

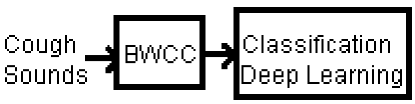

Fig.7 The selected Feature extraction Method

Features of signals of cough sounds are extracted using BWCC as shown in Fig.7. Then RNN of deep learning neural network is applied as classification method.

Extracted features from heavy cough sounds are compared using four algorithms MFCCs, MWCCs, BFCCs and BWCCs then deep learning step is applied as shown in Table 1. The obtained accuracy percent using MFCCs is 88.72%. The excluded accuracy percent using BFCCs is 97.24%. The shown accuracy percent when using MWCCs is 95.49%. The acquired accuracy percent when using BWCCs is 98.25%. The highest selected algorithm is BWCCs using deep learning. BWCCs are better for extracting features of heavy cough sounds than other algorithms because BWCCs contain discrete wavelet transform step instead of FFT step which is suitable for non-stationary signals like heavy cough sounds. As shown in Table 1, there are some metrics of classification of the selected algorithm BWCCs using DLNN. The percent of Sensitivity rate is 97.94%. The specificity rate is 100%. The precision rate is 100%. Recall rate is 97.94%. F-measure rate is 98.96%. G-mean is 0.9896. From all these values, the stability of BWCCs is high and is the best suitable way for feature extraction of heavy cough sounds.

Table 1 The Accuracy rate of 4 algorithms using classification method of DLNN

	MFCCs	BFCCs	MWCCs	BWCCs
Accuracy rate	88.72%	97.24%	95.49%	**98.25%**
Sensitivity rate	86.73%	96.76%	100%	97.94%
Specificity rate	100%	100%	100%	100%
Precision rate	100%	100%	70%	100%
Recall rate	86.73%	96.76%	94.96%	97.94%
F-measure rate	92.89%	98.35%	100%	98.96%
Gmean	0.9313	0.9836	0.8367	0.9896

5. Conclusion

In this paper, new algorithms are applied for analyzing signals of cough sounds of COVD19. These algorithms are BWCCs and MWCC. They are compared to BFCCs and MFCC. The classification technique is DLNN. The accuracy percent of BWCCs is more than the accuracy percent of other algorithms. So, algorithm of BWCCs is selected for feature extraction of heavy cough sounds. In future, a new algorithm will be applied to obtain higher accuracy percent.

References

[1] https://www.who.int.

[2] R. J. Jaeger, J. P. Szidon and P. J. Doucette, "Instrumentation for measuring frequency of cough," Proceedings of 17th International Conference of the Engineering in Medicine and Biology Society, 1995, pp. 1645-1646 vol.2, doi: 10.1109/IEMBS.1995.579871.

[3] K. A. Friend, W. T. Goldsmith, J. S. Reynolds and D. G. Frazer, "Acoustic tube reconstruction for the characterization of cough sounds," Proceedings of the First Joint BMES/EMBS Conference. 1999 IEEE Engineering in Medicine and Biology 21st Annual Conference and the 1999 Annual Fall Meeting of the Biomedical Engineering Society (Cat. N, 1999, pp. 1017 vol.2-, doi: 10.1109/IEMBS.1999.804170.

[4] R. Jane, J. Sola-Soler, J. A. Fiz and J. Morera, "Automatic detection of snoring signals: validation with simple snorers and OSAS patients," Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (Cat. No.00CH37143), 2000, pp. 3129-3131 vol.4, doi:10.1109/IEMBS.2000.901546.

[5] W. Thorpe, M. Kurver, G. King and C. Salome, "Acoustic analysis of cough," The Seventh Australian and New Zealand Intelligent Information Systems Conference, 2001, 2001, pp. 391-394, doi: 10.1109/ANZIIS.2001.974110.

[6] K. Rosenberry, W. T. Goldsmith, J. S. Reynolds, W. McKinney and D. G. Frazer, "Gender differences in voluntary cough sound spectra demonstrated by an inverse power law analysis," Proceedings of the Second Joint 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society Engineering in Medicine and Biology, 2002, pp. 222-223 vol.1,doi: 10.1109/IEMBS.2002.1134463.

[7] A. Van Hirtum, D. Berckmans, K. Demuynck and D. Van Compernolle, "Autoregressive acoustical modeling of free field cough sound," 2002 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2002, pp. I-493-I-496, doi: 10.1109/ICASSP.2002.5743762.

[8] Y. H. Hiew, J. A. Smith, J. E. Earis, B. M. G. Cheetham and A.A. Woodcock, "DSP algorithm for cough identification and counting," 2002 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2002, pp. IV-3888-IV-3891, doi:10.1109/ICASSP.2002.5745506.

[9] S. Matos, S. S. Birring, I. D. Pavord and H. Evans, "Detection of cough signals in continuous audio recordings using hidden Markov models," in IEEE Transactions on Biomedical Engineering, vol. 53, no. 6, pp. 1078-1083, June 2006, doi: 10.1109/TBME.2006.873548.

[10] S. Matos, S. S. Birring, I. D. Pavord and D. H. Evans, "An Automated System for 24-h Monitoring of Cough Frequency:The Leicester Cough Monitor," in IEEE Transactions on Biomedical Engineering, vol. 54, no. 8, pp. 1472-1479, Aug.2007, doi: 10.1109/TBME.2007.900811.

[11] H. R. Tohidypour, S.A.Seyyedsalehi,H. Behbood," Comparison Between Wavelet Packet Transform, Bark Wavelet & MFCC For Robust Speech Recognition Tasks",2010 2nd International Conference on Industrial Mechatronics and Automation, pp329-332.

[12] S. Huq and Z. Moussavi, "Automatic breath phase detection using only tracheal sounds," 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, 2010, pp. 272-275, doi: 10.1109/IEMBS.2010.5627437.

[13] H. Chatrzarrin, A. Arcelus, R. Goubran and F. Knoefel, "Feature extraction for the differentiation of dry and wet cough sounds," 2011 IEEE International Symposium on Medical Measurements and Applications, 2011, pp. 162-166, doi: 10.1109/MeMeA.2011.5966670.

[14] P. Moradshahi, H. Chatrzarrin and R. Goubran, "Improving the performance of cough sound discriminator in reverberant environments using microphone array," 2012 IEEE International Instrumentation and Measurement Technology Conference Proceedings, 2012, pp. 20-23, doi: 10.1109/I2MTC.2012.6229523.

[15] K. Kosasih, U. R. Abeyratne and V. Swarnkar, "High frequency analysis of cough sounds in pediatric patients with respiratory diseases," 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2012, pp. 5654-5657, doi: 10.1109/EMBC.2012.6347277.

[16] V. Swarnkar, U. R. Abeyratne, Y. A. Amrulloh and A. Chang,"Automated algorithm for Wet/Dry cough sounds classification," 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2012, pp. 3147-3150, doi: 10.1109/EMBC.2012.6346632.

[17] S. S. Shirazi and Z. Moussavi, "Silent aspiration detection by breath and swallowing sound analysis," 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2012, pp. 2599-2602, doi: 10.1109/EMBC.2012.6346496.

[18] T. Drugman et al., "Objective Study of Sensor Relevance for Automatic Cough Detection," in IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 3, pp. 699-707, May 2013, doi: 10.1109/JBHI.2013.2239303.

[19] P. Moradshahi, H. Chatrzarrin and R. Goubran, "Cough sound discrimination in noisy environments using microphone array," 2013 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), 2013, pp. 431-434, doi:10.1109/I2MTC.2013.6555454.

[20] U. R. Abeyratne, V. Swarnkar, R. Triasih and A. Setyati, "Cough Sound Analysis - A new tool for diagnosing Pneumonia," 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 5216-5219, doi: 10.1109/EMBC.2013.6610724.

[21] V. Swarnkar, U. R. Abeyratne, Y. Amrulloh, C. Hukins, R.Triasih and A. Setyati, "Neural network based algorithm for automatic identification of cough sounds," 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 1764-1767, doi:10.1109/EMBC.2013.6609862.

[22] S. Le and W. Hu, "Cough sound recognition based on Hilbert marginal spectrum," 2013 6th International Congress on Image and Signal Processing (CISP), 2013, pp. 1346-1350, doi:10.1109/CISP.2013.6743882.

[23] C. Lücio, C. Teixeira, J. Henriques, P. de Carvalho and R. P. Paiva, "Voluntary cough detection by internal sound analysis,"2014 7th International Conference on Biomedical Engineering and Informatics, 2014, pp. 405-409, doi: 10.1109/BMEI.2014.7002808.

[24] K. Kosasih, U. R. Abeyratne, V. Swarnkar and R. Triasih,"Wavelet Augmented Cough Analysis for Rapid Childhood Pneumonia Diagnosis," in IEEE Transactions on Biomedical Engineering, vol. 62, no. 4, pp. 1185-1194, April 2015, doi:10.1109/TBME.2014.2381214.

[25] J. Schröder, J. Anemuller and S. Goetze, "Classification of human cough signals using spectro-temporal Gabor filterbank features," 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2016, pp. 6455-6459, doi: 10.1109/ICASSP.2016.7472920.

[26] J. Amoh and K. Odame, "Deep Neural Networks for Identifying Cough Sounds," in IEEE Transactions on Biomedical Circuits and Systems, vol. 10, no. 5, pp. 1003-1011, Oct. 2016, doi:10.1109/TBCAS.2016.2598794.

[27] C. Infante, D. Chamberlain, R. Fletcher, Y. Thorat and R. Kodgule, "Use of cough sounds for diagnosis and screening of pulmonary disease," 2017 IEEE Global Humanitarian Technology Conference (GHTC), 2017, pp. 1-10, doi:10.1109/GHTC.2017.8239338.

[28] E. Kiliç and A. Erdamar, "Automatic classification of respiratory sounds during sleep," 2018 26th Signal Processing and Communications Applications Conference (SIU), 2018, pp.1-4, doi: 10.1109/SIU.2018.8404462.

[29] R. V. Sharan, U. R. Abeyratne, V. R. Swarnkar and P. Porter, "Automatic Croup Diagnosis Using Cough Sound Recognition," in IEEE Transactions on Biomedical Engineering, vol. 66, no. 2, pp. 485-495, Feb. 2019, doi: 10.1109/TBME.2018.2849502.

[30] S. Khomsay, R. Vanijjirattikhan and J. Suwatthikul, "Cough detection using PCA and Deep Learning," 2019 International Conference on Information and Communication Technology

Convergence (ICTC), 2019, pp. 101-106, doi: 10.1109/ICTC46691.2019.8939769.

[31] C. R. Rodriguez, D. Angeles, R. Chafloque, F. Kaseng and B. Pandey, "Deep Learning Audio Spectrograms Processing to the Early COVID-19 Detection," 2020 12th International Conference on Computational Intelligence and Communication Networks (CICN), 2020, pp. 429-434, doi:10.1109/CICN49253.2020.9242583.

[32] A. Hassan, I. Shahin and M. B. Alsabek, "COVID-19 Detection System using Recurrent Neural Networks," 2020 International Conference on Communications, Computing, Cybersecurity, and Informatics (CCCI), 2020, pp. 1-5, doi:10.1109/CCCI49893.2020.9256562.

[33] M. B. Alsabek, I. Shahin and A. Hassan, "Studying the Similarity of COVID-19 Sounds based on Correlation Analysis of MFCC," 2020 International Conference on Communications, Computing, Cyber security, and Informatics (CCCI), 2020, pp. 1-5, doi: 10.1109/CCCI49893.2020.9256700.

[34] M. Z. Iqbal and M. F. I. Faiz, "Active Surveillance for COVID-19 Through Artificial Intelligence Using Real-Time Speech-Recognition Mobile Application," 2020 IEEE International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan),2020, pp. 1-2, doi: 10.1109/ICCE-Taiwan49838.2020.9258276.

[35] J. Andreu-Perez et al., "A Generic Deep Learning Based Cough Analysis System from Clinically Validated Samples for Pointof-Need Covid-19 Test and Severity Levels," in IEEE Transactions on Services Computing, doi:10.1109/TSC.2021.3061402.

[36] K. Feng, F. He, J. Steinmann and I. Demirkiran, "Deep-learning Based Approach to Identify Covid-19," SoutheastCon 2021, 2021, pp. 1-4, doi: 10.1109/SoutheastCon45413.2021.9401826.

[37] J. Vrindavanam, R. Srinath, H. H. Shankar and G. Nagesh, "Machine Learning based COVID-19 Cough Classification Models - A Comparative Analysis," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), 2021, pp. 420-426, doi:10.1109/ICCMC51019.2021.9418358.

[38] P. Mouawad, T. Dubnov, S. Dubnov," Robust Detection of COVID-19 in Cough Sounds: Using Recurrence Dynamics and Variable Markov Model", SN Computer Science. 2021 ;2(1):34.DOI: 10.1007/s42979-020-00422-6.

[39] R.X. Gao, R.Q. Yan, Wavelets: Theory and Applications for Manufacturing, first ed., Springer, New York, 2011.S. Mallat, A Wavelet Tour of Signal Processing,", Academic press,2nd edition, 1999.

[40] Z. Fang, Z. Guoliang, S. Zhanjiang," Comparison of different implementations of MFCC", J. Comput.Sci. Technol.16,2000, pp 582–589.

[41] C.Lubis and F.Gondawijaya,"Heart Sound Diagnose System with BFCC, MFCC, and Backpropagation Neural Network", IOP Conference Series: Materials Science and Engineering,Indonesia,TICATE,2018.

[42] O. Faust, Y. Hagiwara, T. J. Hong, O. S. Lih, U R. Acharya," Deep learning for healthcare applications based on physiological signals: A review , Computer Methods and Programs in Biomedicine ,Volume 161,2018, pp. 1-13, ISSN 0169-2607.

[43] https://github.com/iiscleap/Coswara-Data