Energy-Efficient Intelligent Pulmonary Auscultation for Post COVID-19 Era Wearable Monitoring Enabled by Two-Stage Hybrid Neural Network

[1]Bingqiang Liu, [1]Ziyuan Wen, [2]Hongling Zhu, [2]Jinsheng Lai, [1]Jiajun Wu, [1]Heng Ping, [4]Wenqing Liu, [1]Guoyi Yu, [4]Jianmin Zhang, [5]Zuozhu Liu, [2]Hesong Zeng and [1,3]Chao Wang

[1] School of Optical and Electronic Information, Huazhong University of Science and Technology, Wuhan, China

[2]Tongji Medical College, Huazhong University of Science and Technology, Wuhan, China

[3]Wuhan National Laboratory of Optoelectronics, Huazhong University of Science and Technology, Wuhan, China

[4]School of Artificial Intelligence, Jianghan University, Wuhan, China

[5]Zhejiang University - University of Illinois at Urbana-Champaign Institute, Zhejiang University, Hangzhou, China

Email: chao_wang_me@hust.edu.cn, zenghs@tjh.tjmu.edu.cn

***Abstract*—This paper proposes an energy-efficient intelligent pulmonary auscultation system for post COVID-19 era wearable monitoring. This system consists of a tightly coupled two-stage hybrid neural network (TC-TSHNN) model and a corresponding multi-task training paradigm to improve prediction accuracy and generalization ability based on the fact that the number of COVID-19 patients is far less than that of normal people. At the first stage, two-category coarse classification is performed to identify normal and abnormal lung sounds. If the lung sound is abnormal, the second stage would be triggered to perform a four-category fine-grained classification. Besides, discrete wavelet transform is utilized for feature extraction, denoising and data reduction. In addition, advanced lightweight convolutional neural networks are used to reduce the model's computation and improve the model's performance. The hybrid network model can achieve 92% computation reduction and energy saving compared with a direct four-category classification when the input lung sound is normal, which is the majority of cases. Experiment results with inter-patient classification on the COVID-19 lung sound dataset from Tongji Hospital in Wuhan City and the ICBHI'17 dataset show that the proposed TC-TSHNN model can significantly reduce power consumption while maintaining competitive performance against the state-of-the-art work.**

Keywords—Post COVID-19 Era, Intelligent Pulmonary Auscultation, Lung Sound, Wearable Monitoring, Inter-patient, Two-Stage Hybrid Neural Network.

I. Introduction

Since first reported in December 2019, the coronavirus disease (COVID-19) has rapidly spread all over the world [1]. The disease is highly contagious and can lead to serious pneumonia. Patients with COVID-19 are classified into four types called mild, moderate, severe and critical according to the severity of disease [3]. People developing with mild symptoms usually can recover without hospitalization, while patients with a critical case of COVID-19 have a higher mortality rate than severe and moderate COVID-19 patients [4], [5]. Therefore, initial screening and pre-diagnosis according to the severity of patients play a pivotal role in reducing mortality [5] and releasing the burden of the medical system.

Recently, researchers have been utilizing machine learning or deep learning methods to detect the severity of COVID-19 patients based on different types of clinical information. They [4]-[9] use machine learning methods including Random Forest (RF) and SVM as well as deep learning methods to predict the severity of COVID-19 patients based on multiple features including CT quantification, the information of radiomic features, imaging texture features, blood and urine tests or other clinical and biological variables. The above methods are radioactive, expensive or invasive.

Since the invention of the stethoscope in the early 1800s, chest auscultation has been widely used for respiratory disease diagnosis in practice [10], [11]. Auscultation provides a low-cost, convenient and effective way to acquire considerable information about lung diseases and their symptoms, which reveals strong potential for severity recognition of COVID-19 patients [12]. However, there are also some problems with auscultation. First, an experienced professional is required to get accurate patient diagnoses. Second, misdiagnosis happens due to subjectivity, variability and inconsistency, as well as vulnerability to ambient noise [14]. To solve the above issues, auscultation based on machine learning and deep learning has been studied to detect respiratory diseases in recent years [13]-[19]. However, to the best of our knowledge, the existing works have not studied how to use deep neural network (DNN) based auscultation to perform initial screening and pre-diagnosis of COVID-19 patients.

In this paper, we propose an energy-efficient intelligent pulmonary auscultation system for post COVID-19 era wearable monitoring, which can be deployed on wearable devices for pre-diagnosis, as illustrated in Fig. 1. Specifically, a tightly coupled two-stage hybrid neural network model with a multi-task training method is proposed to perform a two-category coarse classification of normal and abnormal lung sounds at the first stage. Afterward, a four-category fine-grained classification is performed at the second stage if the lung sound is abnormal. Advanced lightweight convolutional neural network (CNN) structures are used to improve the performance of the model and reduce the model's computation as well as the required power consumption.

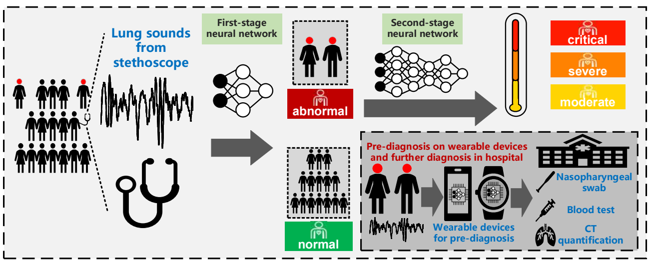
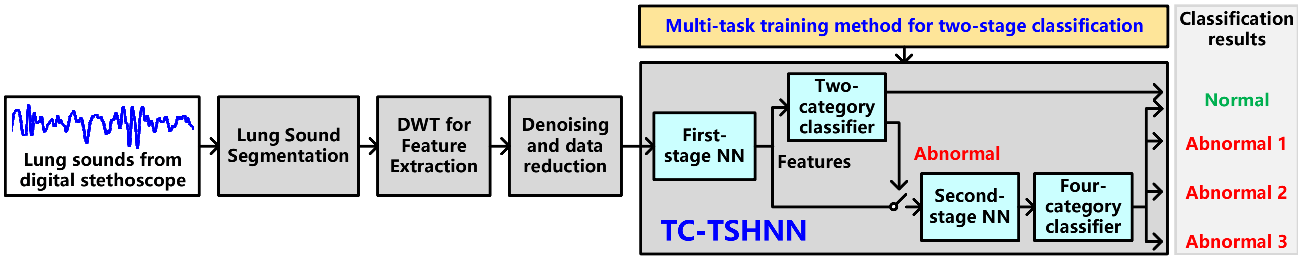


Fig. 1. The proposed energy-efficient intelligent pulmonary auscultation system for post COVID-19 era wearable monitoring



II. Materials And Methods

A. Dataset

For the COVID-19 lung sound dataset used in this study, 172 confirmed cases of COVID-19 treated in Tongji Hospital, Wuhan City, China from Mar 31 to Apr 5, 2020, are included. Another 45 normal patients with normal chest CT scanning, echocardiography and electrocardiography are also included as a control group. The lung sounds from the dataset are recorded in 10 sites per person with 30 seconds for each site according to the diagnosing guidelines through 3M Littmann digital stethoscope [31]. The sampling rate of lung sound is set to 4 kHz/s. The lung sounds from the dataset are diagnosed by a committee consisting of two independent doctors, who are board-certified actively-practicing doctors majoring in cardiology and respirology in the Tongji Hospital.

It is to be noted that in addition to the severity classification of COVID-19 severity levels (i.e., normal, moderate, severe and critical) on the Tongji COVID-19 dataset, this work also studies the classification of major lung sounds (i.e., normal, crackle, wheeze and phlegm sound) on both the Tongji COVID-19 dataset and standard ICBHI'17 public dataset [28], [29].

B. The Proposed Energy-efficient Intelligent Pulmonary Auscultation System

The architecture of the proposed energy-efficient intelligent pulmonary auscultation system is shown in Fig. 2. First, lung sounds from a digital stethoscope are segmented with a duration of 4 seconds. Second, discrete wavelet transform (DWT) is used for feature extraction, denoising and data reduction. After that, the features derived from the DWT will pass through a tightly coupled two-stage hybrid neural network model (TC-TSHNN) with the proposed multi-task training strategy to perform high-dimension feature extraction and two-stage classification. Finally, the classification results are able to be obtained. The detailed description is as follows:

1) Data segmentation and augmentation: The raw records of lung sounds are segmented into 4 seconds audio clips to ensure that at least one breathing cycle is included. As the Tongji COVID-19 patients' data is quite limited, the data augmentation methods [15] including noise addition, time shifting are adopted to expand the dataset by 10 times for deep learning. After the data augmentation, the problem of data imbalance among different categories can be alleviated by randomly selecting the data.

2) Discrete wavelet transform for feature extraction, denoising and data reduction: Discrete wavelet transform (DWT) is chosen considering that different lung sound features have distinct time-frequency characteristics distributed in different frequency bands [13], [14], [21]. By considering both wavelet performance and hardware overhead, db4 wavelet is selected to perform a four-order wavelet transform on the 4-second lung sound segment, which is quite sufficient for the feature extraction, noise and data reduction. Downsampling is performed to adapt the subsequent lightweight CNN engine. The data after downsampling is denoised with the soft threshold method in the wavelet domain [23], which filters out the noise, keeps useful information as much as possible and also increases the sparsity of the input data.

3) Proposed TC-TSHNN model: The TC-TSHNN model is motivated by the fact that normal cases are far more than abnormal cases that are infected by COVID-19. For Wuhan City, there are about 50 thousand people infected with COVID-19 among about 12.32 million people, accounting for about 0.41%, while globally there are about 254 million people infected with COVID-19 among about 7.6 billion people by 18 Nov. 2021, accounting for about 3.34% [2], [32]. Usually, it is not necessary for the proposed intelligent pulmonary auscultation system to directly carry out the four-category classification, and only a two-category classification of normal and abnormal is sufficient for most cases (i.e., normal cases). Therefore, a tightly coupled two-stage hybrid neural network model with a coarse two-category classification in the first stage is proposed to save power consumption and achieve high energy efficiency for post COVID-19 era wearable monitoring.

Specifically, the features derived from DWT are further processed by the first-stage neural network (NN) to extract the first-stage high-dimension features. As shown in Fig. 2, the DWT features are classified by a two-category classifier after the first-stage neural network. If the binary classification result is normal, the output is directly displayed, and the inference ends. If the classification result is abnormal, the second-stage neural network is activated, and the high-dimension features from the first-stage neural network are further processed through the second-stage neural network, then a multi-classification result is able to be obtained from the second-stage high-dimension features.

Fig. 3 shows the details of the proposed two-stage hybrid neural network model. For the first-stage neural network, the efficient lightweight depthwise separable convolution structure in MobileNetV1 [25] is used to replace the conventional convolution structure for minimizing the number of parameters and computation, thus reducing power consumption. For the second-stage neural network, the inverted residual with linear bottleneck structure in MobileNetV2 [30] is adopted to further reduce the number of computations. At the same time, the shortcut structure in the inverted residual structure can efficiently increase the model depth and improve the ability of a gradient to propagate across multiple layers to relieve gradient vanish. From the

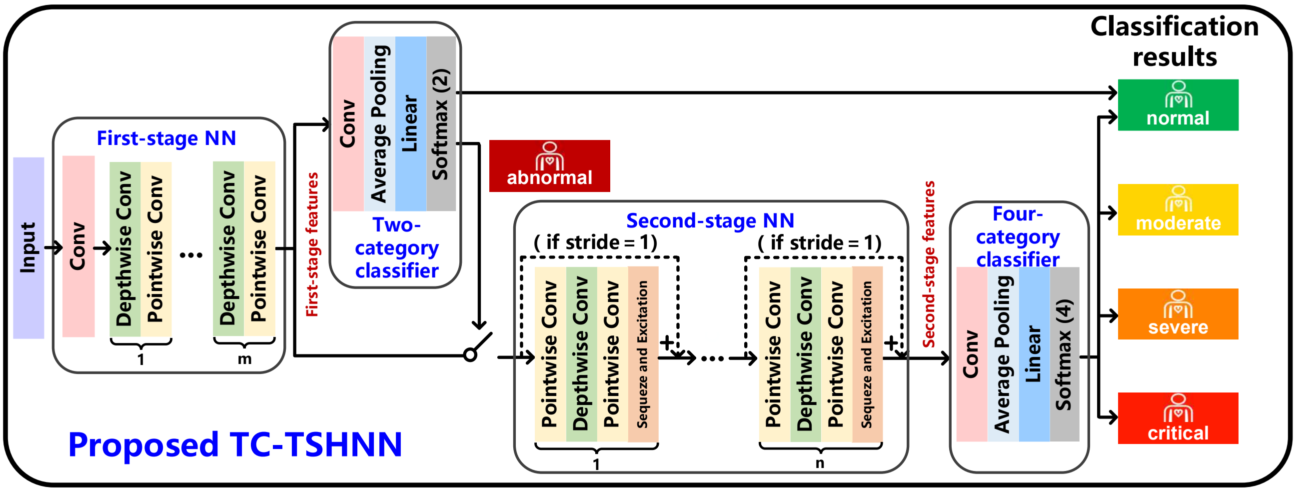


Fig. 3. The proposed tightly coupled two-stage hybrid neural network (TC-TSHNN) structure

experimental results of our investigation, the use of these lightweight structures significantly reduces the amount of computation by 37% compared with the conventional convolution structures. Besides, the Squeeze-and-Excitation structure is utilized to further improve the performance of the second-stage four-category classification by fully capturing channel-wise dependencies, as global spatial information of feature maps can be captured to focus on useful features and suppress less meaningful features [24].

It is to be noted that as there are three classification tests in this study as mentioned previously, the depths of the proposed TC-TSHNN model are slightly different, in terms of parameters m and n as shown in Fig. 3, for the different tests. Specifically, the depth values of (m, n) for the classification of severity levels on the Tongji COVID-19 dataset, classification of major lung sounds on the Tongji COVID-19 dataset, and classification of major lung sounds on the ICBHI'17 dataset, are set to (4, 6), (4, 8), and (3, 4), respectively.

4) Proposed multi-task training method: In order to achieve good performance for both two-category classification and four-category classification with the proposed model, it is required to train the two stages of neural networks and classifiers simultaneously. Specifically, if the first-stage neural network and two-category classifier are trained first, followed by training of the second-stage neural network and four-category classifier, the first-stage high-dimension features may not contain sufficient information required for the four-category classification task. This is because the first-stage neural network is only adjusted to the two-category classification with no regard to the four-category classification, which can lose some key features for the four-category classification. Therefore, a multi-task training method is proposed and the total loss function is described as below:

$$\text{loss} = \text{loss}_2\,(\boldsymbol{x_2}) + \text{loss}_4\,(\boldsymbol{x_4}) \tag{1}$$

where $\boldsymbol{x_2}$ and $\boldsymbol{x_4}$ are the output array of the two classifiers and $\text{loss}_2(\boldsymbol{x_2})$ and $\text{loss}_4(\boldsymbol{x_4})$ represents the loss function of the two-category classification and four-category classification tasks, respectively.

For the loss function, we utilize a manual re-scaling of weights technique described by:

$$\text{loss}(\boldsymbol{x}) = -\sum_{\mathrm{j}} \boldsymbol{w}[\mathrm{j}]\boldsymbol{y}[\mathrm{j}] \log\big(\mathrm{p}(\boldsymbol{x},\mathrm{j})\big) \tag{2}$$

$$\mathrm{p}(\boldsymbol{x},\mathrm{i}) = \frac{e^{\boldsymbol{x}[\mathrm{i}]}}{\sum_{\mathrm{j}} e^{\boldsymbol{x}[\mathrm{j}]}} \tag{3}$$

where $\boldsymbol{x}$ is the output array of the two-category or four-category classifier, $\boldsymbol{w}$ is the manual re-scaling weight array, $\boldsymbol{y}$ is the label of the data encoded by one-hot code, and J is the total class number. For example, if there is a four-category classification, j can be 0,1,2,3, and J is 4. The $\mathrm{p}(\boldsymbol{x},\mathrm{i})$ is the softmax function. The re-scaling method can alleviate the problem of unbalanced data sets and improve the performance of the proposed model [22].

It is also to be noted that the adaptive learning rate optimization algorithm, Adam [26], is chosen for stochastic optimization, and the regularization technique [27] is used to prevent the overfitting problem in the proposed multi-task training.

III. Results And Discussions

A. Evaluation Metrics

In this study, the proposed TC-TSHNN model is evaluated with the Tongji COVID-19 lung sound dataset in the hold-one method and inter-patient way. The COVID-19 lung sound dataset is divided into training, validation and test subsets, of which each account for 70%, 10% and 20% of the total data. The evaluation metrics are defined as:

$$\text{sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{4}$$

$$\text{specificity} = \frac{\mathrm{TN}}{\mathrm{FP+TN}} \tag{5}$$

$$\text{score} = \frac{\text{sensitivity+specificity}}{2} \tag{6}$$

where TP is true-positive rate, TN is true-negative rate, FP is false-positive rate, and FN is false-negative rate.

B. Experimental Results and Discussion

In these experiments, the proposed TC-TSHNN lung sound classification model is implemented with Pytorch in Python and tested on a workstation with an Intel i7-8750H 2.20GHz processor and an Nvidia GTX 1060 graphics card.

Fig. 4 shows the comparison of classification performance results with and without multi-task training. It can be seen that the proposed multi-task training method can significantly improve the performance of the TC-TSHNN, especially for the classification on the ICBHI'17 dataset with a score improvement by 33.0%.

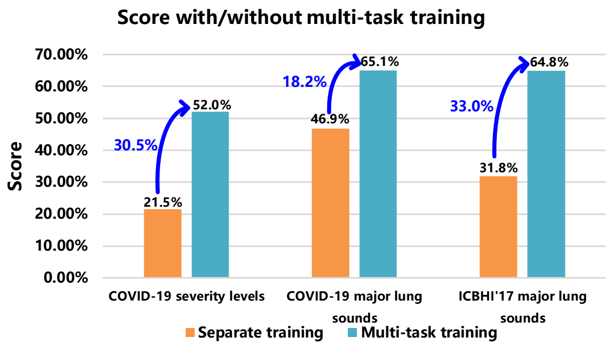


Fig. 4. The performance comparison of classification results with and

Table I shows the performance of the proposed TC-TSHNN model on the Tongji COVID-19 lung sound dataset. For the COVID-19 severity classification, the proposed model achieves 52.0% in the score, which can be hardly achieved through the doctor's manual auscultation. For the major lung sound classification of normal, crackles, wheezes and phlegm sounds, the proposed model also achieves 65.1% in the score, which is a relatively good result as compared to the inter-patient experiments in lung sound classification in the latest literature [13], [15], which can provide vital information for COVID-19 diagnose.

To further evaluate the performance of the proposed TC-TSHNN, this study has compared the classification results of the proposed model against the state-of-the-art works in [13], [15] on the public ICBHI'17 lung sound dataset, as shown in Table II. The overall score of the proposed model has reached the level of the state-of-the-art methods.

For the computational complexity, the proposed TC-TSHNN model has been compared with the Bi-ResNet model, as only the Bi-ResNet model provides open-source codes in public [13]. Table III shows that against the Bi-ResNet model in [13], the proposed model can reduce the amount of computation by ×21 when the input lung sound is abnormal, due to the lightweight deep separable convolution structures utilized in the proposed model. When the input lung sound is normal, the amount of computation can be significantly reduced by ×274, because only the first stage neural network and two-category classifier are activated. In this case, the proposed TC-TSHNN can achieve a 92% saving in computation and energy as compared to a direct four-category classification, which is significant for the energy-efficient design of a wearable auscultation system, as the lung sounds of the major population are normal [20].

From the experiment results, the proposed TC-TSHNN model is more hardware friendly in terms of computation and power consumption than the existing models. Our proposed energy-efficient intelligent pulmonary auscultation system based on the TC-TSHNN is a promising way for energy-constrained wearable monitoring devices. As normal cases are usually far more than abnormal cases that are infected by COVID-19 in the world, the proposed TC-TSHNN model will only work in the two-category classification mode under most situations. Therefore, the proposed intelligent pulmonary auscultation system is a promising solution for initial screening and pre-diagnosis in the post COVID-19 era.

TABLE I. PERFORMANCE ON TONGJI COVID-19 DATASET

Reference	Tongji COVID-19 lung sound dataset	
	Classification of severity levels	*Classification of major lung sounds*
Two-category classification at the first stage		
Sensitivity	87.90%	82.68%
Specificity	56.88%	78.38%
Score	72.39%	80.53%
Four-category classification at the second stage		
Sensitivity	32.83%	55.22%
Specificity	74.26%	66.61%
Score	53.55%	60.91%
Overall results of TC-TSHNN		
Sensitivity	32.74%	51.68%
Specificity	74.90%	78.55%
Score	53.82%	65.12%

TABLE II. COMPARISION WITH STATE-OF-THE-ART WORKS ON ICBHI'17 DATASET

Reference	ICBHI'17 lung sound dataset		
	***LungBRN* [13]**	**[15]**	***This work***
Model	Bi-ResNet	Hybrid CNN-RNN	Proposed TC-TSHNN
Features	STFT+ wavelet	Mel-spectrograms	DWT
Sensitivity	58.54 %	48.63%	37.84%
Specificity	80.06 %	84.14%	88.50%
Score	69.30 %	66.38%	63.17%

TABLE III. CPMPARISION OF COMPUTATIONAL COMPLECXITY WITH THE STATE-OF-THE-ART METHOD

Model		No. Mult	No. Add	Reduction
LungBRN [13]		1.11×10^{9}	1.11×10^{9}	-
Proposed TC-TSHNN	**Abnormal lung sound**	5.19×10^{7}	5.25×10^{7}	×21
	Normal lung sound	4.04×10^{6}	4.04×10^{6}	×274

IV. CONCLUSION AND FUTURE WORK

In this work, a tightly coupled two-stage hybrid neural network (TC-TSHNN) model with a multi-task training method is proposed, which can achieve 92% computation and energy savings against the direct four-category classification under the majority of cases, i.e., the lung sound is normal. The proposed intelligent pulmonary auscultation system based on the TC-TSHNN model is hardware friendly in terms of computation and power consumption against the existing works. In the future, we plan to study how to implement the proposed TC-TSHNN model in a reconfigurable energy-efficient DNN accelerator to perform different classification tasks for efficient initial screening and pre-diagnosis, which is essential for energy-constrained wearable pulmonary auscultation monitoring devices in the post COVID-19 era.

ACKNOWLEDGMENT

This work is partially supported by the National Natural Science Foundation of China (Grant 61974053), Wuhan Science and Technology Foundation of Application Frontier (Grant 2020020601012320), Fundamental Research Funds of the Central Universities of China (Grant 2019KFYXJJS049), and National Natural Science Foundation of China (Grant 82100531). Corresponding authors: Chao Wang and Hesong Zeng. Corresponding email: chao_wang_me@hust.edu.cn and zenghs@tjh.tjmu.edu.cn. Bingqiang Liu and Ziyuan Wen equivalently contributed to this paper.

REFERENCES

[1] C. Huang, et al., "Clinical Features of Patients Infected with 2019 Novel Coronavirus in Wuhan, China," in Lancet, vol. 395, no. 10223, pp. 497–506, 2020.

[2] Coronavirus Disease (COVID-19) Pandemic, WHO. Accessed on: November 18, 2021. [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019.

[3] Diagnosis and treatment protocols of pneumonia caused by a novel coronavirus (trial version 5), National health commission of the people's republic of China. Accessed on: November 18, 2021. [Online]. Available: http://www.nhc.gov.cn/yzygj/s7653p/202002/3b09b894ac9b4204a79db5b8912d4440.shtml.

[4] Yaar E, et al., "Artificial Intelligence-Based Prediction of Covid-19 Severity on the Results of Protein Profiling," in Computer Methods and Programs in Biomedicine, vol. 202, no. 105996, 2021.

[5] C. Li, et al., "Classification of Severe and Critical Covid-19 Using Deep Learning and Radiomics," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 12, pp. 3585-3594, Dec. 2020.

[6] W. Cai, et al., "CT Quantification and Machine-learning Models for Assessment of Disease Severity and Prognosis of COVID-19 Patients," in Academic radiology, vol. 27, no. 12, pp. 1665-1678, 2020.

[7] Lassau. Nathalie, et al., "Integrating Deep Learning CT-scan Model, Biological and Clinical Variables to Predict Severity of COVID-19 Patients," in Nature communications, vol. 12, no. 1, pp. 1-11, 2021.

[8] H. Yao, et al., "Severity Detection for the Coronavirus Disease 2019 (covid-19) Patients Using a Machine Learning Model Based on the Blood and Urine Tests," in Frontiers in cell and developmental biology, vol. 8, pp. 683, 2020.

[9] KC Un, et al., "Observational Study on Wearable Biosensors and Machine Learning-based Remote Monitoring of COVID-19 Patients," in Scientific reports, vol. 11, no. 1, pp. 1-9, 2021.

[10] D. Emmanouilidou, et al., "Adaptive Noise Suppression of Pediatric Lung Auscultations With Real Applications to Noisy Clinical Settings in Developing Countries," in IEEE Transactions on Biomedical Engineering, vol. 62, no. 9, pp. 2279-2288, Sept. 2015.

[11] A. Rao, et al., "Acoustic Methods for Pulmonary Diagnosis," in IEEE Reviews in Biomedical Engineering, vol. 12, pp. 221-239, 2019.

[12] S. Içer, et al., "Classification and Analysis of Non-stationary Characteristics of Crackle and Rhonchus Lung Adventitious Sounds," in Digit. Signal Process, vol. 28, pp. 18–27, May 2014.

[13] Y. Ma, et al., "LungBRN: A Smart Digital Stethoscope for Detecting Respiratory Disease Using bi-ResNet Deep Learning Algorithm," in IEEE Biomedical Circuits and Systems Conference (BioCAS), pp. 1-4, 2019.

[14] S. B. Shuvo, et al., "A Lightweight CNN Model for Detecting Respiratory Diseases From Lung Auscultation Sounds Using EMD-CWT-Based Hybrid Scalogram," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 7, pp. 2595-2603, July 2021.

[15] J. Acharya, et al., "Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient Specific Model Tuning," in IEEE Transactions on Biomedical Circuits and Systems, vol. 14, no. 3, pp. 535-544, June 2020.

[16] B.-S. Lin, et al., "Automatic Wheezing Detection Using Speech Recognition Technique," in J. Med. Biol. Eng., vol. 36, no. 4, pp. 545–554, 2016.

[17] Y. Ma, et al., "Live Demo: LungSys - Automatic Digital Stethoscope System For Adventitious Respiratory Sound Detection," in IEEE Biomedical Circuits and Systems Conference (BioCAS), pp. 1-1,2019.

[18] Y. Ma, et al., "LungRN+ NL: An Improved Adventitious Lung Sound Classification Using Non-Local Block ResNet Neural Network with Mixup Data Augmentation," in Interspeech, pp. 2902-2906, 2020.

[19] J. Li, et al., "LungAttn: advanced lung sound classification using attention mechanism with dual TQWT and triple STFT spectrogram," in Physiological Measurement, vol. 42, no. 10, 2021.

[20] N. Wang, et al., "Energy-Efficient Intelligent ECG Monitoring for Wearable Devices," in IEEE Transactions on Biomedical Circuits and Systems, vol. 13, no. 5, pp. 1112-1121, Oct. 2019.

[21] Sovijarvi ARA, et al., "Characteristic of Breath Sounds and Adventitious Respiratory Sounds," in European Respiratory Review, vol. 10, no. 7, pp. 591-596, 2000.

[22] Ronneberger, et al., "U-net: Convolutional Networks for Biomedical Image Segmentation," in International Conference on Medical image computing and computer-assisted intervention, Springer, Cham, pp. 234-241, 2015.

[23] G. Song, et al., "Three Novel Models of Threshold Estimator for Wavelet Analysis and Its Applications," in Berlin: Springer-Verlag, pp.145-150, 2001.

[24] J. Hu, et al., "Squeeze-and-Excitation Networks," in IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7132-7141, 2018.

[25] Andrew G. Howard, et al., "Mobilenets: Efficient Convolutional Neural Networks for Mobile Vision Applications," in arXiv preprint arXiv:1704.04861, 2017.

[26] D. Kingma, et al., "Adam: A Method for Stochastic Optimization," in International Conference on Learning Representations, May 2015.

[27] S. Nowlan, et al., "Simplifying Neural Networks by Soft Weightsharing," in Neural Computation, vol. 4, no. 4, pp. 473–493, July 1992.

[28] ICBHI 2017 Challenge, [Online]. Available: https://bhichallenge.med.auth.gr.

[29] B. Rocha, et al., "A Respiratory Sound Database for the Development of Automated Classification," in Prec. Med. Powered by pHealth and Con. Health. Berlin, Germany: Springer, pp. 33–37, 2018.

[30] M. Sandler, et al., "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 4510-4520, 2018.

[31] Using Electronic Stethoscopes, 3M Littmann. Accessed on: November 18, 2021. [Online]. Available: https://www.littmann.com/3M/en_US/littmann-stethoscopes/my-stethoscope/using-your-stethoscope/electronic-stethoscopes/.

[32] Epidemic situation of COVID-19 in Wuhan, Wuhan Municipal Health Commission. Accessed on: November 18, 2021. [Online]. Available: http://wjw.wuhan.gov.cn/ztzl_28/fk/tzgg/202111/t20211117_1836009.shtml.