https://www.kaggle.com/vbookshelf/respiratory-sound-database

Context

Respiratory sounds are important **indicators of respiratory health and respiratory disorders**.

The sound emitted when a person breathes is directly related to air movement, changes within lung tissue and the position of secretions within the lung. A wheezing sound, for example, is a common sign that a patient has an obstructive airway disease like asthma or chronic obstructive pulmonary disease (COPD).

These sounds can be recorded using **digital stethoscopes** and other recording techniques. This digital data opens up the possibility of using **machine learning to automatically diagnose** respiratory disorders like asthma, pneumonia and bronchiolitis, to name a few.

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Content

The Respiratory Sound Database was created by two research teams in Portugal and Greece. It includes **920 annotated recordings** of varying length - 10s to 90s. These recordings were taken from 126 patients. The data includes both clean respiratory sounds as well as noisy recordings that simulate real life conditions. The patients span all age groups - children, adults and the elderly.

This Kaggle dataset includes:
920 .wav sound files
920 annotation .txt files
A text file listing the diagnosis for each patient
A text file explaining the file naming format
A text file listing 91 names (filename_differences.txt)
A text file containing demographic information for each patient

Note: filename_differences.txt is a list of files whose names were corrected after this dataset's creators found a bug in the original file naming script. It can now be ignored.

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The demographic info file has 6 columns:

- Patient number
- Age
- Sex
- Adult BMI (kg/m2)
- Child Weight (kg)
- Child Height (cm)

```
101 3 F NA 19 99
102 0.75 F NA 9.8 73
103 70 F 33 NA NA
104 70 F 28.47 NA NA
105 7 F NA 32 135
106 73 F 21 NA NA
107 75 F 33.7 NA NA
108 3 M NA NA NA
```

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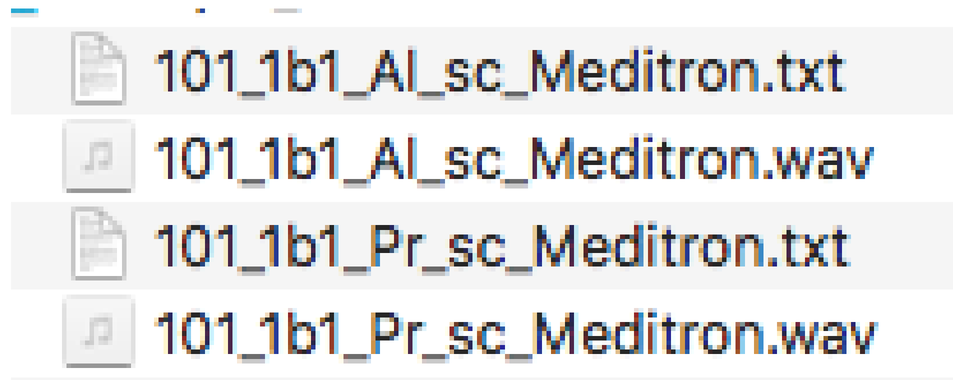
Each audio file name is divided into 5 elements, separated with underscores (_).

1. Patient number (101,102,...,226)
2. Recording index
3. Chest location
    a. Trachea (Tc)
    b. Anterior left (Al)
    c. Anterior right (Ar)
    d. Posterior left (Pl)
    e. Posterior right (Pr)
    f. Lateral left (Ll)
    g. Lateral right (Lr)
4. Acquisition mode
    a. sequential/single channel (sc),
    b. simultaneous/multichannel (mc)
5. Recording equipment
    a. AKG C417L Microphone (AKGC417L),
    b. 3M Littmann Classic II SE Stethoscope (LittC2SE),
    c. 3M Litmmann 3200 Electronic Stethoscope (Litt3200),
    d. WelchAllyn Meditron Master Elite Electronic Stethoscope (Meditron)



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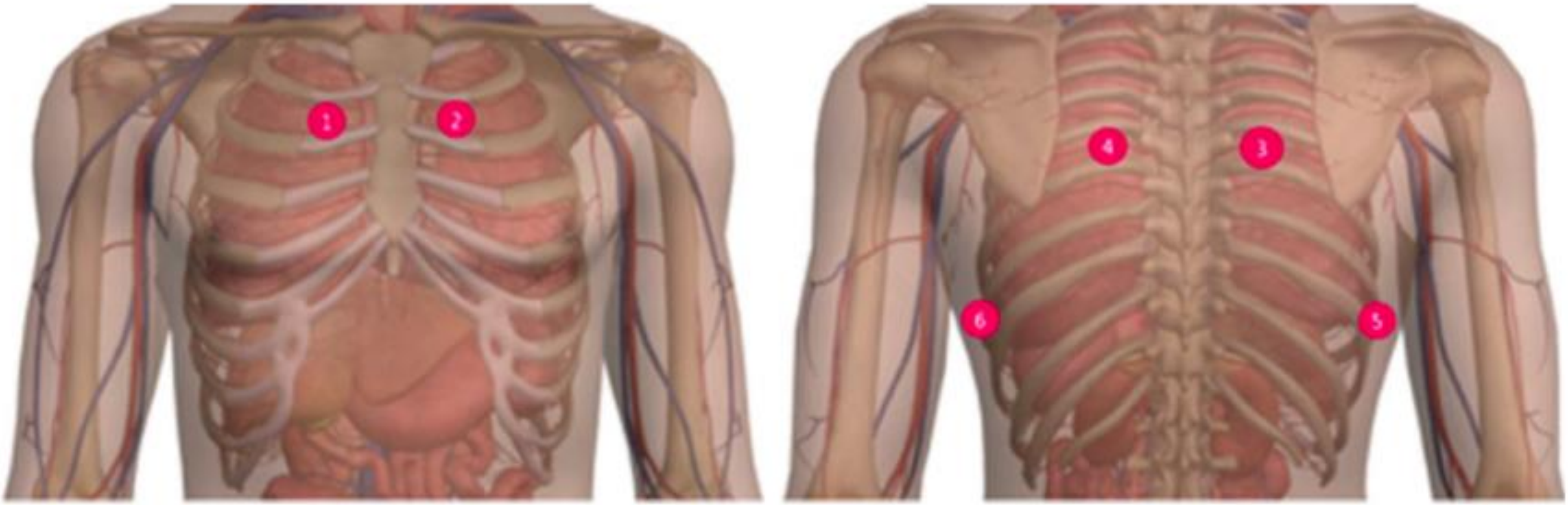

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The annotation text files have four columns:
- Beginning of respiratory cycle(s)
- End of respiratory cycle(s)
- Presence/absence of crackles (presence=1, absence=0)
- Presence/absence of wheezes (presence=1, absence=0)

101_1b1_Al_sc_Meditron.txt

```
0.036	0.579	0	0
0.579	2.45	0	0
2.45	3.893	0	0
3.893	5.793	0	0
5.793	7.521	0	0
7.521	9.279	0	0
9.279	11.15	0	0
11.15	13.036	0	0
13.036	14.721	0	0
14.721	16.707	0	0
16.707	18.507	0	0
18.507	19.964	0	0
```

101	URTI
102	Healthy
103	Asthma
104	COPD
105	URTI
106	COPD
107	COPD
108	LRTI
109	COPD
110	COPD

The abbreviations used in the diagnosis file are:
- COPD: Chronic Obstructive Pulmonary Disease
- LRTI: Lower Respiratory Tract Infection
- URTI: Upper Respiratory Tract Infection

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Inspiration

- Build a model to classify respiratory diseases.
- Build a model to detect if a recording contains crackles, wheezes or both.
- Annotation is a time consuming process. Create a model to automatically annotate respiratory sound recordings.
- Deploy your model as a Tensorflow.js web app so it can be accessed from anywhere in the world.
- Bioelectronics - Can you build your own digital stethoscope using an Arduino? If you are an aspiring inventor, this video will give you some valuable practical advice: https://www.youtube.com/watch?v=jo1cQ-ga2MI

Citation

Paper: A Respiratory Sound Database for the Development of Automated Classification

Rocha BM, Filos D, Mendes L, Vogiatzis I, Perantoni E, Kaimakamis E, Natsiavas P, Oliveira A, Jácome C, Marques A, Paiva RP (2018) In Precision Medicine Powered by pHealth and Connected Health (pp. 51-55). Springer, Singapore.

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- http://bhichallenge.med.auth.gr/

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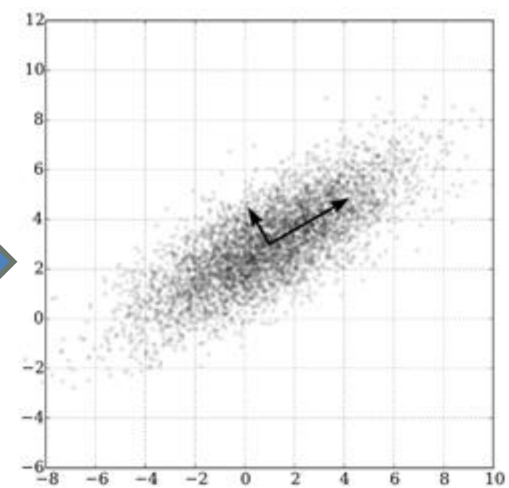
Acquisition

Manipulation

PYTHON DATA SCIENCE FRAMEWORK

NUMPY
PANDAS
MATPLOTLIB

Analysis



Lung Sound Recognition Algorithm Based on VGGish-BiGRU

LUKUI SHI[1,2], KANG DU[1], CHAOZONG ZHANG[3], HONGQI MA[1], AND WENJIE YAN[1,2]
[1]School of Artificial Intelligence, Hebei University of Technology, Tianjin 300401, China
[2]Key Laboratory of Big Data Computing of Hebei, Tianjin 300401, China
[3]Hebei Institute of Scientific and Technical Information, Shijiazhuang 050000, China

Corresponding author: Wenjie Yan (wenjieyanhit@163.com)

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ABSTRACT Pulmonary breathing sound plays a key role in the prevention and diagnosis of the lung diseases. Its correlation with pathology and physiology has become an important research topic in the pulmonary acoustics and the clinical medicine. However, it is difficult to fully describe lung sound information with the traditional features because lung sounds are complex and nonstationary signals. And the traditional convolutional neural network cannot also extract the temporal features of the lung sounds. To solve the problem, a lung sound recognition algorithm based on VGGish-BiGRU is proposed on the basis of transfer learning, which combines VGGish network with the bidirectional gated recurrent unit neural network (BiGRU). In the proposed algorithm, VGGish network is pretrained using audio set, and the parameters are transferred to VGGish network layer of the target network. The temporal features of the lung sounds are extracted through retraining BiGRU network with the lung sound data. During retraining BiGRU network, the parameters in VGGish layers are frozen, and the parameters of BiGRU network are fine-tuned. The experimental results show that the proposed algorithm effectively improves the recognition accuracy of the lung sounds in contrast with the state-of-the-art algorithms, especially the recognition accuracy of asthma.

B. PREPROCESSING OF THE LUNG SOUNDS

During the process of detecting the lung sounds, it is unavoidable to mix the low frequency noise such as noise of the collecting devices, friction sound of the internal organs of the human body and so on. And the frequency range is more concentrated. It can be considered that there are no lung sound signals under 100Hz since the frequency band of the lung sound signals is 100HZ to 2000Hz. Therefore, the low frequency noise under100Hz can be removed by high-pass filters. At the same time, the lung sounds also mix a lot of the heart sounds besides the low frequency noise. The frequency band of the heart sounds in the lung sounds is 5HZ to 600Hz, which highly coincides with the low frequency part of the lung sounds. It is difficult to remove the interference of the heart sounds under without damaging the lung sounds by simple filtering. To remove the noise of the lung sounds, a hybrid de-noising technique is used. At first, the low frequency noise is deleted by a fourth-order Butterworth high-pass filter [30]. Then the heart sounds are removed by the wavelet threshold method.

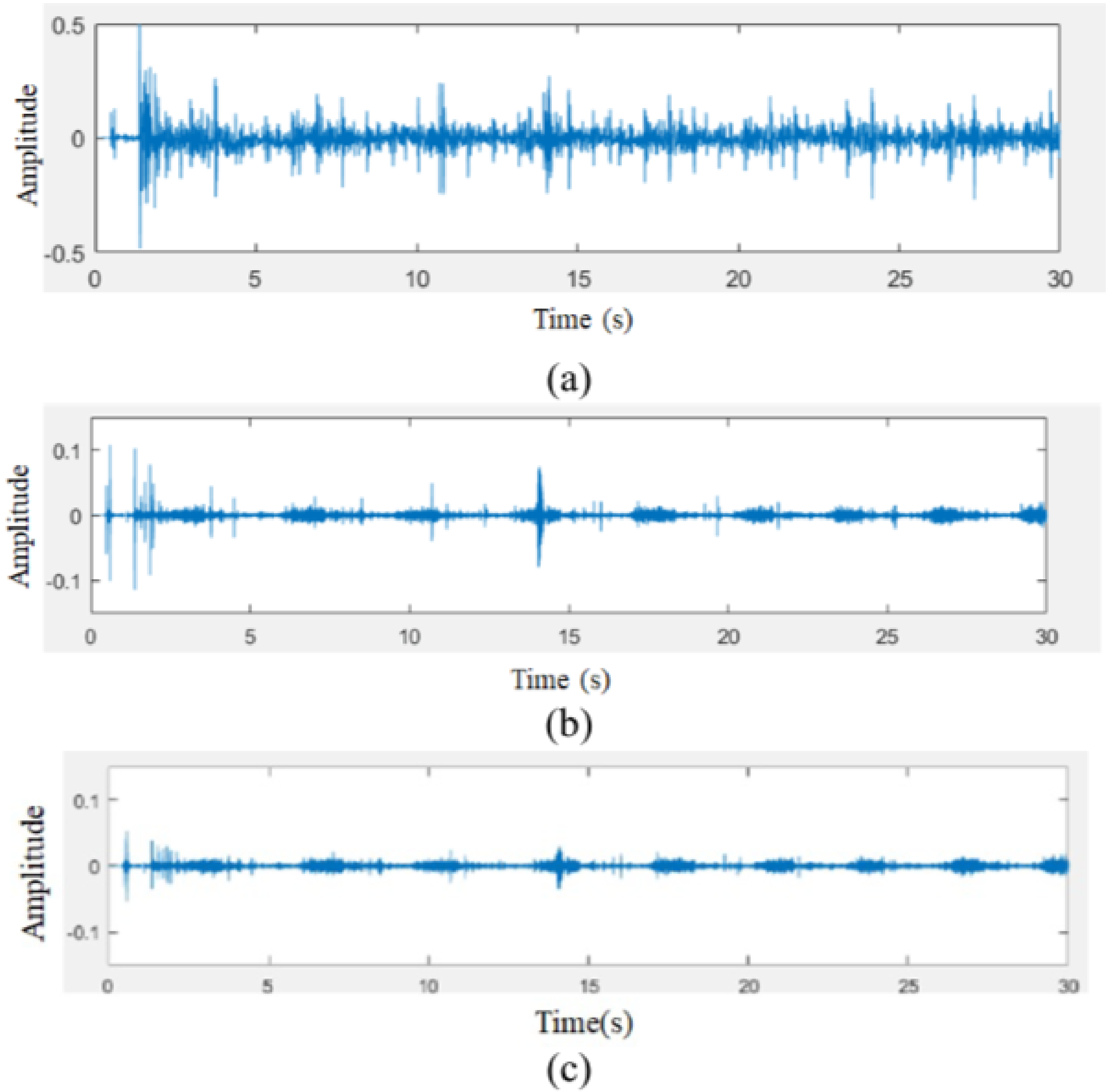

FIGURE 2. Comparison of the lung sound signals before and after Denoising (a) Original lung sound signal (b) The lung sound signal after high-pass filtering (c) The lung sound signal removed the heart sounds.

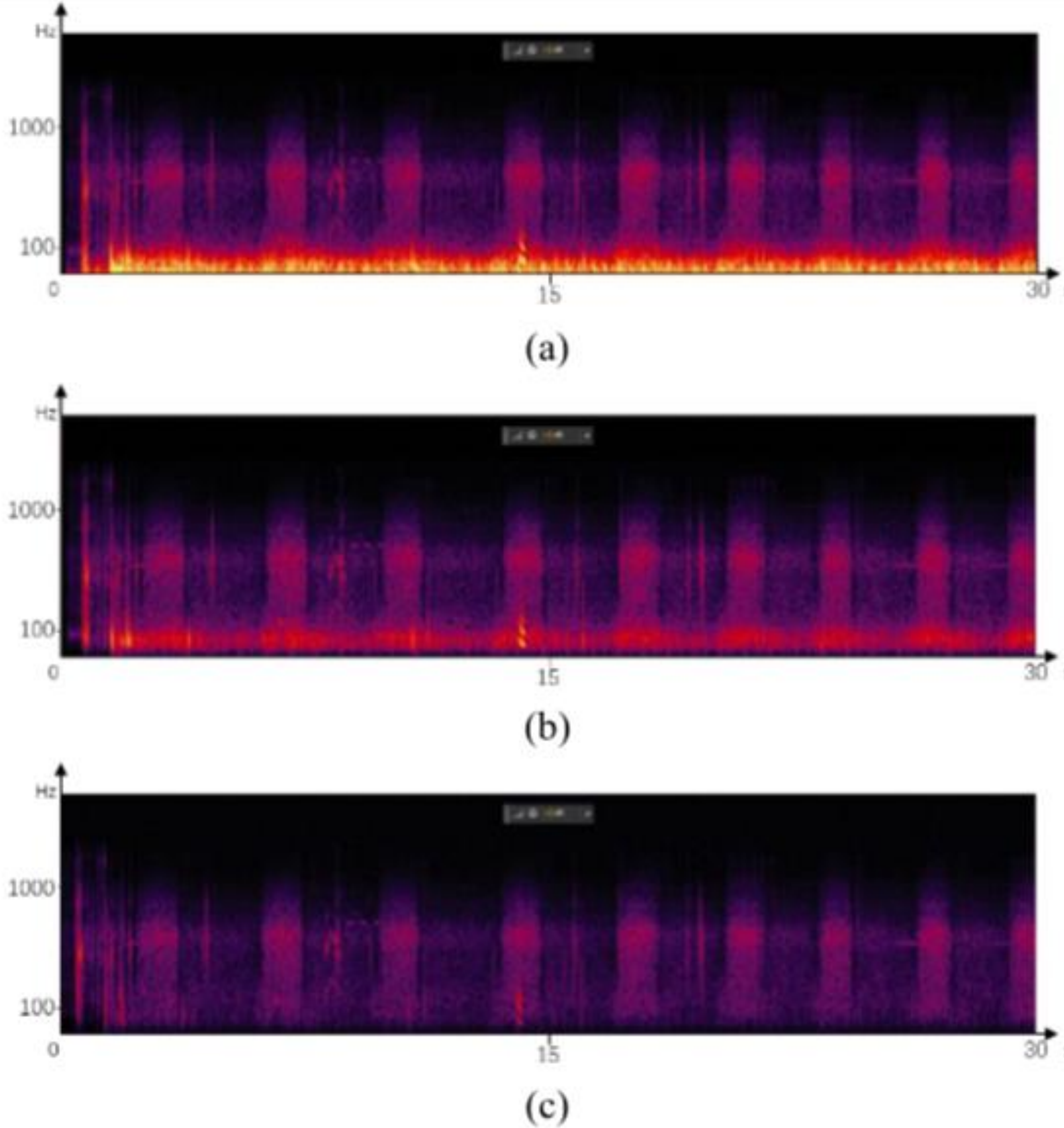

FIGURE 3. Changes in the spectrogram of the lung sound signals (a) The spectrogram of the original lung sound signal (b) The spectrogram of the lung sound signal by high-pass filtering (c) The spectrogram of the lung sound after deleting the heart sounds.