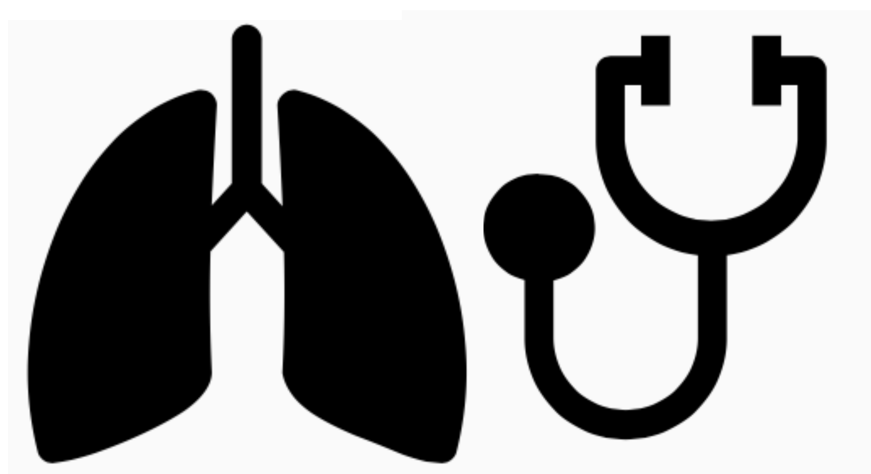
Respiratory Sound Identification using Convolutional Neural Networks

Vinita Shivakumar

Introduction

- Respiratory diseases such as asthma, chronic are amongst the leading causes of death in the world[1].
- Accurate lung auscultation is extremely important[2].
- Significant interest in analysis of lung sounds[3].
- Common adventitious respiratory sounds include[4]:
  - Wheezes: >400 Hz, ~100 ms duration
  - Crackles: discontinuous, 100-2000 Hz, ~20 ms



Dataset

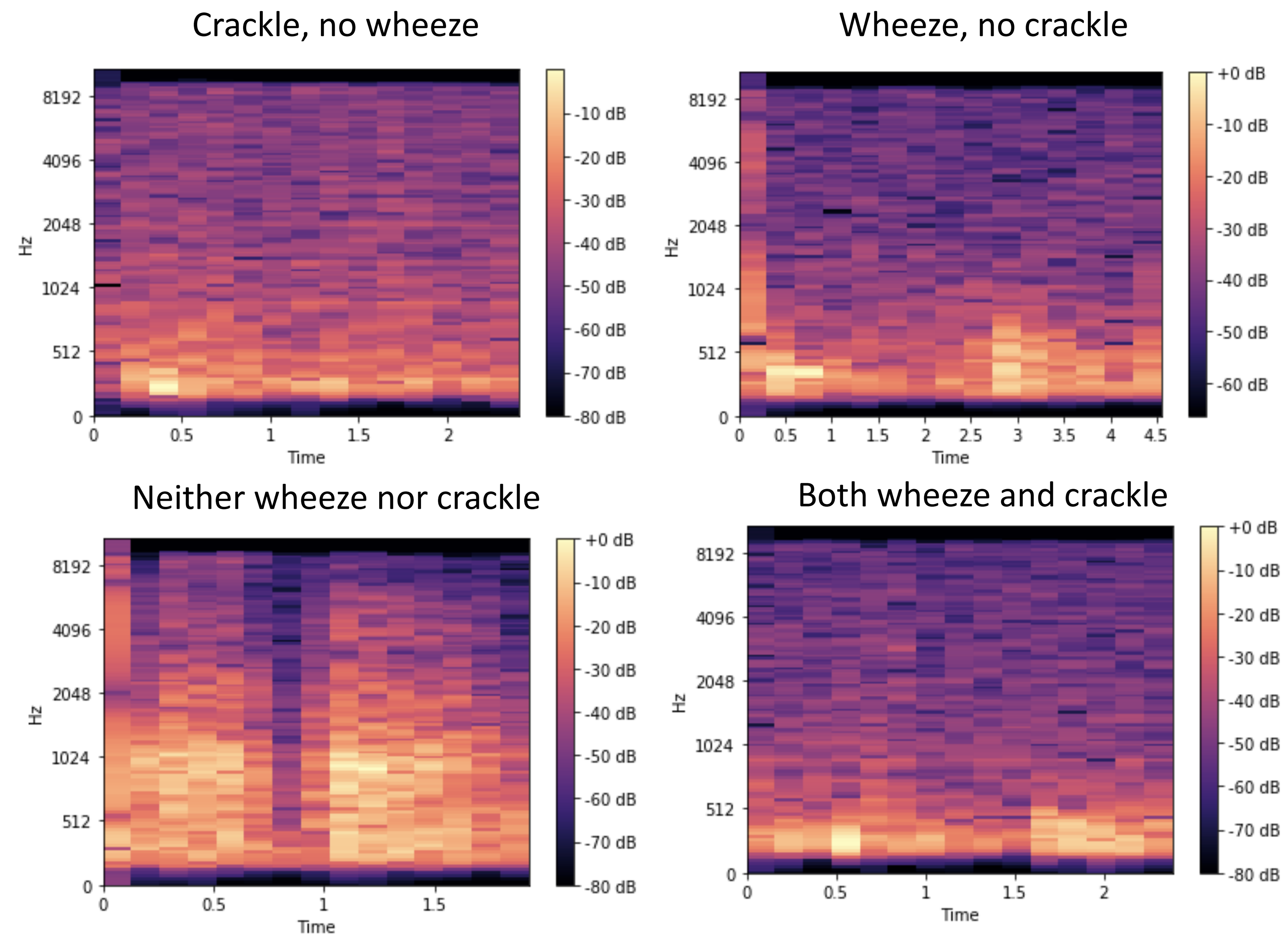
- First publicly available respiratory sounds database from ICBHI 2017 Competition[4,5].
- Collected from 2 sites over several years with different equipment, settings and chest locations: 6898 respiratory cycles in 920 audio files from 126 patients annotated with wheezes and/or crackles
- Annotation file contains beginning and end of respiratory cycle, presence of wheeze, and of crackle.
- 1864 crackles, 886 wheezes, 506 both.

For example:
- 112_1p1_Ll_sc_Litt3200.txt
- Patient ID 112
- Recording index 1p1
- Location Lateral left
- Single channel acquisition mode
- Recording equipment 3M Littman 3200 Electronic Stethoscope

0	4.3188	0	0
4.3188	7.6336	0	0
7.6336	11.015	0	0
11.015	14.557	0	1
14.557	17.446	0	1
17.446	20.078	0	1
20.078	22.967	0	0
22.967	25.647	0	1
25.647	28.214	0	1
28.214	29.36	0	0

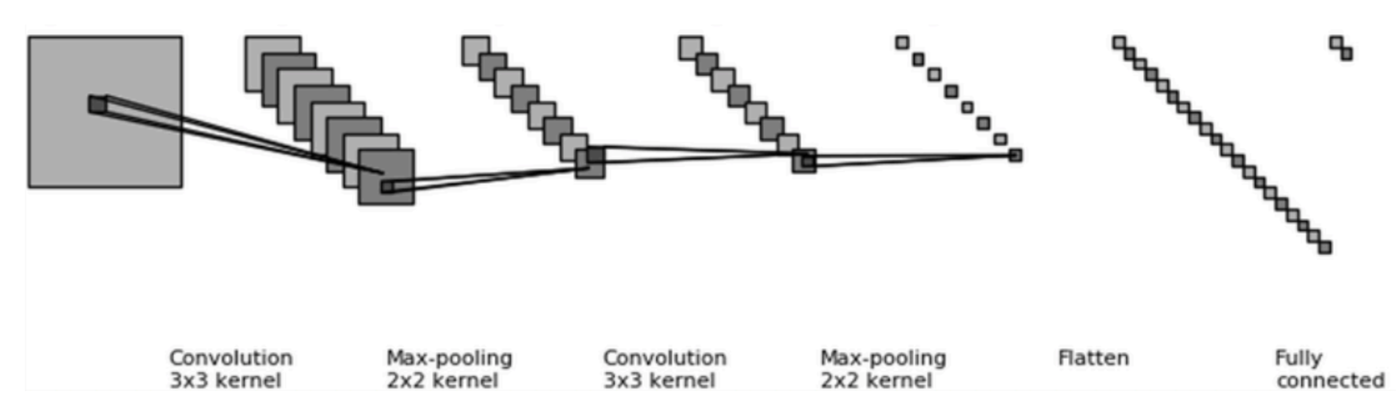
Methods

1. Raw Data Processing
- Splice audio files by respiratory cycle
- Process: resample, band filter 120-1800
- Convert to Mel Spectrogram

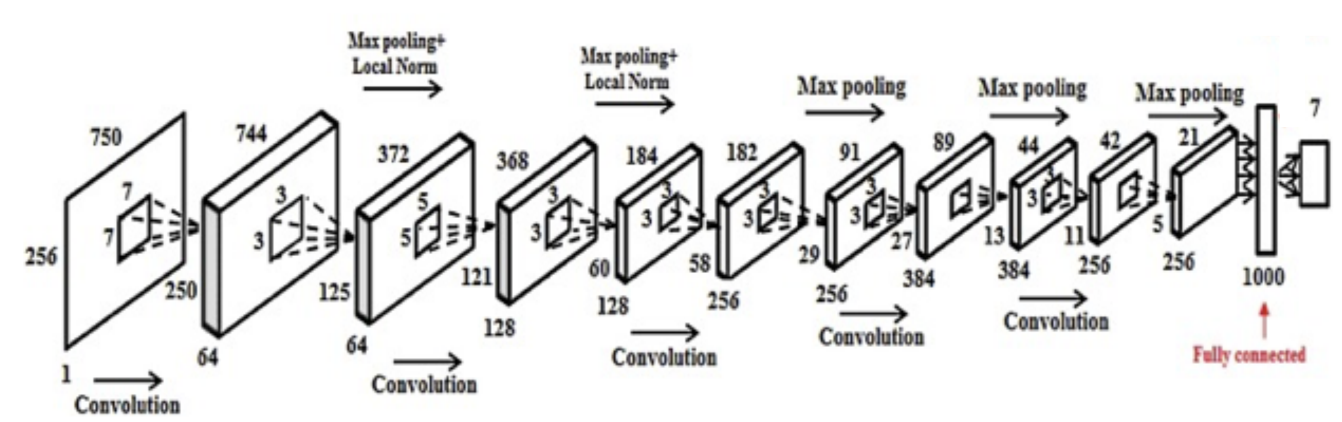


2. Convolutional Neural Networks

From 2017 paper[6], input (128, 16, 1), output 1



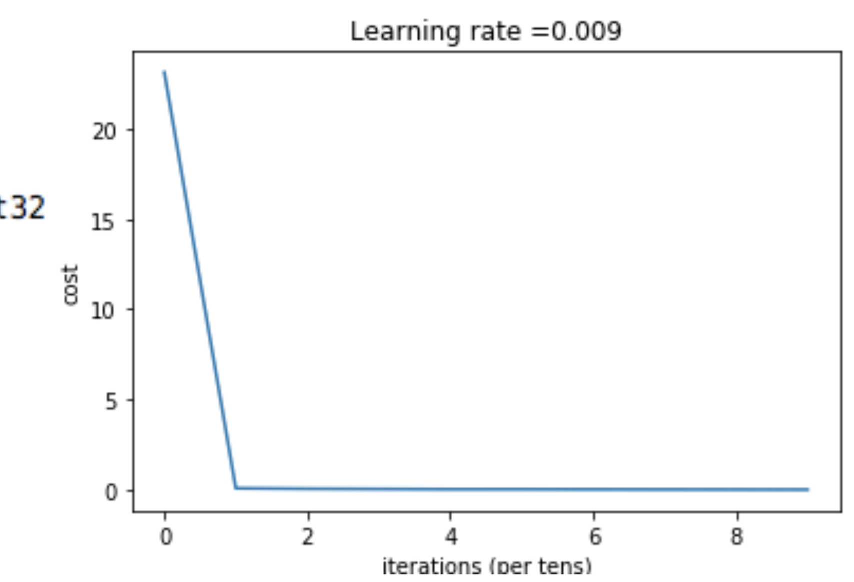
From 2018 paper[7], input (750, 256, 1), output 1



Results

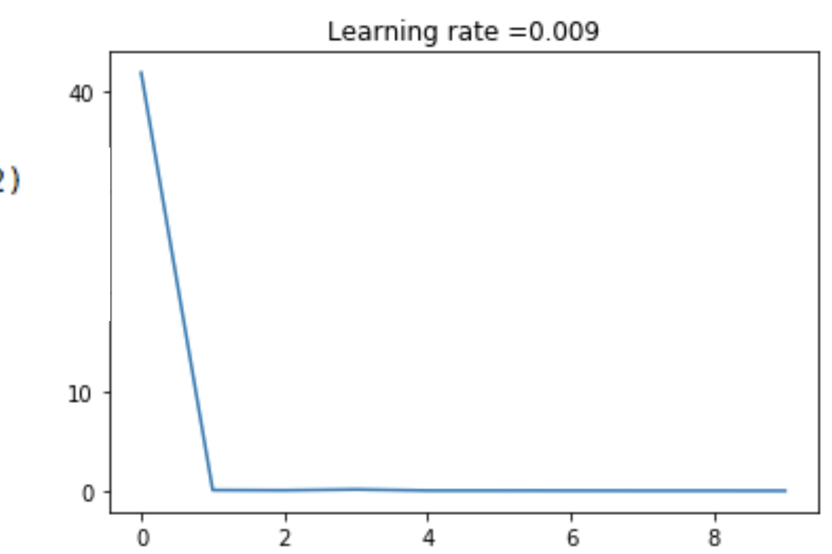
1. 2017 Model, wheezes and crackles together

```
Tensor("Mean_1:0", shape=(), dtype=float32
Train Accuracy: 0.4869523
Test Accuracy: 0.5
<Figure size 432x288 with 0 Axes>
```



2. 2017 Model, wheezes and crackles separate

```
Tensor("Mean_1:0", shape=(), dtype=float32)
Train Accuracy: 1.0
Test Accuracy: 1.0
<Figure size 432x288 with 0 Axes>
```



Discussion

- Compared to the 40% accuracy achieved by Support Vector Machines[8], CNN achieved higher accuracy.
- As expected, sounds of different frequency and different lengths need to be evaluated in separate models for optimal performance.
- Further steps include acquiring more data and hyperparameter tuning. Deeper network will be explored if bias problem is encountered again.

References

1. Forum of International Respiratory Societies. The Global Impact of Respiratory Disease – second edition. Sheffield, European Respiratory Society, 2017.
2. H Pasterkamp, SS Kraman, G Wodicika. “Respiratory sounds”, AJRCCM 156, 974-987, 1997.
3. R Palaniappan, K Sundaraj, NU Ahamed. “Machine learning in lung sound analysis: a systematic review”, Biocybern Biomed Eng 33(3), 129-135, 2013.
4. BM Rocha, D Filos, L Mendes, et al. “An open access database for the evaluation of respiratory sound classification algorithms,” Physiol Meas 40(3), 2019.
5. BM Rocha, D Filos, L Mendes, et al. “A Respiratory Sound Database for the Development of Automated Classification,” Precision Medicine Powered by Health and Connected Health, 33–37, 2018.
6. M. Aykanat, O. Kilic, B. Kurt, S. Saryal. “Classification of lung sounds using convolutional neural networks,” Eurasip Journal on Image and Video Processing, vol. 65, 2017.
7. D. Bardou, K. Zhang, S.M. Ahmad. “Lung sounds classification using convolutional neural networks,” Artificial Intelligence in Medicine, vol. 88, pp. 58-69, 2018.
8. G Serbes, S Ulukaya, YP Kahya. “An Automated Lung Sound Preprocessing and Classification System Based On Spectral Analysis Methods,” PMPHCH, 66, 45-49, 2018.