Classification of lung disorders based on lung sounds using deep learning

Reshma P Joy¹, Nishi Shahnaj Haider²

¹PG Student, Department of Biomedical Engineering, India
²Faculty of Biomedical Instrumentation, Department of Biomedical Engineering, India

E-mail: reshmap@karunya.edu.in, nishishahnaj@karunya.edu

ABSTRACT

Treatment of lung sicknesses, that are the 0.33 maximum not unusual place reason of demise within the world, is of high-quality significance within the clinical field. Many research the use of lung sounds recorded with stethoscope had been carried out within side the literature so as to diagnose the lung sicknesses with synthetic intelligence-well suited gadgets and to help the professionals of their diagnosis [5]. Lung sounds carry applicable records associated to pulmonary problems, and to assess sufferers with pulmonary conditions, the medical doctor or the medical doctor makes use of the conventional auscultation method. However, this method suffers from limitations. For example, if the medical doctor is not properly trained, this will result in a incorrect diagnosis. Moreover, lung sounds are non-stationary, complicating the duties of analysis, popularity, and distinction. This is why growing computerized popularity structures can assist to address those limitations [1]. Classification of lung sounds on the earliest may be very important to customize their treatment. In this project, the lung problems are categorized primarily based totally on the time, frequency in addition to photograph capabilities extracted from auscultatory datasets and categorized the use of deep gaining knowledge of method. The set of rules used is a Convolutional Neural Network the use of Mel Frequency Cepstral Coefficient feature extraction.

Keywords- Convolutional Neural Network (CNN), Mel Frequency Cepstral Coefficient (MFCC)

1. INTRODUCTION

Respiratory sound (RS) is appeared one of the maximum good sized bio alerts used to diagnose sure respiration abnormalities. It is hooked up that breath sounds are created within the larger airlines because of vibrations which are generated because of air speed and turbulence. RSs are recognized to be relatively non-desk bound and non-linear because of versions within side the airflow price and airflow volumes in the course of the respiration cycle. The non-linearity of the RS stems especially from the complicated turbulent flow dynamics and its structural interplay with the bigger airway walls. RSs detected from the chest wall and mouth can be categorized as ordinary and adventitious sounds. Owing to the presence of adventitious (bizarre) sounds, such alerts deliver precious records relating the underlying malfunctioning of the pulmonary system. On the opposite
hand, ordinary sounds consist of the ones generated via way of means of healthful lungs and airlines thru ordinary spontaneous breathing. The approach used for type must keep in mind all the homes of RSs. Furthermore, it must be strong because of the large inter-situation variability associated with gender, age, weight, physiology, and recording conditions, in addition to sizable intra-situation variations associated to the evolution nation of pathology [3]. In cutting-edge society, elements such as air pollution, unbalanced diets, immoderate stress, and bizarre sleep styles have ended in greater human beings stricken by respiration system illnesses. According to latest Department of Health statistics, lung- and respiration-associated illnesses ranked fourth and 7th the various pinnacle 10 leading reasons of death. On average, one man or woman dies from this sort of illnesses each hour [6].

Fig 1.1 Lung sound classification

Lung sounds may be divided more or less into normal and extraordinary sounds, as proven in Figure 1.1. Normal breath sounds may be divided into bronchial, vesicular-bronchial, vesicular, and tracheal sounds, while extraordinary breath sounds may be divided into crackles, rhonchi, and wheezes. Patients with lung sickness have extraordinary breath sounds, so extraordinary breath sounds are crucial aspect within side the analysis of lung sicknesses. Different lung sicknesses purpose exceptional lung sounds [6].

1.1 RESPIRATION TEST

a) Spirometry: Simple lung test. The doctor measures how much air goes in and out of lungs. Spirometry test can identify the amount of air the patient can hold.

b) Challenge test: This test is done by breathing a spray of drug meth choline, which irritate the airway and make them narrow and this test is done until the wheeze sound is heard. The challenge test is done specially for asthma patient.

c) Peak flow measurement: Uses a plastic device to see how much air can be blown out.
2. METHODOLOGY

2.1 LUNG SOUND DATABASE

In our experiment, we used the ICBHI dataset, which become constructed within side the context of a venture on breathing information evaluation prepared along with the 2017 Int. Conf. on Biomedical Health Informatics (ICBHI). The audio samples of breath information ICHBI venture database have been amassed through laboratories in special countries, inclusive of a complete of five. Five hours of records, inclusive of 6898 breathing cycles, of which 1864 contained cracks, 886 contained wheezes, and 506 contained both cracks and wheezes. These samples have been from 126 subjects. The ICBHI provides the beginning role of every breathing cycle in every breathing sound frequency, wherein the audio of every respiratory cycle is marked as normal, crackle, wheeze, or both [7].

2.2 DATA PREPROCESSING

Based on our model, we also propose a novel data preprocessing method to deal with the uniqueness of ICBHI data. The MFCC feature of audio is extracted as the input of the model. MFCC is the abbreviation of Mel frequency cepstrum coefficient. It is based on the auditory characteristics of human ears, and it has a nonlinear relationship with Hz frequency. And Mel frequency cepstrum coefficient (MFCC) is the frequency spectrum characteristics calculated by using the relationship between them. Because the length of each cycle of ICBHI data is not equal and there is a certain duration of respiratory cycle, MFCC features extracted by the same window length and frame shift have different dimensions. In the experiment, the feature vector extracted from each breathing cycle audio is (x, 20) dimension, where x depends on the duration of each breathing cycle audio. In order to avoid different dimensions of input vectors, we flatten the extracted features into one dimension, and then fill the data with 0 to a custom length. We fill each cycle data to 20000 sample points. Before inputting the model, reshape the data into the shape required by the first layer network [7].

2.3 CNN CLASSIFICATION

Convolutional neural community have become a enormous fashion in device learning, and it had much achievement in speech recognition, laptop vision, and lots of different fields. In this work, we explored the energy of the CNN within side the category of lung sounds [1]. In addition, convolutional neural community (CNN) also can be utilized in audio processing. Convolutional neural community (CNN) is a type of feed ahead neural community. Its synthetic neurons reply to a part of the encircling units in the coverage. It is first used for picture processing, after which used for herbal language. The maximum crucial components of CNN are convolution layer and pool layer. There is a convolution kernel within side the convolution layer, which is calculated with the aid of using sliding home windows one after the other at the top enter layer. Each parameter within side the convolution kernel is equal to the burden parameter of the intensity neural community, and is hooked up with the corresponding nearby pixels. Multiply the sum of the convolution kernel parameters with the corresponding nearby pixel values, after which upload them to get the convolution layer result [7].

Accuracy (acc) is selected as the usual of version robustness.
Where \( tp \) = true positive
\( tn \) = true negative
\( fp \) = false positive
\( fn \) = false negative

3. EXPERIMENTAL RESULTS

Figure 3.1 describes the ROC curve. A Receiver Operating Characteristic (ROC) Curve is a way to compare diagnostic tests. It is a plot of the true positive rate against the false-positive rate. A ROC plot shows the relationship between sensitivity and specificity.
Fig 3.2 Confusion Matrix

Figure 3.2 describes the confusion matrix. A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.

4. DISCUSSION

Table 4.1 Parameters used in the project

| LAYERS                  | Conv1D, Flatten layer, Activation layer, Max Pooling layer, Dropout |
|-------------------------|---------------------------------------------------------------------|
| PREPROCESSING STEPS     | Deleting, Splitting, and Formatting new data                        |
| FEATURES LINKED         | Auscultatory and Image Features using MFCC                          |
| EPOCH                   | 70                                                                  |
| BATCH SIZE              | 60                                                                  |
| ACTIVATION FUNCTION     | ReLu                                                                |
| OPTIMIZER               | Adam                                                                |
| INPUT SIZE              | (193,193,1)                                                         |
| ACCURACY                | 95%                                                                 |

The table 4.1 describes the parameters used in the project that includes layers of convolutional neural network, preprocessing steps for getting an efficient result, feature extraction, epoch used is 70 that is the number complete pass through the dataset, batch size is 60 that is the number of samples processed before the model is updated. The activation function used is ReLu. The input size represents the height, width and pixel size. The testing accuracy obtained is 95%.

5. CONCLUSION

Thus from the above study, it's miles concluded that lung sounds being non-desk bound in nature it might be tough to investigate and classify the usage of the conventional technique.
Prevention and early detection are important steps in dealing with the respiratory disease. The disadvantage of this technique are that medical doctors require enjoy and ear acuity to offer a greater correct analysis to the patient. It is in particular tough because a few sounds are more difficult to discover due to the obstacles of the human ear. Hence right here the time and frequency functions from lung sounds in addition to the photograph functions are extracted from the lung sounds the usage of MFCC and fed to the CNN version and the lung issues are classified effectively primarily based totally on crackle and wheeze lung sound and received an accuracy of 95%. This early prediction and type might assist the medical doctors from late analysis and remedy might be finished faster.

6. FUTURE SCOPE

By further improving the model with the large number of datasets, varying the input and output parameters, we can predict the pulmonary disorder more efficiently. Early predictions may help the doctors to diagnose the severity of the pulmonary disorder and personalize their treatments.

REFERENCE

1. Demir, Fatih, Abdulkadir Sengur, and Varun Bajaj. "Convolutional neural networks based efficient approach for classification of lung diseases." Health information science and systems 8, no. 1 (2020): 1-8.
2. Palaniappan, Rajkumar, Kenneth Sundararaj, and Sebastian Sundararaj. "A comparative study of the svm and k-nn machine learning algorithms for the diagnosis of respiratory pathologies using pulmonary acoustic signals." BMC bioinformatics 15, no. 1 (2014): 1-8.
3. Oweis, Rami J., Enas W. Abdulhay, Amer Khayal, and Areen Awad. "An alternative respiratory sounds classification system utilizing artificial neural networks." Biomed J 38, no. 153 (2015): e61.
4. Bardou, Dalal, Kun Zhang, and Sayed Mohammad Ahmad. "Lung sounds classification using convolutional neural networks." Artificial intelligence in medicine 88 (2018): 58-69.
5. Tocchetto, Marco A., Alexandre S. Bazanella, L. Guimaraes, J. L. Fragoso, and A. J. I. P. V. Parraga. "An embedded classifier of lung sounds based on the wavelet packet transform and ANN." IFAC Proceedings Volumes 47, no. 3 (2014): 2975-2980.
6. Chen, Chin-Hsing, Wen-Tzeng Huang, Tan-Hsu Tan, Cheng-Chun Chang, and Yuan-Jen Chang. "Using k-nearest neighbor classification to diagnose abnormal lung sounds." Sensors 15, no. 6 (2015): 13132-13158.
7. Li, Chenghan, Huaichang Du, and Bing Zhu. Classification of lung sounds using CNN-Attention. No. 4356. EasyChair, 2020.
8. Altan, Gokhan, Yakup Kutlu, and Novruz Allahverdi. "Deep Learning on Computerized Analysis of Chronic Obstructive Pulmonary Disease." IEEE Journal of Biomedical and Health Informatics 24, no. 5 (2019): 1344-1350.
9. Lin, Bor-Shing, Huey-Dong Wu, and Sao-Jie Chen. "Automatic wheezing detection based on signal processing of spectrogram and back-propagation neural network." Journal of healthcare engineering 6 (2015).
10. Zhang, Kexin, Xuefeng Wang, Fangfang Han, and Hong Zhao. "The detection of crackles based on mathematical morphology in spectrogram analysis." Technology and Health Care 23, no. s2 (2015): S489-S494.
11. Mendes, Luis, I. M. Vogiatzis, Eleni Perantoni, Evangelos Kaimakamis, Ioanna Chouvarda, Nicos Maglaveras, Venetia Tsara et al. "Detection of wheezes using their signature in the spectrogram space." Society (EMBC), pp. 5581-5584. IEEE Journal of Biomedical and Health Informatics, (2015).

12. Demir, Fatih, Abdulkadir Sengur, and Varun Bajaj. "Convolutional neural networks based efficient approach for classification of lung diseases." Health Information Science and Systems 8, no. 1 (2020): 4.

13. Chambres, Gaëtan, Pierre Hanna, and Myriam Desainte-Catherine. "Automatic detection of patient with respiratory diseases using lung sound analysis.", pp. 1-6 IEEE Journal of Biomedical and Health Informatics, (2018).

14. Ulukaya, Sezer, Gorkem Serbes, and Yasemin P. Kahya. "Overcomplete discrete wavelet transform based respiratory sound discrimination with feature and decision level fusion." Biomedical Signal Processing and Control 38 (2017): 322-336.

15. Lozano, Manuel, José Antonio Fiz, and Raimon Jané. "Automatic differentiation of normal and continuous adventitious respiratory sounds using ensemble empirical mode decomposition and instantaneous frequency." IEEE journal of biomedical and health informatics 20, no. 2 (2015): 486-497.

16. Chamberlain, Daniel, Rahul Kodgule, Daniela Ganelin, Vivek Miglani, and Richard Ribón Fletcher. "Application of semi-supervised deep learning to lung sound analysis." IEEE journal of biomedical and health informatics 20, pp. (2016): 804-807.

17. Andrès, E., R. Gass, A. Charloux, C. Brandt, and A. Hentzler. "Respiratory sound analysis in the era of evidence-based medicine and the world of medicine 2.0." Journal of medicine and life 11, no. 2 (2018): 89.

18. Kulkarni, K. Ritwik, Abhijitsingh Gaonkar, V. Vijayarajan, and K. Manikandan. "Analysis of pulmonary disorder using deep learning." In IOP Conference Series Materials Science and Engineering, vol. 12, no. 1, pp. 263-277. 2017.

19. Hafezi, Maziar, Nasim Montazeri, Kaiyin Zhu, Hisham Alshaer, Azadeh Yadollahi, and Babak Taati. "Sleep apnea severity estimation from respiratory related movements using deep learning." In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1601-1604. IEEE, 2019.

20. Amiriparian, Shahin, Maurice Gerczuk, Sandra Ottl, Nicholas Cummins, Michael Freitag, Sergey Pugachevskiy, Alice Baird, and Björn W. Schuller. "Snore Sound Classification Using Image-Based Deep Spectrum Features." In INTERSPEECH, vol. 434, pp. 3512-3516. 2017.

21. Kandaswamy, A., C. Sathish Kumar, Rm Pl Ramanathan, S. Jayaraman, and N. Malmurugan. "Neural classification of lung sounds using wavelet coefficients." Computers in biology and medicine 34, no. 6 (2004): 523-537.

22. Loudon, Robert, and Raymond LH Murphy Jr. "Lung sounds." American Review of Respiratory Disease 130, no. 4 (1984): 663-673.

23. Shuvo, Samiul Based, Shams Nafisa Ali, Soham Irtiza Swapnil, Taufiq Hasan, and Mohammed Imamul Hassan Bhuivan. "A lightweight cnn model for detecting respiratory diseases from lung auscultation sounds using emd-cwt-based hybrid scalogram." arXiv preprint arXiv:2009.04402 (2020).
24. Li, Chenghan, Huaichang Du, and Bing Zhu. *Classification of Lung Sounds Using CNN-Attention*. No. 4356. EasyChair, 2020.

25. Deng, Muqing, Tingting Meng, Jiwen Cao, Shimin Wang, Jing Zhang, and Huijie Fan. "Heart sound classification based on improved MFCC features and convolutional recurrent neural networks." *Neural Networks* 130 (2020): 22-32.

26. Peng, Liying, Lanfen Lin, Hongjie Hu, Huali Li, Qingqing Chen, Xiaoli Ling, Dan Wang, Xianhua Han, Yutaro Iwamoto, and Yen-wei Chen. "Classification and quantification of emphysema using a multi-scale residual network." *IEEE journal of biomedical and health informatics* 23, no. 6 (2019): 2526-2536.

27. Humphries, Stephen M., Aleena M. Notary, Juan Pablo Centeno, Matthew J. Strand, James D. Crapo, Edwin K. Silverman, David A. Lynch, and Genetic Epidemiology of COPD (COPDGene) Investigators. "Deep learning enables automatic classification of emphysema pattern at CT." *Radiology* 294, no. 2 (2020): 434-444.