Electronic Stethoscope with Android Based Lung Sound Analyzer Using Convolutional Neural Network

Maria Victoria C. Padilla[1], Russell C. Allera, Jeremy James R. Javier[2], Janet J. Martinez[3],
Cedie M. Morcilla, Angela Marie C. Pedragoza
Technological University of the Philippines
Ayala Blvd. corner San Marcelino Sts., Ermita Manila, Philippines
[1]mariavictoria_padilla@tup.edu.ph
[2]jeremyjames.javier@tup.edu.ph
[3]janet.martinez@tup.edu.ph

***Abstract* – One of the concerns in the Philippines is the shortage of health professional, especially in the remote areas. Majority of Filipinos only rely on the public health center that has 4.6% doctors out of 66,000 in total. Adding up with this is the growing number of health cases in terms of respiratory ailments, with the combination of these problems, the proponents proposed to develop a device that will help professionals, both new and experienced, and health workers in rural area. This study aims to develop a device that will classify lung sounds using Machine Learning through Convolutional Neural Network. Specifically it aims to meet the following (1) to modify an acoustic stethoscope for the data gathering using electret microphone, (2) to determine a suitable filter for the pre-processing of the sound data sets, (3) to develop a machine learning algorithm in Python Language that can be used for feature extraction and for the training for each lung sound, (4) to develop an android based design for the user interface of the device and the connection of the model in Python to Android Studio. The recognition algorithm is a Convolutional Neural Network with the parameters of Zero Crossing Rate, Variance and Mel-Frequency Cepstral Coefficients. The output device is a mobile phone with easy-to-navigate user interface which enables the user to record the lung sound, playback the recorded audio and then the algorithm will analyze the patient's lung sound – whether it's normal, rales or wheeze then indicates the possible sickness per lung sound. The machine's results were tested and validated by a licensed professional in the field of medicine with a good accuracy of 255 out of 300 samples or 85%.**

***Index Terms* – Auscultation, Adventitious, Android, Convolutional Neural Network.**

I. INTRODUCTION

Respiratory sounds establish an important source of data for the trial of condition of the lungs, it is the basic segment of pulmonary ailment diagnosing and patient's monitoring. These sounds can be acquired through a procedure called lung auscultation. Lung auscultation is the initial step in the checking of the patient's wellbeing, it is simple and non-invasive. Respiratory sounds can be classified as normal, for healthy people, and abnormal lung sounds, for people with sickness. The main categories of these abnormal lung sounds are: wheeze and crackles, also called rales. Wheeze is heard with a high-pitch whistling noise during inhalation or exhalation caused by narrowing of airways blocking the air flowing through them. Its dominant frequency is usually over 600 Hz and more than 100 ms duration. Patients with wheeze can be diagnosed with asthma, COPD, bronchitis or pneumonia. On the other hand, crackles or rales are series of short, and explosive sounds and can be heard mostly during inspiration but can also be heard during expiration. It lasts shorter than 100 ms and characterized by frequency of 2000 Hz. When Rales is heard during breathing, it indicates that the lung's air sacs are filled with fluid. Rales can be caused by pneumonia, heart disease, pulmonary fibrosis or lung infections. Although, stethoscope, instrument used for auscultation, is still widely used tool today, the inevitable human error still occurs when conducting the auscultation test manually. As the time passes by, the booming of technology greatly helps in the field of medicine, and one of it is the enhancement of the classic stethoscope. The aim of this study is to develop a portable and automatic Lung Sound Analyzer with a modified acoustic stethoscope, for the hardware, that records the lung sound of the patient, and for software, apply the principle of filtering to reduce ambient noise and heart sound interference, and apply machine learning technology in training the data for the automation of the lung sound recognition.

II. METHODOLOGY

A. Hardware Development

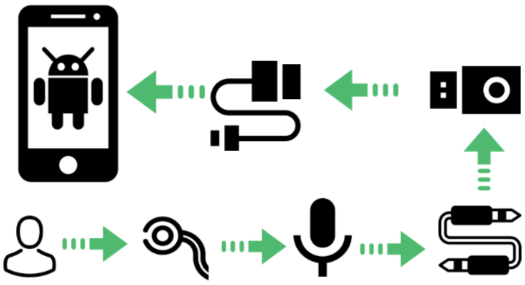

Fig. 1. Hardware Connection Diagram

In the hardware part, the proponents used an acoustic stethoscope specifically designed for lung sound auscultation and an electret microphone connected to 3.5mm audio jack to record the lung sound directly to the mobile device. For the compatibility of the jack, the proponents used a sound card and USB OTG for the additional connections.

B. Software Development

Major part of this study is composed of software development, from the pre-processing part, the training and recognition of the model, up to the design of the user interface of the device.

1) Pre-processing

The pre-processing of the sound is needed for the lessening of the environmental noise in the recorded lung sound. For this section, the proponents conducted the study for the suitable filter by using the test of hearing. And create a representation using the features extracted from the lung sound, before and after the filtering. The parameters used is the Zero Crossing Rate and the Spectral Energy. The Zero Crossing rate determines the rate at which the signal changes from positive to negative, this determines the number of the signal's frequency. The decrease in Zero Crossing Rate proves that the signal is filtered. Spectral Energy describes how the energy of the signal is distributed with frequency.

2) Training Algorithm

The set of programs needed in this part were done using Python Language and using the Wing IDE 6.0 as the platform. Wing IDE 6.0 was used for the data extraction of the lung sound and the training of the machine.

3) User Interface

Android Studio 3.2 was the platform used in the design of the android application, it is coded using Java Language for the Software Development Kit (SDK) and C++ for the Native Development Kit (NDK) provided by the Tensorflow Library.

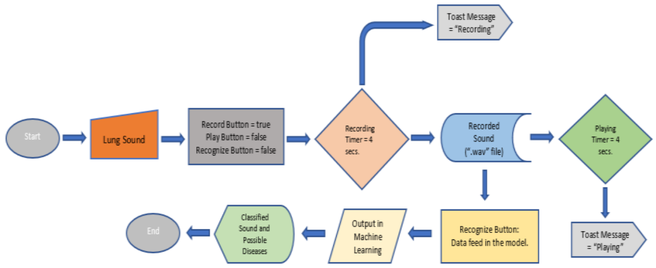

Fig. 2. Flowchart of Android Application

C. Data Gathering

The gathering of the data was done in clinic and school. It is gathered from people ages 5 years old and above. The modified stethoscope was used in gathering the lung sound then it is directly connected to device where the recording is happening. The gathered sound was classified by a professional before using it for the training. The data was divided into two, the training and the testing of the machine. The results of the classification of the device were checked and verified by Head Doctor of a Public Health Center in Las Pinas City.

III. RESULTS AND DISCUSSION

A. Filtering

Every sound file in our data is composed of recorded lungs sound with one cycle of respiratory breathing and has exact length of 4 seconds and sampled at 44100 Hz, the required sampling rate of wav and mp3 files. The study focuses on normal and the two major abnormal lung sound – Wheeze and Rales. These abnormal lungs sound is ranging from the 600 Hz to 2000 Hz.

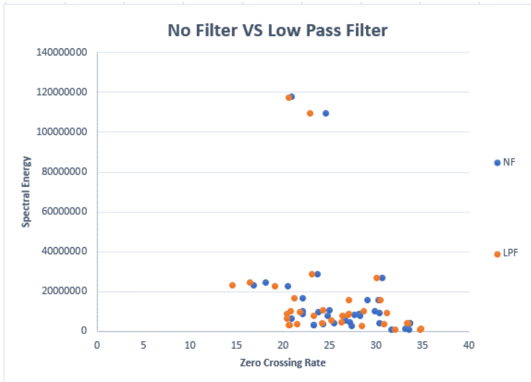

Fig. 3. Scattered Plot of Low Pass Filtering

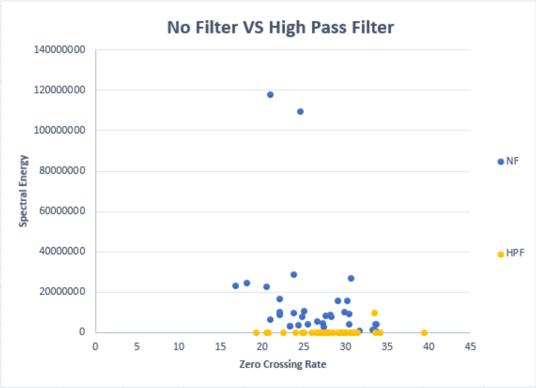

Fig. 4. Scattered Plot of High Pass Filtering

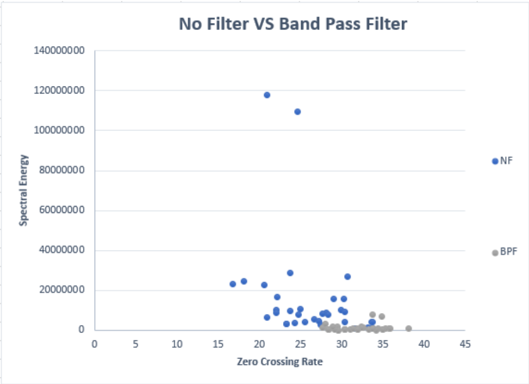

Fig. 5. Scattered Plot of Band Pass Filtering

Comparing the three scattered plots, it shows their differences in the compression of the Zero Crossing Rate. Except with the manual hearing test for whether the sound is enough filtered. he proponents made this representation to prove that graphically, Band Pass Filter is the suitable filter for the lung sound extraction. The compressed Zero Crossing Rate proves that the filtered sound sticks to the same rate of the its positive and negative cycle, cutting off the unwanted frequencies. For the Spectral Energy the limiting of frequency leads to the lessening of energy distribution. With the results, it is proven that Band Pass filter with the limit of 600Hz-2000Hz is suitable in the pre-processing part.

B. Feature Selection and Training Algorithm

In feature selection, the proponents consider the both time and frequency domain of the sound for it is important for the classification of the abnormal lung sounds. In the frequency domain, Mel Frequency Cepstral Coefficient (MFCC) is used. Variance and Zero Crossing Rate of the sound is for the time domain. Rales or Fine Crackles is more dependent on the time domain because of its short duration crackling nature while Wheeze has long-lasting snoring sound.

1) Variance

Variance is a time domain-based feature, it is defined as the measurement of the spread of a distribution, wherein in this study, this distribution is the amplitudes/time. Based on the results in Figure 6, Rales has more variance than wheeze and normal sound because of its explosive nature.

2) Zero Crossing Rate

Zero Crossing rate determines the rate at which the signal changes from positive to negative, this determines the number of the signal's frequency. In this feature, normal sounds are more varying in this feature and it is shown Figure 6.

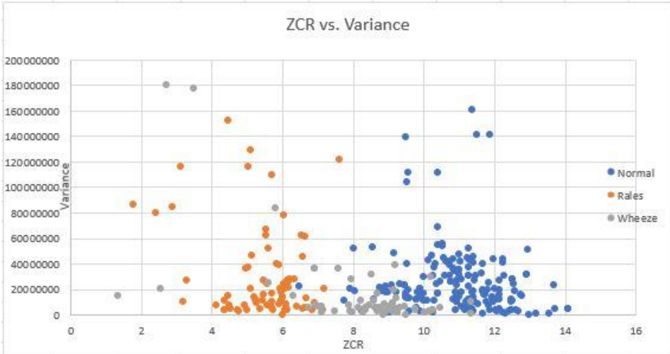

Fig. 6. Scatterplot of Zero Crossing Rate and Variance of Sounds

3) Mel Frequency Cepstral Coefficients

The MFCC technique for the extraction of feature is widely used in the both speech and music recognition. In simplest explanation, in Mel Frequency Cepstral Coefficient, the sound is converted to a spectrogram in form of an arrayed numbers. This spectrogram provides the spectral content in Hertz of the audio file. Applying the Mel-filterbank that converts the frequency into Mel-scale. This Mel-Scale is a scale of pitch that models it to what the human can hear rather than the actual values of Hertz. In this study, the proponents used the Tensorflow library wherein the MFCC algorithm is provided in simple form as a command available in there. The output in the command is an array of cepstral coefficients of the sound, this is the cepstral representation, it contains the information such as the rate of change at different spectrum band and it is called the Mel-frequency bins. MFCC is used for the determination of Wheezing Sound, in Figure 8, the intense horizontal line is the Wheeze sound.

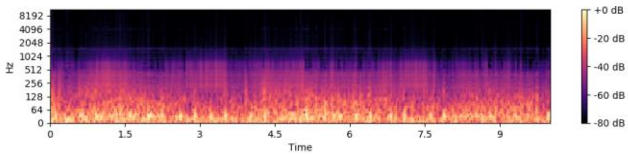

Fig. 7. Spectrogram of Normal Sound

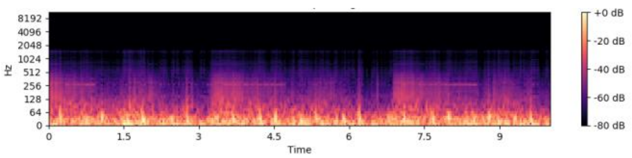

Fig. 8. Spectrogram of Wheezing Sound

Along with the Feature Extractors is the sequence classifier. In this study, the classifier used is the Convolutional Neural Network (CNN), it is most commonly applied for analyzation of visual imagery. CNN used a variation of multilayer perceptrons designed for the minimal processing. Using these feature extractors and the CNN classifier, the device accuracy is in 85%

C. User Interface Design

The user interface design in the device was coded in Java Language using the Android Studio platform. The UI is composed of buttons for recording, playback and recognition. There is a visualizer used for the representation of the audio waveform. It has and easy to navigate interface.

Fig. 8. Actual User Interface of the Mobile phone.

IV. CONCLUSION

In conclusion, the Automated Lung Sound Analyzer was able to provide a reliable result with the accuracy of 85% using the Convolutional Neural Network classifier and the extracted features such as the Variance, Zero Crossing Rate and Mel Frequency Cepstral Coefficients. The device has a friendly mobile user interface which enables the user to record the lung sound, playback the recorded audio and an algorithm that will determine the status of the patient's lung sound and indicates the possible sickness in the average process speed of 15 seconds. The possible sickness is all validated by a professional doctor, that still needed to be verified by doing further tests before stating the final diagnosis. This machine will be a good help as an aid for the patients in the remote areas that lacks doctors in doing the basic test such as the automation of auscultation, it is also a great help for the new medical practitioners who are a bit confused in the differentiating these lung sounds. The Automated Lung Sound Analyzer is also portable and can be installed in any android devices, and the hardware parts are all available in the market.

ACKNOWLEDGEMENTS

The researchers would like to thank the following persons from CAA-B Health Center, Las Pinas: Dr. Rea Dalida, Head Doctor, Marilyn A. Arandillo, RN in and all of the health workers. Capt. Filemon S. Villanueva, Baranggay captain of Brgy. Tonsuya, Malabon.

REFERENCES

Jennifer Robinson, MD, *Lung Sounds: What do they mean?* WebMD Medical Reference, 2018. Retrieved from: https://www.webmd.com/lung/lung-sounds#3.

Pourazad, M. T., et al. *Heart Sounds Separation From Lung Sounds Using Independent Component Analysis.* 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference. 2005

Khan, April. *Breath Sounds*. Retrieved from: https://www.healthline.com/health/breath-sounds

K.A.Unnikrishna Menon, Drishya, Dilraj Nadarajan. *Monitoring and Analysis of Lung sounds for the Diagnosis of Lung Abnormalities*. Amrita Center for Wireless Networks & Applications, 2014.

Gronnesby, Morten. *Automated Lung Sound Analysis.* Master Thesis in Computer Science, 2014.

Grønnesby, M. *Pulmonary crackle detection using signal processing and machine learning.* Capstone Project in Computer Science, University of Tromsø. 2015

Hadjileontiadis, Leontios J. *Lung Sounds: An Advanced Signal Processing Perspective.* Synthesis Lectures On Biomedical Engineering # 9, 2009.