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Smart Stethoscope

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Abstract—In this study, a device named smart stethoscope that uses digital sensor technology for sound capture, active acoustics for noise cancellation and artificial intelligence (AI) for diagnosis of heart and lung diseases is developed to help the health workers to make accurate diagnoses. Furthermore, the respiratory diseases are classified by using Deep Learning and Long Short-Term Memory (LSTM) techniques whereas the probability of these diseases are obtained.

Keywords — stethoscope, long short-term memory, deep learning, filters, amplifiers, heart and lung sounds, diagnosis.

I. INTRODUCTION

Acute lower respiratory infections such as pneumonia and other lung ailments kill nearly 1 million children each year worldwide, causing more deaths than HIV and malaria combined [1]. But fewer than 5 percent of people in the developing world have access to the X-ray imaging that's considered the gold standard for pneumonia diagnoses. For the sake of saving lives, in the countries with limited resources, the World Health Organization (WHO) recommends antibiotic treatment for all children with observed symptoms of shortness of breath, cough, and rapid breathing, with the result that half of the children who get treated for pneumonia don't really need them indeed. This approach puts unnecessary costs on communities, as well as contributing to the growing problem of antibiotic-resistant bacteria.

In this paper, we propose a technological solution: A device that uses digital sensor technology for sound capture, active acoustics for noise cancellation, with artificial intelligence (AI) which we call a smart stethoscope, to help the health workers to make accurate diagnoses. Invented in the early 1800s, the classical stethoscope has some limitations. For best results, the user should be in a quiet environment, as background noise can easily mask the subtle sounds coming from the lungs. The physician must be well trained in positioning the chest piece properly on the body and in interpreting the sounds, which can be rather difficult in some cases.

Sounds generated by organs in the body can cause a vibration in the stethoscope's chest piece, which acts as a resonator. This module has two sides with specific shapes a flat, disk like diaphragm and a hollow cup called a bell naturally oscillates with different frequency ranges that are used for different diagnostic tasks. The acoustic vibration is transmitted via an air filled tube that is connected to the earpieces thus, relaying the sounds of the patient's body to the listener. Although the stethoscope is designed to maximize sound collection and delivery to the user, sound levels are usually quite low. Contemporary electronic stethoscopes convert the sounds into electrical signals by microphones, that are processed in the device for amplification. The double-sided chest piec substituted with one gadget that transduces the acoustic signals to voltages/currents with minimal distortion or noise effects. Users can toggle between "diaphragm" and "bell" modes, and can also adjust the sounds.

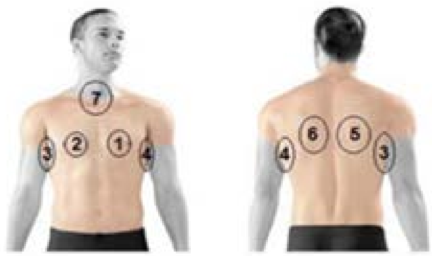

Fig. 1. Body areas where lung and heart sounds are taken.

The proposed device amplifies sound waves from the Anterior Left (1), Anterior Right (2), Posterior Right (5), Posterior Left (6) , Lateral Right (3), Lateral Left (4), and Trachea regions (7) and from the heart, which are obtained from patients as well as from the healthy people, as shown in Fig. 1.

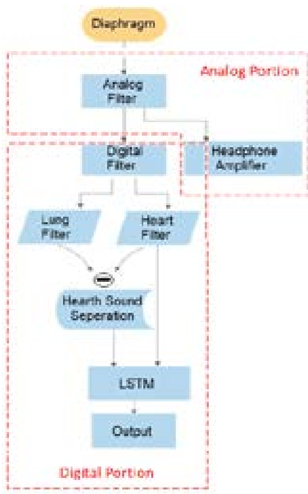

Fig.2. Block diagram of the system.

After amplifying and digitizing, the signal is recorded and with the "Deep Learning" algorithms the patient is classified as healthy or ill. If the latter, the type of the disease is proposed. The classification process employes time series analysis. When a patient is tested, his/her condition, whether he/she is healthy or not and the type of the disease will be displayed on the screen therefore, the physicians will be able to make diagnoses more accurately. Sound taken through the diaphragm is applied to an analog filter and distributed into 2 paths, one on the physician's ear-piece, the other to the microprocessor. Microprocessor filters the signal by a digital filter and detaches heart sounds from lung sounds, all transferred to Long Short-Term Memory LSTM for diagnosis and results are displayed. The principle of operation is shown in Fig. 2.

The paper is organized as follows: In section 2 analog filtering part is explained. In section 3, the method of heart and lung sounds seperation is given. In section 4 classification of lung sounds is explained briefly. Results and discussions are given in the last section.

II. ANALOG FILTERING

The operation of the analog portion of the system given in Fig.3 is explained module-by-module as follows,

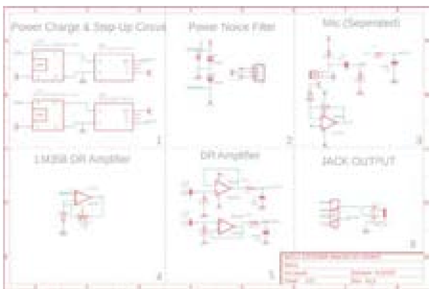

Fig.3 Analog circuit modules.

A. Charging and Step-Up Circuit

This module includes two circuits. The TP4056, which is the LiPo charging IC, charges the batteries. Since the microprocessor and several circuit components operate with 5V, there is also a voltage boost (DC-DC Converter) circuit. Symmetrical sources (+5V and -5V) are necessary for the opamps therefore, 2 individual batteries are employed.

B. Noise Filters

The 1000uF capacitors are used for eliminating the noise for both negative and positive voltages.

C. Pre-Amp and Pre-Filtering Stage

Since the system should only focus on heart and lung sounds, the DC signals and other sounds in the ambient have to be prevented, and only the frequencies in the target range should be allowed via analog filtering. As is well known, the active filters contain Op-Amps, which are able to increase or decrease the gain of the signal besides the filtering process .

An important point in the filter design is to narrow the filter range. In many articles about the electronic stethoscopes, the pass band range for the heart sounds is accepted as 60-150Hz, the lung sounds 100-600Hz and in general 60-600Hz. [2].

Since the input circuit needs to operate as a pre-amplifier and a filter at the same time, to suppress the unwanted sounds in the medium an "Active Band Pass Filter" with cut-off frequencies of 60 and 600Hz and having a gain of 10, is designed [3]. The output signal of this circuit is distributed to the microprocessor and to the ear-piece.

D. Amplifier for the Doctor's Ear-Piece

In this module, an "Inverting Amplifier" circuit is employed, which is designed to adjust the sound level that the doctor will receive through the headset [3][4]. It is possible to change the gain between 0 and 5. Since the gain in the active band pass filter stage was already 10, the total amplifying will be up to 50.

E. Heart and Lung Filters

In this circuit, access to 2 different active filters are provided to the doctor to receive the lung and heart sounds by separate filters with cut-off frequencies of 60-150Hz for heart, 100-600Hz for lung sounds [4].

F. Mode Selection and Ear-Piece Output

The switch on the left allows the doctor to use the stethoscope either in heart or lung mode. The component at the right represents the 3.5mm female jack, which is the ear-piece output.

III. SEPARATION OF HEART AND LUNG SOUNDS

In order to analyze only lung sound, it is required to separate the heart sound from the stethoscope raw sound. It is known that the frequency range of the heart sounds and lung sounds are between approximately 60-85 Hz and 60-300 Hz respectively [5][6]. By considering the aforementioned frequency ranges, using a band-pass filter, the heart and lung sounds can be separated roughly. Figure 4a shows the original stethoscope sound. Figure 4b and 4c show the lung and heart sounds, obtained from original stethoscope sound using a 10th order butterworth digital band-pass filter, respectively.

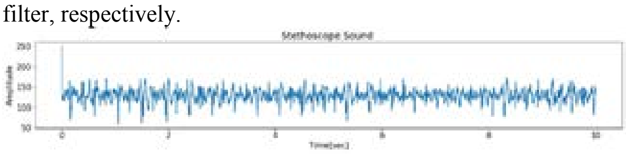

Fig.4a. Stethoscope Sound

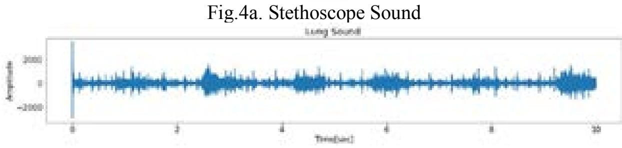

Fig.4b. Lung Sound

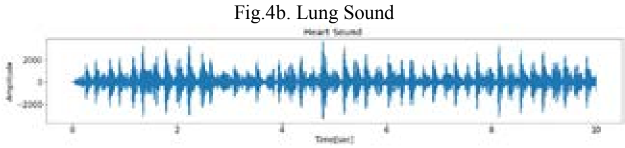

Fig.4c. Heart Sound

Since the range of lung and heart sounds frequencies overlap, the effect of one sound cannot be removed from the other by using only simple digital filtering method. Therefore in the literature, different methods are proposed to separate heart and lung sounds from each other. In [7] and [8] wavelet analysis is used to reduce the heart sound noise from the lung sound. [7] proposes a hard thresholding technique in the wavelet transform domain for reduction of heart sound noise from the lung sounds. In [8], heart sounds cancellation from lung sound is obtained using the multiresolution analysis of the wavelet approximation coefficients of the original signal to detect heart sound included segments. [9] proposes an adaptive noise cancellation method for the heart noise reduction of lung sounds. In [10], by using a multi-sensor system, the proposed method performs time-split channel identification, adaptive signal separation and noise cancellation with recursion from cycle to cycle. In our study, spectral noise gating method is performed to separate heart noise signal from lung sounds [11]. At the first step, by using band-pass filter, heart sound is extracted from the original sound as a noise signal and then lung sound is obtained from the original signal. Then a threshold value is calculated based on some Short Time Fourier Transform (STFT) statistics of the heart noise signal and a mask is created by comparing STFT values of the lung signal with the threshold value. When the lung sound signal is below the threshold level, the gate closes and hence the noise level reduces. In this way the effect of the heart noise signal is almost removed from the lung signal. The heart noise signal removed lung signal is shown in Fig.5.

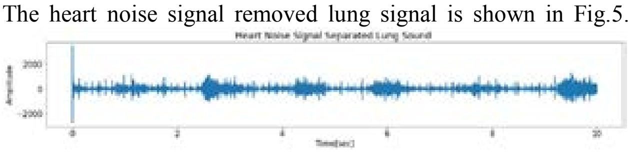

Fig. 5. Heart Noise Signal Separated Lung Sound

IV. LUNG SOUNDS CLASSIFICATION

After obtaining the lung sounds, sounds are classified using Recursive Neural Network. RNN model has been used in many areas such as speech recognition, language modeling, translation, and subtitle. The greatest success of RNN studies is achieved by modeling called LSTM. One of the important features of RNNs is to combine previous information with new information and create a new solution using this information. RNNs sometimes draw conclusions by dealing with the most recently used information instead of performing the current task. RNNs can learn to use historical information when there is little difference between the information we need and related information. But it may happen that we need more conditions. Therefore, the gap between the relevant information and the point may be larger than necessary, and with the increase of this gap, RNNs become unable to learn to connect the information. [12]

In this work, a special type of RNN called Long Short-Term Memory (LSTM) network is used for classification. LSTM can learn long term information. LSTM networks have a structure consisting of repetitions of the neural network like a chain [13]

80 Different lung sound data with 6 different classes is used for training process [14]. The data has the following six classes:

Pneumonia is an infection that inflames the air sacs in one or both lungs. [15]

An upper respiratory tract infection (URTI) is an illness caused by an acute infection, which involves the upper respiratory tract, including the nose, sinuses, pharynx, or larynx. [16]

Chronic obstructive pulmonary disease (COPD) is a type of obstructive lung disease characterized by long-term breathing problems and poor airflow. [17]

Bronchiolitis is a common lung infection in young children and infants. It causes inflammation and congestion in the small airways (bronchioles) of the lung. [18]

Bronchiectasis is a long-term condition where the airways of the lungs become abnormally widened, leading to a build-up of excess mucus that can make the lungs more vulnerable to infection.[19]

Healthy is free from any lung disease

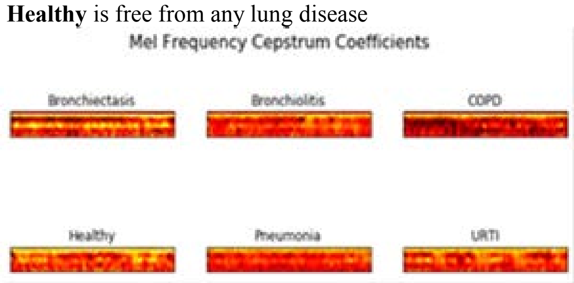

Fig. 6. Mel-frequency cepstral coefficients of diseases

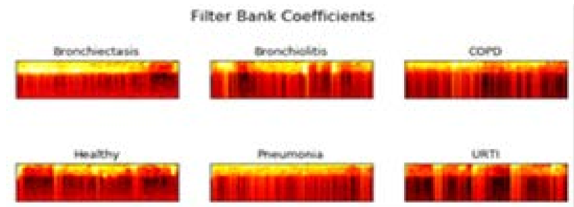

Fig. 7. Filter Bank Coefficients of Disease

Since the most data have different sampling rate, before classification, sample and bit rate values of all audio files are arranged to have same sample and bit rate. Also to avoid overfitting data augmentation is used to increase the size of the data. Training time series data is not directly used in the training. Mel Frequency Cepstrum and Filter Bank Coefficients are used for training as feature of time series

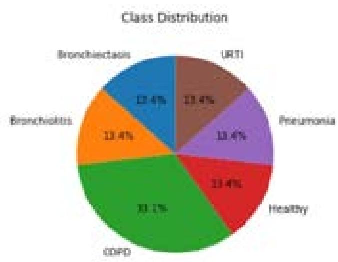

Fig.8. Class Distribution of Diseases

training data. Fig.6 and Fig.7 show MFCC and Filter Bank Coefficients of the data. The distribution of these audio files is shown in the Fig. 8.

A. Model Parameters

Dropout: In this layer, some neurons in our network are randomly disabled. The example of dropout is shown in Fig. 9.

The most important point of this feature is that it provides the system better efficiency by giving independence to neurons during training. For example, let us suppose dropout is 0.1. In each Epoch, 10% of neurons get to sleep. themselves to sleep. The remaining 90% are forced to be trained. Thus, the most functional neurons are determined. Increasing dropout means that half of the neurons go to sleep. This may cause many neurons to become lazy at the end of the training. [20]

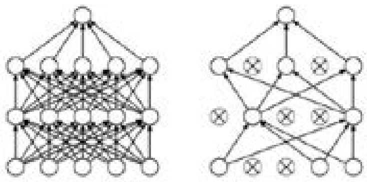

Fig. 9. Before and After Dropout

Output Function: "Softmax" is preferred as the output function. This function has a structure very similar to the sigmoid function. It performs quite well when used as a classifier, just like sigmoid. It is preferred especially in the output layer of deep learning models when it is necessary to classify the most important difference more than two, such as sigmoid function. It ensures that the probability of the input belonging to a certain class is determined by producing values in the range of 0-1. In other words, it performs a probabilistic interpretation. [19]
Error Function: Categorical Crossentropy is preferred for error function.
Train and Test Ratio: In this study train and test ratios are obtained as 90% and 10%, respectively,

V. SIMULATION AND RESULTS

Simulations are carried out using Python Programming Language with Keras Deep Learning Model. The proposed deep learning model's train and test accuracies are obtained as 0.8221 and 0.6947 respectively. 150 different lung sounds are used for testing. Test results are shown in Fig. 10. Also 25 lung sounds recorded with our stethoscope are used for testing. Some classification results are shown in Table 1.

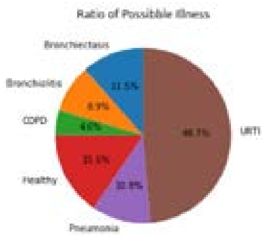

Fig. 10. Ratio of Possible Illness

fname	label	Bronchiectasis	Bronchiolitis	COPD	Healthy	Pneumonia	URTI	y_pred
test1	Healthy	0.30%	22.20%	24.20%	51.89%	0.54%	0.86%	Healthy
test2	Healthy	3.14%	10.55%	30.77%	46.02%	3.80%	5.71%	Healthy
test3	Healthy	0.03%	17.55%	23.61%	56.89%	1.33%	0.55%	Healthy
test4	Healthy	0.45%	14.82%	12.99%	71.11%	0.12%	0.48%	Healthy
test5	Healthy	0.07%	31.12%	10.36%	56.38%	0.17%	1.87%	Healthy
test6	Healthy	3.66%	24.22%	9.95%	58.30%	1.14%	2.67%	Healthy
test7	COPD	0.08%	9.21%	81.31%	1.50%	0.77%	7.10%	COPD
test8	COPD	0.56%	1.99%	75.08%	18.29%	3.85%	19.00%	COPD
test9	COPD	1.08%	2.53%	40.55%	35.34%	18.18%	2.09%	COPD
test10	COPD	14.02%	16.66%	13.34%	39.25%	10.20%	6.50%	Healthy

Table 1. Some Classification Results

VI. CONCLUSION

In this work, a technological solution is proposed to diagnose and classify heart and lung diseases. The proposed solution is based on listening and classfying of the internal sounds of a human body. To listen, record and classify the sounds, a classical stethoscope is equipped with a microcomputer system. Before classification of the sounds, lung and heart sounds are seperated from each other using band pass filering and STFT statistics. LSTM algorithm is used for the classification of the signals and it is trained for 6 different classes. As a future work, it is aimed to increase the classification performance of the proposed system by collecting much more sound data and using different features for training data.

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