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Cough Sound Analysis for Pneumonia and Asthma Classification in Pediatric Population

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***Abstract*—Pneumonia and asthma are the common diseases in pediatric population. The diseases share some similarities of symptoms that make them difficult to separate without the proper diagnostic tools. The majority of pneumonia cases occur in the third world countries wherein even the basic diagnostic tools (e.g.: x-ray) are extremely rare. In these countries, the WHO recommends using rapid breathing and chest in-drawing as approach to diagnose pneumonia in children with cough. As the results, many asthma patients were misdiagnosed as pneumonia and prescribed for unnecessary antibiotic treatment. In this study, we propose a cough sound analysis based method to differentiate pneumonia from asthma. Cough is the major symptom of pneumonia and asthma. Past studies showed the acoustic of cough sounds may carry important information related with the diseases. However, there were no attempts to use cough sounds to separate pneumonia and asthma in pediatric population. Our method extracted sound features such as Mel-frequency cepstral coefficients, non-Gaussianity score and Shannon entropy. The features were then used to develop artificial neural network classifiers. Tested using leave one out validation technique in eighteen subjects, our method achieved sensitivity, specificity and Kappa of 89%, 100%, and 0.89 respectively. The results show the potential of our method to be developed as a tool to differentiate pneumonia from asthma in remote areas.**

Keywords-cough sound analysis, neural network, pediatrics, pneumonia, asthma.

I. INTRODUCTION

Pneumonia is a serious threat for children, especially those who live in the third world countries. In the population of children younger than five years, there were around 120 million of pneumonia cases [1]. It was estimated that around 1.3 million children in that age died due to pneumonia every year. Around 97% of pneumonia cases occurred in developing countries and 74% of the cases occurred in south Asia and sub-Saharan regions [2].

In similar, asthma is one of the most common chronic respiratory diseases in pediatric population [3]. In United States, around 14% of children admitted to hospital were diagnosed with asthma [4]. The cost for pediatric asthma treatment is estimated over $3 billion per year [5].

Pneumonia and asthma share similar symptoms such as the difficulty of breathing and cough. In developed countries, pneumonia be diagnosed more accurately using imaging devices such as X-ray, CT-scan and supported by blood tests as well as culture tests; whereas asthma by lung function tests [5]. However, those diagnostic tools are not readily available in the primary level of health care in third world countries.

To accommodate diseases management in third world countries, the World Health Organization (WHO) has developed guidelines on Integrated Management of Childhood Illnesses (IMCI) [6]. It contains the procedure for diagnosing pneumonia and asthma in pediatric population. According to that guideline, the clinical signs of rapid breathing (respiratory rate greater than 50/min in children younger than 12 months and greater than 40/min in children older than 12 months to 60 months) in children with cough should be treated as pneumonia and prescribed antibiotics. The existence of lower chest in-drawing indicates the severe pneumonia.

The evaluation on IMCI implementation in the field showed that the guideline has relatively high sensitivity (69-94%) but low specificity (16-67%) [7-9]. This means many non-pneumonia children were misdiagnosed as pneumonia. As the consequences, the children received unnecessary antibiotics treatments. The misdiagnosis occurred because the symptoms used to screen pneumonia also exist in asthma. Recently, a study in Uganda [10] showed that 95% of 253 children with asthma received antibiotics treatments meant for pneumonia. The similar results were reported in India [11] where 46% of 200 children with diagnosed as pneumonia actually had asthma.

Researchers have attempted to improve the IMCI guideline by augmenting extra symptoms such as fever and nasal flaring [12-14]. However, the augmentation of symptoms complicates the guidelines and requires skilled health workers for the implementation. An alternative method for screening pneumonia in remote areas is urgently required.

Cough is one of the major symptoms of pneumonia as well as asthma. Cough sound is believed carried information

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related to diseases. The study in [15] showed that the wavelet coefficients extracted from the voluntary cough sounds capable of differentiating groups of healthy, asthmatic, and chronic obstructive pulmonary diseases (COPD) subjects with accuracy 85-90%. However, the study only included adult subjects and excluded pneumonia. Our recent study [16] showed the plausibility of cough sound analysis to differentiate pneumonia and non-pneumonia diseases.

In this paper, we proposed an artificial neural network (ANN) based classifier for pneumonia-asthma classification using cough sounds. To the best of our knowledge, the work on pneumonia-asthma classification using cough sounds is the first effort in this field. As the novelty of this paper, it contributes the following:

- This paper addresses the basic problem of pneumonia and asthma misdiagnosis, especially in the primary level of health care in third world countries, where experienced physicians and diagnosis tools are extremely rare.
- It demonstrates the use of cough sound analysis as a novel tool to classify pneumonia from asthma.

The outcome of this study is significantly useful to support the existing WHO guideline in pneumonia/asthma management.

II. Materials and Method

A. Data acquisition

The data for this work were recorded at Sardjito Hospital, Yogyakarta, Indonesia, from pediatric patients admitted on respiratory complaints. The inclusion criteria used in the recruitment was patients with at least two of the following symptoms: cough, sputum, breathlessness, and temperature higher than 37.5°C. We excluded patients having advanced disease where recovery is not expected, diseases with droplet precautions and patients undergoing mechanical ventilation treatment. The recordings were started after physicians had examined the subjects, begun the initial treatment, and informed consent had been completed. The duration of recording for each subject was from 1 – 6 hours depending on the condition of the patients. The research protocol had received ethics clearances from Sardjito Hospital and The University of Queensland, Australia.

The data acquisition system consisted of a low-noise microphone (Model NT3, RODE®, Sydney, Australia), followed by a pre-amplifier and an A/D converter (Model Mobile Pre-USB, M-Audio®, CA, USA). The output of the Mobile Pre-USB was connected to the USB port of a laptop computer. The nominal distance from the microphones to the mouth of subjects was 50 cm. The actual distance could vary from 40 cm to 100 cm due to the subject movement. We kept the sampling rate at 44.1 k samples/s and 16-bit resolution to obtain the best sound quality.

B. Construction of cough dataset

In this study, we involved M pediatric subjects (M = 18) admitted to hospital with respiratory complaint. In the dataset, the ratio of pneumonia and asthma subjects was equal (9 of each disease). The clinical diagnosis of pneumonia/asthma was established by the professional pediatricians from Sardjito Hospital Yogyakarta Indonesia.

The cough dataset used in this study were constructed by manually picking W first coughs (W = 50) from each recording. The criteria of the cough selection were: i) cough signal were not overlapped with other sounds and ii) cough signal were not clipped. If the number of cough in a recording less than W, then the maximum number of cough that fulfilled the criteria were used. These coughs were used to form cough dataset D. This dataset was then used to train and test the artificial neural network (ANN) for pneumonia/asthma classification. Details of this process are described in the following section.

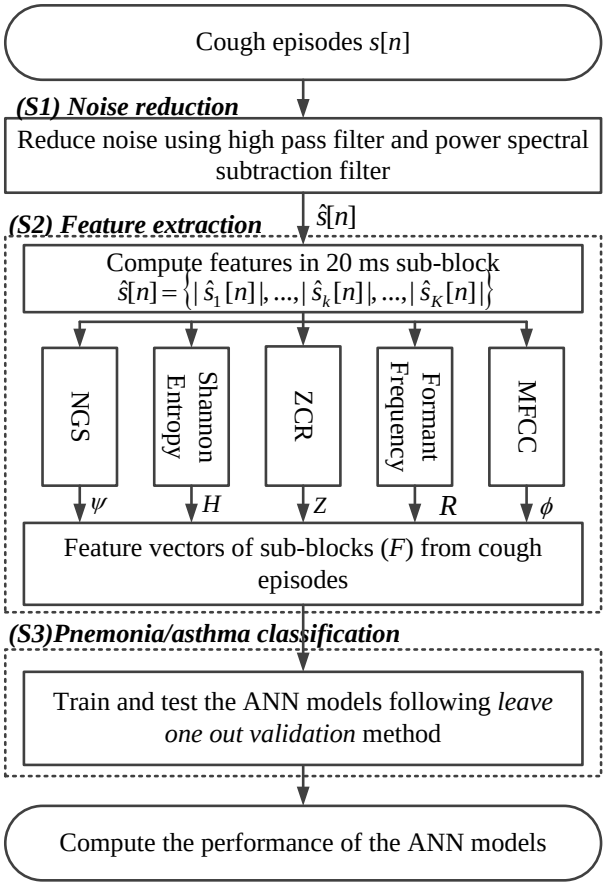

Figure 1. Block diagram of the proposed method for automatic pneumonia/asthma classification.

C. Classification of pneumonia and asthma

To classify pneumonia and asthma subjects we process the cough episodes through three steps (S1-S3) as illustrated in Fig 1. The steps are as follows:

(S1) Noise reduction: Let $s[n]$ denotes a discrete time signal of a cough episode in dataset D. Process $s[n]$ through high pass filter (HPF) and power spectral subtractions (PSS) filter. The HPF was designed as a fourth order Butterworth filter with cut off frequency (f_c = 10 Hz). The particular f_c was selected based on the low frequency noise profile in the recordings due to the microphone stands vibration. The PSS filter was used to reduce the Gaussian noise [17]. The filtered cough episode was denoted by $\hat{s}[n]$.

(S2) Feature extraction: We computed the feature vector of each filtered cough episode $\hat{s}[n]$. The process of feature vector follows the steps:

i. Apply a rectangular sliding window $w_r[n]$ of length N (N = 882 samples, equal to 20 ms) to $\hat{s}[n]$, generating data sub-blocks. Let $\hat{s}[n] = \{|\hat{s}_1[n]|, \ldots, |\hat{s}_k[n]|, \ldots, |\hat{s}_K[n]|\}$ represents the filtered sound recording where $\hat{s}_k[n]$ represents the k^{th} (k = 1, 2, …, K) sub-block in $\hat{s}[n]$.

ii. For each sub-block $\hat{s}_k[n]$ we computed the following features:

Mel-frequency cepstral coefficients (MFCCs): The MFCCs ($\emptyset_k$) of a sub-block $\hat{s}_k[n]$ can be computed using (1).

$$\phi_k = \sum_{c=1}^{C} L_k(c)\cos\left\{\frac{r(2c-1)\pi}{2C}\right\} \qquad (1)$$

where L_k is log energy output of c Mel Filter banks (c = *1*, *2*, …, *40*) of a sub-block $\hat{s}_k[n]$ and r is the number of cepstral coefficients (r = *0*, *1*, …, *12*).

Formant frequency: In speech, formant frequency shows the characteristics of vocal tract resonances. We included the first five formant frequencies (R = *R1*, *R2*, *R3*, *R4*, *R5*) in our feature set. We computed the *R1- R5* by peak picking the LPC spectrum. For this work we used 14th order LPC spectrum and its parameters were determined via Yule-Walker autoregressive method along with the Levinson-Durbin recursive procedure [18].

Zero crossing rate (ZCR): The ZCR (Z_k), defined as the total time a signal crosses the zero axis.

Non-Gaussianity score (NGS): The NGS provides an easy method to quantify the deviation of a given signal from a Gaussian model. The NGS (ψ_k) of a sub-block $\hat{s}_k[n]$ can be calculated using (2) [19], where p and q are the normal probability plot of the reference normal data and analyzed data, respectively.

$$\psi_k = 1 - \left(\frac{\sum_{j=1}^{N}(q_j - p)^2}{\sum_{j=1}^{N}(q_j - \bar{q})^2}\right), \quad 1 \le j \le N \qquad (2)$$

Shannon entropy: The Shannon entropy (H_k) of a sub-block $\hat{s}_k[n]$ was obtained using definition in (3).

$$H_k = -\sum_{n=1}^{N-1}\left(\hat{s}_k(n)^2\right)\ln\left(\hat{s}_k(n)^2\right), \quad 1 \le n \le N\text{-}1 \qquad (3)$$

The feature vectors of $\hat{s}_k[n]$ can be notated as $F_k = [\emptyset\ R\ Z\ \psi\ H]^T$. It comprised of 22 feature vectors.

iii. Repeat steps (i) and (ii) to all cough episodes in dataset D and form feature vector matrix G ($G = F_1, F_2, \ldots, F_K$).

In the next stage, the feature vector matrix G was processed through the neural network classifier to differentiate pneumonia to asthma subjects.

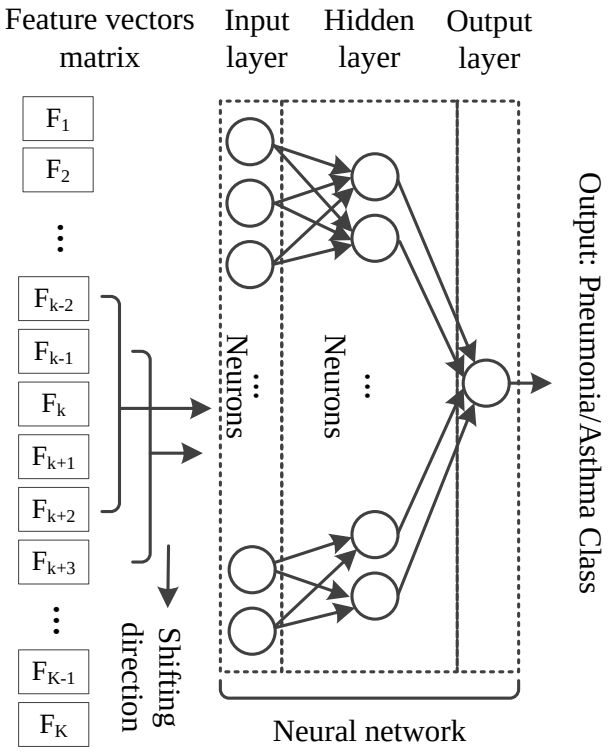

Figure 2. Illustration of ANN classification process. The ANN is used to classify the sound features ($F_1, F_2, \ldots F_K$) computed from sub blocks of cough episodes ($s_1[n]$, $s_2[n]$, … s_K[n]) into Pneumonia/Asthma class.

(S3) Classification of pneumonia and asthma using neural network: To classify pneumonia and asthma subjects, we designed an artificial neural network (ANN) based classifier. The description of the classification procedure and the ANN structure are as follows:

a. **Classification procedure**: Let $Q = [F_{k-2}\ F_{k-1}\ F_k\ F_{k+1}\ F_{k+2}]$, the element of feature vector matrix G, represents the feature vectors of five successive sub-blocks $\hat{s}_{k-2}[n]$, $\hat{s}_{k-1}[n]$, $\hat{s}_k[n]$, $\hat{s}_{k+1}[n]$, $\hat{s}_{k+2}[n]$, respectively. In total, there are 5 x 22 = 110 feature vectors in Q. We used Q as input to the ANN and classified it into Pneumonia class ("1") or Asthma class ("0"). This process was repeated for *k+1, ..., K* to cover the whole signal $\hat{s}[n]$ ($\hat{s}[n] = \{|\hat{s}_1[n]|, \ldots, |\hat{s}_k[n]|, \ldots, |\hat{s}_K[n]|\}$). The ANN was trained to set the output to "1" for pneumonia class and "0" for asthma. Let μ_o is the average of ANN output after processing the sound features of all sub block of cough

episodes from a patient. The classification of pneumonia or asthma follows the rule:

if $\mu_o > \gamma$ **then** patient classified as pneumonia

if $\mu_o \leq \gamma$ **then** patient classified as asthma

where γ is the optimized threshold.

b. **ANN structure**: The ANN structure comprised of an input layer (L_i), two hidden layers (L_{h1} and L_{h2}), and an output layer (L_o). The number of neurons in L_i, L_{h1}, L_{h2}, and L_o are 110, 20, 10, and 1 respectively. The numbers of neurons in the input and output layers were designed based on the number of feature vectors used as input for the ANN and the required output. The neurons in hidden layers were designed to achieve maximum performance without over fitting. We used a linear activation function for neurons in L_o layer and sigmoid activation functions for neurons in L_{h1} and L_{h2} layers. To determine initial weights and bias values, we used the Nguyen-Widrow initialization method [20]. For updating weights during the training process, we employed the resilient back propagation (RPROP) algorithm [21].

We followed *leave one out validation* where all subjects were used in training except one for testing. This process was systematically repeated such that each subject was used as the testing data once.

We show the neural network diagram and classification procedure in Fig 2.

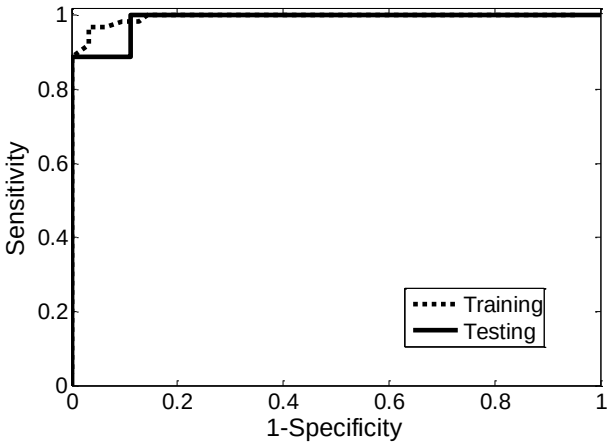

Figure 3. ROC curve of ANN used for pneumonia/asthma classification.

III. RESULTS

A. Dataset

In this study, we used recordings from $M = 18$ subjects consisted of 7 male and 11 female. The age of the subjects ranges from 1 – 86 months (average age = 25 months). Chest x-ray was used to confirm 8 of the pneumonia subjects and 1 subject was clinically diagnosed pneumonia.

The total number of cough episodes in the data set D was 674. It consisted of 412 cough episodes from pneumonia subjects and 262 cough episodes from asthma subject. The average number of cough in pneumonia subjects is larger than asthma subjects (41 coughs by 26 coughs, respectively). The length of pneumonia coughs varied from 0.18 – 1.22 s (mean = 0.33 s, median = 0.32 s and standard deviation = 0.12 s) while duration of asthma coughs varied from 0.2 – 1.44 s (mean = 0.49 s, median = 0.4 s and standard deviation 0.27 s). The results show that pneumonia coughs have relatively shorter coughs than asthma.

According to physical examination findings, 8 of pneumonia subjects and 5 of asthma subject had respiratory rate above the threshold. Fever (body temperature > 37.5°C) was presence in 6 pneumonia subjects and 4 asthma subjects. Abnormal lung sounds found in these subjects were crackles (pneumonia = 8 and asthma = 1) and wheeze (pneumonia = 1 and asthma = 7). Respiratory distress symptoms (sub costal retractions) were presence in all pneumonia subjects and in 3 asthma subject.

TABLE 1**.** The results of pneumonia/asthma classification following leave one out validation technique. Tr, Te, γ, Sens, Spec, Acc, PPV, NPV and κ, respectively denote training, testing, optimized threshold, sensitivity, specificity, accuracy, positive predictive value, negative predictive value and Cohen's Kappa statistic.

	γ	Sens	Spec	Acc	PPV	NPV	κ
Tr	0.6	92.1	100.0	96.0	100.0	92.6	0.92
Te	0.6	88.9	100.0	94.4	100.0	90.0	0.89

B. Pneumonia/asthma classification

In Fig 3, we show the receiver operating characteristic curve (ROC) of the ANN models used for pneumonia/asthma classification. By optimizing the sensitivity and specificity in the training set, we defined an optimum threshold ($\gamma = 0.6$).

The results of pneumonia and asthma classification using the optimum threshold γ are shown in Table 1. It can be seen, the testing results generated from *leave one out validation* show that the developed algorithm is capable of classifying pneumonia and asthma with high sensitivity 88.9 % and specificity 100%. The Kappa agreement with the diagnosis from the professional pediatricians is also very high (0.89).

IV. DISCUSSION AND CONCLUSION

The physical examination findings show that more than 50% of asthma subjects had respiratory rate higher than threshold and 30% of them had sub-costal retraction. It means that if IMCI guidelines applied for diagnosing these patients, they will be misclassified as pneumonia. Study in [12] suggested adding fever to improve the specificity of pneumonia diagnosis. However, 44.4% of asthma subjects had fever. The physical examinations also show that crackles sounds is not specific to pneumonia.

In this paper we proposed an ANN based classifier to differentiate pneumonia subjects with asthma subjects using their cough sounds. Tested in 18 subjects following leave one out validation technique, our method achieved high sensitivity, specificity and Kappa. This result supports our previous study [16] that cough sound carry important information useful to screen respiratory diseases. Our study shows that cough sound analysis has potential to be developed as screening tool for differentiating pneumonia from asthma in remote areas. However, these positive results should be followed by study in the larger dataset.

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