Wavelet Augmented Cough Analysis for Rapid Childhood Pneumonia Diagnosis

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***Abstract*—Pneumonia is the cause of death for over a million children each year around the world, largely in resource poor regions such as sub-Saharan Africa and remote Asia. One of the biggest challenges faced by pneumonia endemic countries is the absence of a field deployable diagnostic tool that is rapid, low-cost and accurate. In this paper, we address this issue and propose a method to screen pneumonia based on the mathematical analysis of cough sounds. In particular, we propose a novel cough feature inspired by wavelet-based crackle detection work in lung sound analysis. These features are then combined with other mathematical features to develop an automated machine classifier, which can separate pneumonia from a range of other respiratory diseases. Both cough and crackles are symptoms of pneumonia, but their existence alone is not a specific enough marker of the disease. In this paper, we hypothesize that the mathematical analysis of cough sounds allows us to diagnose pneumonia with sufficient sensitivity and specificity. Using a bedside microphone, we collected 815 cough sounds from 91 patients with respiratory illnesses such as pneumonia, asthma, and bronchitis. We extracted wavelet features from cough sounds and combined them with other features such as Mel Cepstral coefficients and non-Gaussianity index. We then trained a logistic regression classifier to separate pneumonia from other diseases. As the reference standard, we used the diagnosis by physicians aided with laboratory and radiological results as deemed necessary for a clinical decision. The methods proposed in this paper achieved a sensitivity and specificity of 94% and 63%, respectively, in separating pneumonia patients from non-pneumonia patients based on wavelet features alone. Combining the wavelets with features from our previous work improves the performance further to 94% and 88% sensitivity and specificity. The performance far surpasses that of the WHO criteria currently in common use in resource-limited settings.**

***Index Terms*—Automated cough analysis, childhood cough, pneumonia, wavelet transform (WT).**

I. Introduction

PNEUMONIA is a major cause of child morbidity around the globe. Pneumonia kills an estimated 1.3 million children under 5 years old in 2011 [1]. Nearly 75% of these deaths are concentrated in Africa and South East Asia regions, mainly affecting the underprivileged and the poor population. As much as 65% of the deaths could have been prevented with the right interventions [2]. The unavailability of low cost, field-deployable, rapid diagnostic technology is one of the key challenges in combating pneumonia mortality. There is currently an absence of gold standard for pneumonia diagnosis even in hospitals. The process is not straightforward, but rather a combination of clinical, radiological, and laboratory diagnostics that is often inaccessible to much of the population affected by the disease [3].

TABLE I
WHO/IMCI Guidelines for Pneumonia Classification in Resource-Poor Regions [4], [5]

Criteria	Classification
·History of cough and/or difficult breathing of less than 3 weeks duration	Nonsevere pneumonia
·Increased respiratory rate: ≥60/min if age <2 months, ≥50/min if age 2–11 months, ≥40/min if age 12–59 months	
·Lower chest wall in-drawing	Severe pneumonia
·Cyanosis or inability to feed or drink	Very severe pneumonia

The World Health Organization (WHO) has developed a simple clinical algorithm to classify childhood pneumonia in resource poor regions of the world (see Table I). This algorithm is based on the existence of symptoms (e.g., cough, breathing difficulty, chest-in-drawing, breathing rate) and is simple enough to be implemented by community health care workers in disease endemic regions.

The criteria present good sensitivity (77–81%) and specificity (77–80%) when combined with clinical and radiological examinations [6]. In the absence of clinical and radiological examinations, however, the WHO algorithm has unacceptably low specificity (16–47%) in diagnosing pneumonia [5], [7], [8]. The low specificity largely comes from the use of breathing rate and chest in-drawing in the algorithm, both of which may be associated with other conditions such as anxiety, anemia, reactive airway disease, lower airway obstruction, bronchiolitis, and asthma [9], [10].

Low specificity is harmful to the patient and the society; it leads to excessive antibiotic prescription and wastage of rare drug stocks. Antibiotics also kill beneficial bacteria, causing unintended health problems in patients. Excessive usage also leads to the proliferation of drug resistant bacteria leading to subsequent treatment failures.

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The WHO criteria have been designed with simplicity and high diagnostic sensitivity in mind. This maximizes access to life-saving antibiotics. WHO recognizes the need to improve specificity especially in nonsevere pneumonia cases [11].

In this paper, we propose an innovative method to address these challenges. Our method is based on automated cough sound analysis to diagnose pneumonia. This opens up the possibility of having low-cost, noncontact, noninvasive way of testing potential pneumonia cases without the need for comprehensive training in the field. We aim to achieve a higher specificity compared to WHO criteria and maintain sensitivity at $>90\%$.

In a previous study [8], we have shown the basis for using cough to diagnose pneumonia. That study relied on combination of several mathematical features, some of which are widely used in speech signal processing, such as formant frequencies (FF) and Mel Frequency Cepstral Coefficients (MFCC). In this paper, we propose another class of features inspired by the adventitious lung sounds known as crackles, which are commonly found in pneumonia and routinely observed over the chest musculature using stethoscopes. We recorded cough sounds in free-air outside the mouth and analyzed them (wavelet decomposition), targeting crackle-like components. We then combined the two feature sets and developed pattern recognition technology to diagnose childhood pneumonia.

Crackles are short random bursts of popping, rattling, crackling lung sound commonly found in pneumonia [12], but are not specific to the disease. These are also found, to a lesser extent, in diseases such as asthma, bronchitis, congestive heart failure, pulmonary edema, and emphysema [13], [14].

Trained physicians can use the existence and the nature of crackles (coarse, low frequency crackles versus fine, higher frequency crackles) in a clinical diagnosis of pneumonia. In the current clinical practice, physicians observe crackles over the chest/back musculature using a stethoscope (auscultation). The lungs and the chest muscles heavily low-pass filter sounds, and the low-bandwidth (<3 kHz) of stethoscopes further eliminates high frequency components from observations. The clinical detection of adventitious lung sounds in children requires specialist training and experience. Such skills are simply not available in frontline healthcare facilities in resource-poor regions of the world. Our paper seeks to provide a solution to this problem.

In this paper, we focus our attention to cough sounds measured from the air outside the mouth, at much higher bandwidths (20 kHz) than available in traditional stethoscopes (<3 kHz). We hypothesize that sounds generated in lungs, including crackles, may be embedded in cough sounds, hidden among the louder sound components contributed by the upper airways. During a cough, lungs are directly connected to the atmosphere through a column of air in which information can propagate at the speed of sound. This air column can support a much higher bandwidth than the pathway through the musculature. It should be noted that crackles are also audible from the surface of the neck (outside the trachea) [12], well away from the chest surface.

In this paper, we propose several new features to analyze cough sounds, which are inspired by crackles in pneumonia. Our features are designed to be particularly sensitive to crackles but are capable of extracting additional properties of pneumonia related cough. Considering the transient, nonstationary nature of crackles, we chose wavelet analysis as our tool to develop the technology. Wavelets provide a good way of decomposing nonstationary signals in both time and frequency domains [15], [16], the ability to focus on localized signal structures with a zooming procedure very efficient in detecting singularities in signals [17], and a powerful multiresolution analysis tool to capture changes in frequency characteristics at any moment in time [18].

TABLE II
PATIENT RECRUITMENT CRITERIA

Inclusion criteria	Exclusion criteria
·Patients with symptoms of chest infection.	·Advanced disease where recovery is not expected e.g.
·At least 2 of:	·Terminal lung cancer
Cough	·Droplet precautions
Sputum	·NIV required
Increased breathlessness	
Temperature >37.5 °C	
·Consent	·No informed-consent

A systematic review of 34 studies in stethoscope-based automated lung sound analysis has also found time–frequency analysis such as wavelets to be effective for detection and classification of respiratory diseases [19]. Wavelet transform (WT) has been successfully used previously in developing cough classification technology for respiratory diseases such as asthma and chronic obstructive pulmonary disease (COPD) [20]. There have been no studies to date showing evidence of wavelet features within cough sounds being used to diagnose pneumonia.

The diagnosis of childhood pneumonia using cough sound analysis is a pristine research area. To the best of our knowledge, no other work exists except our own [8]. In this paper, we aim to explore how effective wavelets can be in decomposing cough sounds and developing features specific to pneumonia. We also investigate its use, alone and in combination with our existing cough-derived features [8], in the diagnosis of childhood pneumonia.

In Section II, we describe the recording environment as well as the equipment used. Section III describes how the wavelets are used as cough features, and Section IV details the process of designing the classifier model and performance validation. The classification results for each wavelet types are presented in Section V and compared with results from our previous study. Concluding remarks and future work as well as study limitations are given in Section VI.

II. MATERIALS

The cough sounds used in this work were collected from the Respiratory Medicine Unit of the Sardjito Hospital, Gadjah Mada University, Indonesia. Patients showing symptoms of acute respiratory illnesses were recruited in the first 12 h of admission. The most common diagnosis found in patients was pneumonia, followed by bronchitis, asthma, and rhinopharyngitis. Table II lists the recruitment criteria for patients.

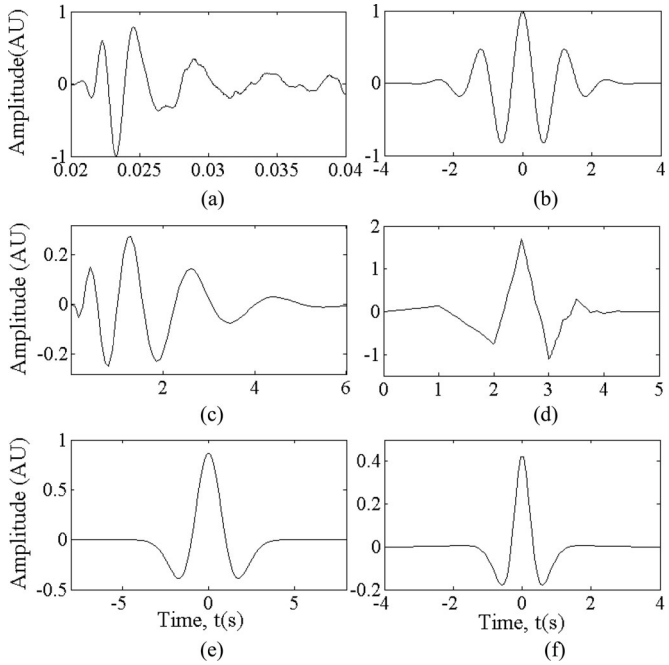

Fig. 1. Side-by-side comparison of (a) example infant expiratory crackle [22] with various wavelets: (b) Morlet, (c) Du, (d) Daubechies3, (e) Mexican hat, and (f) Paul. The shape of crackle within the 2CD is very similar to wavelets (AU = arbitrary units).

This study was approved by the ethics committee of Gadjah Mada University and The University of Queensland.

Not all patients were subjected to X-ray imaging for concern of inflicting unnecessary radiation exposure to children. Consent was sought prior to each recording following explanation of the study and the strictly noncommercial, research only, use of the data. Sound recording began as soon as the patient was ready and stable. Patients were mostly placed in single occupancy rooms, often with one or more relatives accompanying the patient at all times.

The recording setup comprised of high fidelity recordings from two bedside microphones (Rode NT3, cardioid beam pattern, 16 bits/sample, 44.1 kHz sampling rate). Distance from the microphone to the patient's mouth varied from 40 to 70 cm, taking into account patient movement on the bed. The second microphone was aimed at opposite direction to help with identifying background interferences as well as cough sounds from other patients. The background interferences included human speeches, footsteps, periodic tones from medical equipment, and various other sounds from interactions between parents and their child.

The lengths of recordings had a mean of 4 h 3 min, with standard deviation (SD) of 1 h 39 min. Sessions were occasionally interrupted due to noisy nebulizer treatment, groups of visitors, power blackouts, patient falling asleep or being taken out of room, and medical emergencies.

In total, recordings from 91 patients were collected for this study and proportionally split into training and testing group. Patients were exclusively assigned by order of presentation to a group, either training or testing group. In this way, we keep data from each group mutually independent of each other. In the end, there were 66 patients (46 pneumonia and 20 non-pneumonia) in the training group and 25 patients (17 pneumonia and 8 non-pneumonia) in testing group.

In the absence of a commonly accepted method for automatic cough identification, manual segmentation was employed to identify the cough samples. This is still the gold standard in clinical work as well as in literature. In this paper, each cough sample was manually segmented out following a careful listening process applicable by any adult person as cough sound is characteristic. For subjects in the training set, we handpicked from each patient 5–10 clean cough samples that cover a wide spectrum to develop a well-represented model. Clean cough sample is defined as free of background interferences mentioned earlier, has sufficient gain, and no clipping. For testing group, first 15 coughs uncorrupted with interferences were picked from each patient to preserve objectiveness of the study. The beginning and end of a cough were marked out by listening to the cough sound and assisted by visual representation of each cough (in time and frequency domains). Segmented samples include the 100 ms of recordings prior to and after each cough. This is done to cover the possibility of crackles occurring in those brief moments.

III. Wavelet as Cough Feature

For each cough sample, the wavelet features, f_c, are calculated to form the feature matrix, F_M. Wavelet has the advantage over time and frequency domain features in its ability to localize signals in both domains simultaneously. Compared to short time Fourier transform (STFT), wavelet has more accurate representation for nonstationary signals with discontinuities like cough and crackle sounds. Over the years, various wavelets have been proposed, some tailored for specific purposes, others with more general application. In this section, we cover some properties of wavelets and described the motives behind wavelet selection for this study.

A. WT for Crackle Detection

Given a cough sample in time domain, x_i, where *i* denotes the cough number in the set, the continuous wavelet transform (CWT) is given by [21]

$$CWT_{x_i}(a,b) = x_i, \psi_{\,a,b} = \int x_i \overline{\psi_{a,b}} dt \qquad (1)$$

where *a* is the dilation parameter and *b* is the translation. The dilation is equivalent to the scale, which determines the time-scale resolution of the resulting CWT operation. More details on CWT in Appendix A. By analyzing x_i over a range of different scales, CWT offers multiresolution frequency filtering capability to target specific frequency bands. This translates to different crackle types (coarse, medium, or fine) based on two cycle duration (2CD) of the detected crackles.

Fig. 1 shows a time-domain example of an infant expiratory crackle (top left) [22], in comparison with various wavelets such as Morlet, Du, Daubechies3, Mexican Hat, and Paul. It can be observed here that the crackle waveform has some similarity to

the basic shape of the various wavelets. It is quite useful because wavelets can detect and localize self-similar phenomena [21]. Other researchers have utilized this aspect in detecting crackles amongst vesicular sounds and other adventitious sounds [23], [24], automatic classification of crackles to fine and coarse groups [25], [26], and separation of healthy and pathological subjects [15]. The latest study by Serbes *et al.* compared performance of various wavelets for crackle detection in lung sound recordings, all of which achieved performance above 90% accuracy [24]. The study compared 6000 samples from 26 subjects equally divided to three sets: training, validation, and test. Each set contains equal proportion of crackle and noncrackle signal. The wavelets used were Morlet, Paul, and Mexican Hat. In these studies, lung sounds were recorded using stethoscopes.

In the case of noncontact cough sound analysis, wavelet was used by Knocikova *et al.* for classification of adult asthma bronchiale, COPD, and healthy subjects [20]. Sixty-five subjects were studied, with roughly equal numbers in each group. Their use of Daubechies3 concluded with a correct classification rate of 85–90% for a training set. Results from a testing set were not reported. Wavelet features were shown by Al-khassaweneh *et al.* to be potentially useful for asthma classification [27], with 100% accuracy in classifying eight children in the testing set. However, the authors also warned that their use of children with similar age and gender pose a statistical weakness and there is a need for universal features. Abaza *et al.* used wavelets among many other features to classify coughs from 112 adults with abnormal lung physiology. They reported a sensitivity and specificity of 98% [28]. Meanwhile, Du *et al.* proposed a crackle-based wavelet using matched wavelet analysis for crackle detection from contact recording of lung sound, though this was only tested on a very limited number of samples $(n = 13)$ [26].

In this study, one of our targets is to explore whether crackle-like features extracted from noncontact cough sounds can help in diagnosing childhood pneumonia. Our work is inspired by existing literature on crackle detection in lung sounds acquired with contact instrumentations (e.g., stethoscopes) and also other successful respiratory diagnostic applications of wavelets on cough sounds. The work reported in this paper is novel in the application (e.g., cough analysis for pneumonia diagnosis), the targeting of crackle-like components from cough sounds, and the study population (pediatric). This paper also aims to combine other feature classes with wavelets to diagnose childhood pneumonia.

IV. Experimental Methods

A. Choice of Scale

As mentioned in Section III, the scale selection can be used for targeting different crackle types (e.g., fine versus coarse) based on direct conversion of its 2CD to frequency. Scale selection in wavelets is akin to window sizes in STFT, which determines the frequency resolution of the representation of each cough sounds and directly affects the shapes of the output. A coarse crackle with 2CD of 10 ms or larger would be comparable to having a center frequency of 200 Hz and under.

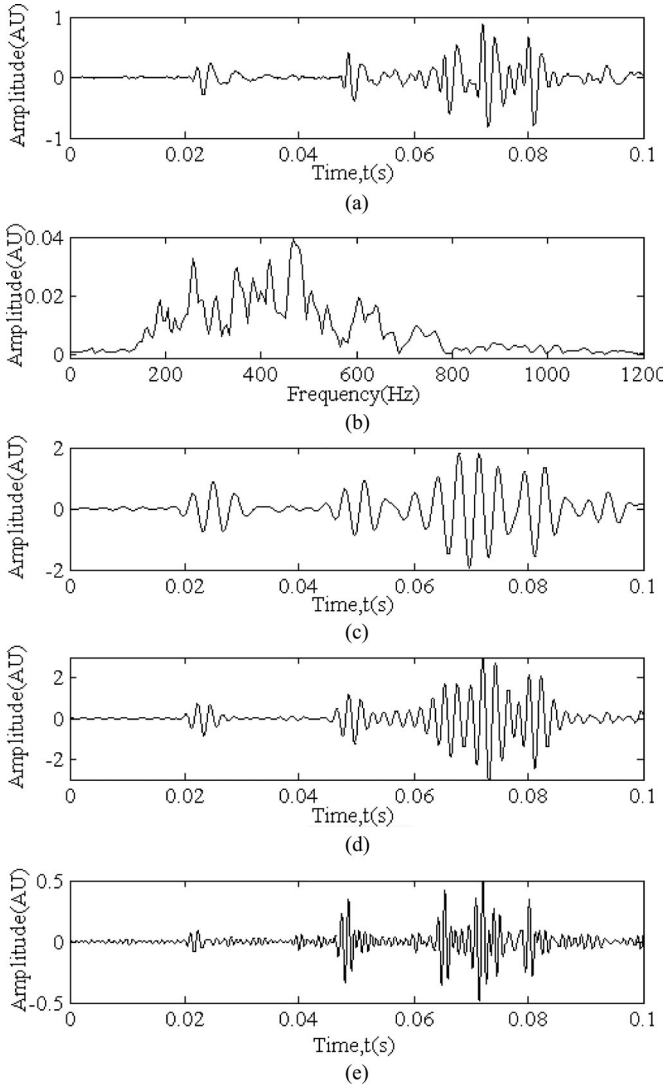

Fig. 2. Effects of varying scale representations of crackle signals. (a) Example infant expiratory crackle [22], (b) FFT representation, (c) Morlet CWT on scale 128, $f = 280$ Hz, (d) Morlet CWT on scale 74, $f = 484$ Hz, and (e) Morlet CWT on scale 35, $f = 1024$ Hz. Crackles may not be clearly separated by looking at individual scale alone.

Fig. 2 shows an example of crackles as recorded from a contact lung sound recording (top), followed by FFT, CWT at scale 128, 74, and 35. The recording contains two individual crackles followed by three successive crackles [22]. FFT analysis shows dominant frequencies around 484 and 280 Hz. At scale 128 ($f = 280$ Hz), the first two individual crackles were distinctly visible, but the following two seemed to merge and the last one barely separate.

Similarly, these observations were also found at scale 74 ($f = 484$ Hz), where the supposedly most dominant frequency was. On the other hand, separation of the last three crackles was clearly visible at scale 35 ($f = 1024$ Hz), while the first crackle was very small this time. Given the variable spectral characteristics in each sample, crackle detection based on wavelet features is not straightforward. In order to objectively compare crackles in one sample to another, one needs to simultaneously consider

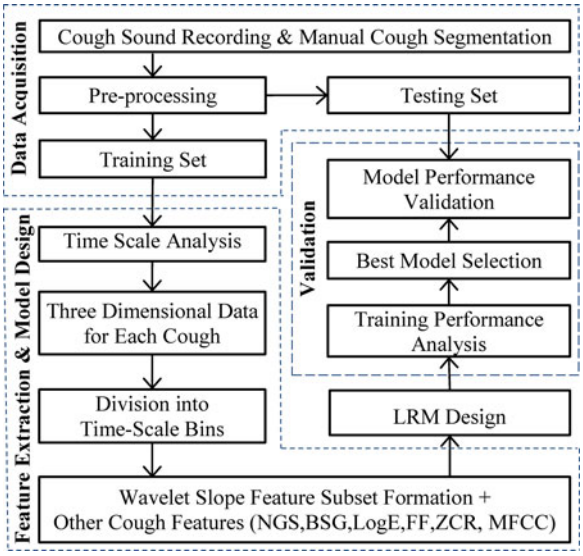

Fig. 3. Overall block diagram of proposed method for pneumonia cough classification using crackle detection. LRM is abbreviation for LRM. A more detailed description is provided in Section 2.

a multitude of scales. This is also expected for crackles in a cough sample.

In this study, 64 scales were calculated and analyzed for each cough sample. The number 64 was chosen following a selection process aimed at maximized classification performance and minimized computational complexity. Detailed description of the process is given in Appendix B.

B. From Preprocessing to Classification to Validation

Cough events from the training set, $\mathrm{D_T}$, are used to develop a model for pneumonia cough classification. Our approach is centered on the use of logistic regression model (LRM) and leave-one-out-validation (LOOV) for the model design. The major stages in this process are shown in Fig. 3. Stage 1 involves cough segmentation and preprocessing; Stage 2 covers the feature extraction using various wavelet types as well as other features identified from our previous work, feature selection with stepwise regression and model design/selection based on LRM and LOOV applied to the training set. Stage 3 details performance validation with independent testing set based on models created from Stage 2.

Stage 1: Preprocessing. In this step, cough samples are normalized to the same root mean square (RMS) value to remove the effects of sound intensity variation in calculating wavelet features for each cough. This is necessary for an objective comparison, as WT is adversely affected by differing sound intensity.

As WT produces a multiresolution representation of cough signals, the wavelet feature set has a built-in band pass filtering process already for noise reduction and frequency filtering. By splitting the original signal to 64 scales of wavelet representations, we have band pass filtered each signal to 64 frequency bands. In the following stages, any local noise that is present in specific time and scale will be identified and removed via the feature selection process.

Stage 2.1: Calculate time scale feature matrix. Following normalization, wavelet features for each cough is calculated for use in developing the classifier. The following process is repeated for each wavelet type used (Morlet, Paul, Mexican Hat, Daubechies3, and Du). The wavelet features from each cough in $\mathrm{D_T}$ were computed as follows.

1) Let *x* denote an RMS normalized cough sample.
2) Apply CWT on *x* to 64 scales. Let c_i represent wavelet representation of *x* on the *i*th scale, where $i = 1, 2, 3, \ldots, 64$.
3) Segment each c_i to 12 equal nonoverlapping subsegments and calculate the energy concentration by sum of absolute values in each segment, c_{ij}, where $j = 1,2,3, \ldots ,12$. Each cough sample, c_i, is now represented by a vector of 12 numbers.
4) For each c_i, calculate the slopes for each c_{ij} along the time axis. For the first segment, it is the ratio of $c_{ij} : c_{i(j+1)}$. For segments 2–11, it is the ratio of $c_{i(j-1)} : c_{i(j+1)}$. For the last segment, it is the ratio of $c_{i(j-1)} : c_{ij}$.
5) Repeat for each c_i in $\mathrm{D_T}$.

The segment number was defined as 12 following a preliminary study comparing different numbers ranging from 1 to 20. Given that most cough samples are less than 400 ms length, segmenting each cough sample to 12 time bins was found to be most effective for identifying crackle-like signals. At the end of this process, the training dataset $\mathrm{D_T}$ is represented by a cough feature matrix, $\mathrm{M_T}$, of size $\mathrm{C_T} \times \mathrm{F_T}$, where $\mathrm{C_T}$ is the number of cough events in $\mathrm{M_T}$ and $\mathrm{F_T} = 768$, representing the number of scales, *i*, multiplied by the number of segments, *j*.

Stage 2.2: Calculate Other Cough Features. In our previous work [8], our group has identified a set of 30 mathematical features for use in pneumonia classification. The features consist of one from non-Gaussianity score (NGS), two from bispectrum score (BSG), two from log energy (LogE), three each from FF and zero-crossing rate (ZCR), and 19 MFCC features. These 30 features were calculated for each cough samples in $\mathrm{D_T}$ and $\mathrm{D_V}$, generating a second set of feature matrix. A brief description of these features can be found in Appendix C. In the following stages, each step was executed firstly with the time-scale feature matrix alone, then again with combined time-scale feature matrix and the features described in this stage.

Stage 2.3: LRM Design and Feature Selection. LRM is a type of statistical classification model useful for calculating the probability of a dependent variable based on multiple independent variables. The dependent variable *Y* in this case is pneumonia (when $Y = 1$) and non-pneumonia (when $Y = 0$). Each cough events from the training set $\mathrm{D_T}$ is labeled as "one" or "zero" depending on whether the subject was clinically classified as pneumonia or non-pneumonia. As a generalized linear model, the probability of *Y* with respect to the independent cough features can be written as follows:

$$Prob(Y = 1)|_{f_T} = \frac{e^t}{e^t + 1} \tag{2}$$

$$t = \beta_0 + \beta_1 \cdot f_1 + \beta_2 \cdot f_2 + \ldots + \beta_{n-1} \cdot f_T. \tag{3}$$

The slope ($\beta_1, \beta_2, \beta_3, \ldots, \beta_{n-1}$) and intercept, β_0, in (3) represents the best-fitting equation in the model for predicting *Y*. The slopes are weights assigned to each feature *f* depending on their significance in predicting *Y*. Finding the best decision threshold μ for predicted *Y* is achieved with receiver operating curve (ROC) analysis. For example, when $\mu = 0.5$, the probability *Y* is classified as pneumonia when $Y > 0.5$ and non-pneumonia otherwise.

In the training process, LOOV is used, where coughs from one person are set aside and used for validating trained model using the rest of the training dataset, $\mathrm{D_T}$. The process is iterated with a different person each time, resulting in creation of N_T models, where N_T is the number of patients in $\mathrm{D_T}$. The performance of each model is evaluated by calculating the sensitivity (SEN), specificity (SPE), accuracy (ACC), positive predictive value (PPV), and the negative predictive value (NPV). SEN is a measure of the proportion of actual pneumonia cases correctly classified by the algorithm, while the SPE is the proportion of actual non-pneumonia cases correctly identified. ACC denotes the proportion of all correct identifications, both pneumonia and non-pneumonia. PPV is the proportion of actual pneumonia cases within the group classified as pneumonia by the algorithm. NPV is the proportion of actual non-pneumonia cases within the group classified by the algorithm as non-pneumonia.

In each of the LOOV iteration, a feature selection process is undertaken by way of stepwise forward addition of features from the feature set, F_T. In each step, the feature that contributed most to reduction in the residual sum of squares error is added to the model, until further addition of features no longer contributes to the model [8].

Stage 2.4: Optimal LRM selection. To find the best model following the LOOV iterations, we use *k*-means clustering algorithm, where *q* data points in *d*-dimensional space are divided into *k* clusters to minimize the sum of squared distance of each cluster from the centroid. With *k* set to 2, we divide our models into high performance and low performance clusters [8]. We then calculate the centroid of the high performance cluster via averaging to represent the best model. Let $\mathrm{R_T}$ represent the selected model and μ_T be the optimal decision threshold for the final model.

Stage 2.5: Pneumonic cough index (PCI). The output of the model $\mathrm{R_T}$ is a classification for each cough sample irrespective of the subject the samples are taken from. For it to be useful for classifying a subject, the PCI is used as a decision maker. Let *P* be the number of coughs from a patient and *Q* the number of coughs classified as pneumonic for the same person, the PCI is defined as follows:

$$PCI = \frac{Q}{P}. \tag{4}$$

Since the result from (4) is a ratio between 0 and 1, another threshold, $\mathrm{PCI_{TH}}$, is calculated using ROC for the best performance in pneumonia classification on a person basis [8].

Stage 3: Model validation. With the final model and thresholds determined, it is time to validate the model performance with an independent dataset previously set aside, the validation dataset, $\mathrm{D_V}$. Since none of the patients in $\mathrm{D_V}$ were used in the training process, it will provide an objective test for the final training model, $\mathrm{R_T}$.

For each cough events in $\mathrm{D_V}$, we computed the feature matrix, $\mathrm{M_V}$, and use the model $\mathrm{R_T}$ to predict the class each cough belongs to. In the same way as the training results, we calculate PCI for each person and compare it against $\mathrm{PCI_{TH}}$ for final classification. The results are compared with reference diagnostics provided by clinicians for each patient and the performance statistics are calculated.

V. Results and Discussion

A. Subject Database and Clinical Diagnosis

In this paper, there were 91 patients recruited in total for the study, with near equal male to female ratio of 48:43. The age distribution of the subjects has a mean of 3 years 1 month (SD = 3 years 11 month), with the youngest subject being a month old and the oldest at 15 years old. Most subjects were under 60 months old (79%, 71 out of 91 patients). Pneumonia and non-pneumonia patients numbered 63 and 28, respectively. Chest X-ray (CXR) confirmation was obtained for 65 subjects, with the remainder based on clinical diagnosis only (eight pneumonias and 18 non-pneumonias).

B. Data Acquisition

The total number of cough samples analyzed in this study was 815 samples, with pneumonia coughs numbering at 561 samples and non-pneumonia at 254 samples. The training dataset consist of 440 cough samples from 66 patients (46 pneumonia and 20 non-pneumonia). In training set, on average six cough samples (minimum 2 and maximum 15) were extracted from each patient. The testing dataset had 375 cough samples from 25 patients (17 pneumonia and 8 non-pneumonia, 15 coughs from each subject). The mean SNR for the dataset was 15.8 and 16.7 dB for the training and testing set, respectively.

C. Feature Extraction and Selection

Cough sounds are usually thought to start with a sharp peak followed by a gradually decreasing tail, but this is not always the case. This is especially true in children with respiratory diseases such as pneumonia. Following our observations, it became apparent that single scale representations of pneumonia cough on a select group of scales often consists of individual segments with clear separation along the time axis. By separating each scale into 12 segments (see Section IV-B, Stage 2.1) along the time axis and calculating the energy in each segment, it is possible to track and localize these events in both time and scale axis. The classifier then uses these features for classifying cough sounds into pneumonia and non-pneumonia groups.

In the case of Morlet wavelet, the classifier found 13 such features following the forward stepwise addition process described in Stage 2.3, equally spread out over both time and scale axis. Features for other wavelets vary as they resonated differently with coughs on each scale and time segment.

TABLE III
PNEUMONIA CLASSIFICATION PERFORMANCE OF THE 66 LRM ON THE LOOV TRAINING DATASET

Wavelet type	By sample					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	88.36 ±0.69	67.03 ±1.17	81.88 ±0.50	85.96 ±0.39	71.63 ±0.81	76.00 ±0.93
Paul	86.28 ±0.85	44.25 ±2.58	73.50 ±0.71	77.96 ±0.60	58.53 ±1.46	71.12 ±0.70
Mexh	86.22 ±0.71	48.08 ±1.51	74.61 ±0.59	79.13 ±0.54	60.45 ±0.98	73.32 ±0.43
Db3	86.68 ±1.04	42.72 ±2.21	73.31 ±0.88	77.56 ±0.68	58.45 ±1.45	72.31 ±0.55
Du	86.20 ±0.99	61.63 ±1.26	78.73 ±0.83	83.69 ±0.56	66.21 ±1.30	72.93 ±0.41
Wavelet type	By person					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	91.20 ±1.02	89.84 ±1.33	90.79 ±0.79	95.38 ±0.54	81.65 ±1.62	88.52 ±2.49
Paul	89.10 ±0.66	52.70 ±4.57	78.09 ±1.27	81.29 ±1.16	67.64 ±2.93	71.82 ±2.41
Mexh	93.30 ±0.78	59.84 ±1.88	83.17 ±0.80	84.23 ±0.71	79.57 ±1.90	74.56 ±1.23
Db3	89.06 ±0.60	49.74 ±3.34	77.15 ±1.01	80.31 ±1.00	66.35 ±2.27	70.09 ±2.58
Du	91.33 ±1.14	75.15 ±1.53	86.43 ±0.93	89.42 ±0.66	79.10 ±2.08	84.05 ±1.32

TABLE IV
PNEUMONIA CLASSIFICATION PERFORMANCE OF THE CHOSEN LRM ON THE LOOV TRAINING DATASET

Wavelet type	By sample					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	87.58	67.91	81.59	86.17	70.54	76.47
Paul	85.94	44.77	73.40	78.04	58.25	71.32
Mexh	86.27	48.51	74.77	79.28	60.75	74.70
Db3	86.93	42.54	73.41	77.55	58.76	73.05
Du	85.62	61.19	78.18	83.44	65.08	83.90
Wavelet type	By person					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	91.30	90.00	90.91	95.45	81.82	93.17
Paul	91.30	50.00	78.79	80.77	91.30	72.94
Mexh	93.48	60.00	83.33	84.31	80.00	74.33
Db3	89.13	50.00	77.27	80.39	66.67	70.33
Du	91.30	75.00	86.36	89.36	78.95	83.61

TABLE V
PNEUMONIA CLASSIFICATION PERFORMANCE OF THE CHOSEN LRM ON THE INDEPENDENT TESTING DATASET

Wavelet type	By sample					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	77.65	54.17	70.13	78.26	53.28	68.28
Paul	85.49	40.83	71.20	75.43	56.98	70.32
Mexh	83.53	46.67	71.73	76.90	57.14	74.22
Db3	84.31	40.83	70.40	75.17	55.06	70.51
Du	82.75	53.33	73.33	79.03	59.26	76.05
Wavelet type	By person					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	94.12	62.50	84.00	84.21	83.33	82.35
Paul	94.12	50.00	80.00	80.00	80.00	82.72
Mexh	88.24	50.00	76.00	78.95	66.67	81.25
Db3	82.35	50.00	72.00	77.78	57.14	81.25
Du	88.24	75.00	84.00	88.24	75.00	89.34

D. Training Performance

The initial training results for the LOOV group using all 66 models can be seen in Table III. Each set of numbers consist of average and SD as the performance measure. The model performance was calculated separately for evaluation of coughs as individual samples and as a group of coughs belonging to the same person. Our target was to maximize SPE subject to the constraint that SEN is $>$90%.

The optimum threshold μ_T for each sample and $\mathrm{PCI}_{\mathrm{TH}}$ for each person were found to be the same at 0.6. Considerable improvements were found when classifying coughs with respect to each person instead of treating each cough independently. It is shown here that the best results were found using Morlet wavelet, followed closely by Mexican hat and Du wavelet.

Following the model selection process, the best model is chosen and fixed. The performance of this model on the training dataset can be seen in Table IV. With the final model, the best training performance on a person level is 91% SEN and 90% SPE using the Morlet wavelet. From this point on, the parameters for each feature in the LRM model are fixed along with μ and $\mathrm{PCI}_{\mathrm{TH}}$.

E. Testing Performance

Each cough in the testing set follows the same feature extraction process applied to the training set. When the trained model was applied to the test feature set, the model based on Du wavelet performed best for individual cough samples with 83% SEN and 53% SPE, as shown in Table V. Paul, Mexican hat, and Daubechies wavelets are comparable in sensitivity but performed worse in specificity. Morlet wavelet in this case has the best specificity at 54% and PPV second only to Du wavelet, with lowest sensitivity compared to others.

On the patient level, where cough classifications are aggregated by the person they belong to, there is marked increase in performance across the board, especially SPE and NPV. The Morlet wavelet performed best with 94% SEN and 63% SPE. Sensitivity-wise, the Paul wavelet performed at the same level (94%), whereas specificity-wise the Du wavelet is the highest at 75%. The best accuracy was achieved at 84% using Morlet and Du wavelets.

From our previous study on the same dataset [8], we have shown the WHO criteria to perform at diagnostic sensitivity of 83%, specificity of 47%, and an accuracy of 75%. In that same study, our LRM-based cough features alone achieved sensitivity and specificity of 94% and 75%, respectively. Compared to that, wavelet-based LRM performed better than WHO criteria and matched our previous study on sensitivity.

Taking it a step further, we combined our wavelet feature set with features from our previous study and repeated the model

TABLE VI
PNEUMONIA CLASSIFICATION PERFORMANCE OF COMBINED FEATURES ON THE INDEPENDENT TESTING DATASET

Wavelet type	By sample					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	81.18	50.00	71.20	77.53	55.56	74.54
Paul	79.61	45.00	68.53	75.46	50.94	70.93
Mexh	80.78	51.67	71.47	78.03	55.86	75.13
Db3	78.82	45.00	68.00	75.28	50.00	70.77
Du	77.25	45.83	67.20	75.19	48.67	69.90
Wavelet type	By person					
	SEN	SPE	ACC	PPV	NPV	AUC
Morlet	94.12	87.50	92.00	94.12	87.50	86.40
Paul	76.47	62.50	72.00	81.25	55.56	79.78
Mexh	82.35	87.50	84.00	93.33	70.00	87.87
Db3	76.47	62.50	72.00	81.25	55.56	78.31
Du	76.47	62.50	72.00	81.25	55.56	83.09

creation and validation process. Table VI shows the performance of the combined model on the prospective dataset.

At individual cough level, there were only slight variations in the classification performance for all wavelet types combined with the other cough features. On a patient-level diagnosis, significant improvements were again observed in all cases, but more markedly on Morlet and Mexican hat models. The Morlet model combined with other cough features had 94% SEN and 88% SPE, a significant improvement from previous results and is the best performing model in both SEN and SPE this time. The Mexican hat model matched the performance in SPE, but has slightly reduced SEN. Paul and Daubechies models exhibited reduced SEN and increased SPE, while Du model suffers following the combination. In the end, the Morlet and Mexican Hat wavelet equally contributed to the highest classification specificity when combined with other features.

The method proposed in this paper outperforms the WHO criteria for resource-poor regions. Our approach also boasts of a good potential for automation, ease of use and low overheads for mass deployment. To the best of our knowledge, there is no comparable work in literature on cough analysis in pneumonia, even though cough had been used in diagnosing other respiratory diseases. Such work (e.g., Al-khassaweneh *et al.* (asthma) [20]; Knocikova *et al.* (COPD & asthma) [27]) encouraged us to explore wavelet analysis in pneumonia.

VI. CONCLUSION

In our previous study [8], we have shown that it is feasible to classify childhood pneumonia based on cough sounds alone. That paper presented classification performance of 94% sensitivity and 75% specificity. In this paper, we were able to achieve 94% sensitivity and 63% specificity on pneumonia classification performance using wavelet features alone, based on the same dataset. A new dimension to the study was added by investigating wavelet features of cough sounds to improve the classification performance. Combining the wavelet features with features from our previous work, the specificity was further increased to 88% with sensitivity kept at 94%.

The simplicity of the proposed features and opportunities for low cost implementation of this technology on portable devices make our approach valuable. Current development of our technology is ongoing on smartphones as well as a dedicated low cost device for cough analysis.

We know crackles are characteristic of pneumonia, but not uniquely. This is reflected in our initial results obtained with wavelet features alone. Large proportion of pneumonia cases will have crackles, translating to high sensitivity. However the existence of crackles does not necessarily mean the patient has pneumonia, thus leading to a reduction in specificity.

Wavelet features increased the performance of our algorithms but what fraction of that increase was contributed to by the actual existence of crackles is not clear at the moment. Wavelet features can capture many other transient properties of a cough in addition to the existence of crackle. In the future, we will be addressing these issues through a detailed study involving clinical experiments. Irrespective of the existence of crackles in coughs, however, the method we propose will be useful in diagnosing pneumonia in remote regions of the world.

The results may be further optimized through systematic control of the recording environment where possible. The recording environment and background noise may affect the performance of the algorithm. We are greatly encouraged, however, that our method well outperformed the existing WHO algorithm, which is in widespread use in the field.

Our methods have yet to be clinically tested in trials involving higher participant numbers from a community-based population. In addition, the reference standard used in pneumonia diagnosis is the overall clinical diagnosis aided by laboratory testing, X-ray assessment (only when clinically required) and the clinical course of the disease. Not all subjects were put through X-ray imaging. Results presented in this study should be interpreted in this context.

APPENDIX A

WT: Our method requires the computation of CWT from cough sounds. Here, we describe the application of CWT on a recorded cough sound *f*(*x*).

Let $\psi_{a,b}(x), a \in \mathbb{R}\setminus\{0\}, b \in \mathbb{R}$ be a family of functions comprising of translations and rescales of function $\psi(x) \in 2(\mathbb{R})$, where *x* is the cough signal in time domain. The wavelet function, ψ, can be written as follows:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{x-b}{a}\right). \tag{5}$$

Also called the mother wavelet, ψ must satisfy the admissibility condition:

$$C_\psi = \int_{\mathbb{R}} \frac{|\Psi(\omega)|^2}{|\omega|} d\,\omega < \infty \tag{6}$$

where $\Psi(\omega)$ is the Fourier transformation of $\psi(x)$. This implies [21]

$$\Psi(0) = \int \psi(x)\, dx = 0. \tag{7}$$

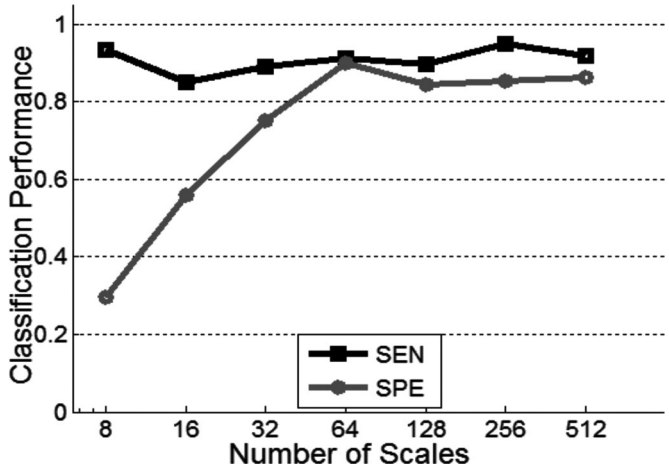

Fig. 4. Pneumonia classification performance on training dataset using various numbers of scale. Sensitivity fluctuates slightly while specificity shot up as number of scales was increased to 64.

This property of the function ψ motivates the name wavelet, for it is well localized and can be made arbitrarily fine via sufficient scaling. This allows adjustment of the time and frequency resolution of the wavelet to better correlate with the target signal, in this case various crackle types with different 2CDs. For a cough function $f(x)$, the continuous wavelet transformation is defined as a function of two variables:

$$\mathrm{CWT}_f(a,b) = \langle f, \psi_{a,b} \rangle = \int f(x)\overline{\psi_{a,b}\,(x)}dx. \qquad (8)$$

The scale and translation parameters, a and b, vary continuously over $\mathbb{R}\setminus\{0\} \times \mathbb{R}$.

APPENDIX B

Choice of scales: Appendix A outlines the details in the scale selection process. We performed WT on each cough in the training dataset with Morlet wavelet. The number of scales used was varied from 8 to 512 scales in power of two increments. For each scale, a wavelet feature set was calculated for each of the 440 cough samples in the training set as per the method described in Section IV. The training performance was calculated and tabulated for comparison.

The result of this analysis is shown in Fig. 4, where sensitivity and specificity performance for each scale is shown. The performance of the algorithm increases as the number of scales increase, and plateaus after $n = 64$. The computational complexity increases with increasing n. Thus, we picked $n = 64$ as the best compromise. Other performance measures are listed below in Table VII.

APPENDIX C

In this appendix, we briefly describe the additional mathematical features of cough we used in Section IV-B Stage 2.2. Detailed description of these with mathematical implementation can be found in [8].

TABLE VII
PNEUMONIA CLASSIFICATION PERFORMANCE BASED ON FEATURES DERIVED FROM WAVELET REPRESENTATION ON VARIOUS SCALES

Scale	SEN	SPE	ACC	PPV	NPV	n
8	93%	29%	74%	75%	66%	3
16	85%	56%	76%	82%	62%	8
32	89%	75%	85%	89%	75%	9
64	91%	90%	91%	95%	82%	17
128	90%	85%	88%	93%	78%	17
256	95%	85%	92%	93%	88%	20
512	92%	86%	90%	94%	83%	20

$n =$ number of features selected.

1) *The BGS:* The third-order spectrum of a signal is known as the bispectrum. The bispectrum is a 2-D signal. However, it is proved that any 1-D oblique slice of the bispectrum other than the slices parallel to the axes: $\omega_1 = 0$, $\omega_2 = 0$ and $\omega_1 + \omega_2 = 0$ carries sufficient information to characterize the entire 2-D bispectrum. We used bispectrum slice inclined to the ω_1 by 45^0 and pass through the origin. From this bispectrum slice, we computed the BGS by computing the ratio of area under the curve for following frequencies $f_1 = 90$ Hz, $f_2 = 5$ kHz, $f_3 = 6$ kHz, and $f_4 = 10.5$ kHz.
2) *NGS:* NGS is a numerical measure of non-Gaussianity of a given segment of data. The normal probability plot was utilized to obtain a measure of the Gaussianity of a set of data.
3) *FF:* In speech analysis, FF are referred to as the resonances of the vocal tract. In cough, it is reasonable to expect that the resonances of the overall airway will be represented in the formant structure. A classic example for this is wheeze. Existence of mucous can also change acoustic properties of airways. We included the first four formants (F1, F2, F3, and F4) in our candidate feature set. We computed these by peak picking the linear predictive coding spectrum of cough segments.
4) *LogE:* The LogE for every subsegment of cough event was computed.
5) *ZCR:* The number of zero crossings was counted for each subsegment of cough event.
6) *Kurtosis (Kurt):* The kurtosis is a measure of how peaky the probability density distribution of a data segment.
7) *MFCC:* The computation of MFCC involves the estimation of short-term power spectra, mapping to Mel frequency scale and then computing the cepstral coefficients. We included 12 MFCCs in our feature set.

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