On Smartphone-based Discrimination of Pathological Respiratory Sounds with Similar Acoustic Properties using Machine Learning Algorithms

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Abstract: This paper explores the capabilities of mobile phones to distinguish sound-related symptoms of respiratory conditions using machine learning algorithms. The classification tool is modeled after some standard set of temporal and spectral features used in vocal and lung sound analysis. These features are extracted from recorded sounds and then fed into machine learning algorithms to train the mobile system. Random Forest, Support Vector Machine (SVM), and k-Nearest Neighbour (kNN) classifiers were evaluated with an overall accuracy of 86.7%, 75.8%, and 88.9% respectively. The appreciable performance of these classifiers on a mobile phone shows smartphone as an alternate tool for recognition and discrimination of respiratory symptoms in real-time scenarios.

1 INTRODUCTION

Respiratory sounds such as cough, sneeze, wheeze, stridor, and throat clearing are observed as clinical indicators containing valuable information about common respiratory ailments. Conditions such as Asthma, Vocal Cord Dysfunction (VCD), and Rhinitis provoked by prolonged and vigorous exercise, are often associated with these symptoms which sometimes overlap; thus, making it difficult for proper diagnosis and treatment of the underlying ailment symptomized by the respiratory sounds. Given the similarity of their acoustic properties, these sounds at times, are conflated and misinterpreted in medical assessment of patients with respiratory conditions using conventional methods. Further, the evaluation of these sounds is somewhat subjective to physicians' experience and interpretation, as well as the performance of the medical device used for monitoring and measurement (Aydore et al., 2009; El-Alfi et al., 2013).

Several studies in recent times have proposed different approaches for objective detection and classification of respiratory sounds using computerized systems. However, with improvement on the storage and computational capabilities of mobile devices, there is a gradual move from the use of specialized medical devices and computer systems to wearable devices for recording and analysing respiratory sounds in real-time situations (Larson et al., 2011; Oletic et al., 2014). Much efforts have been focused on the analysis of wheezing sounds given its clinical importance in the evaluation of asthma, COPD and other pulmonary disorders (Lin and Yen, 2014). Considerable attention has also been given to physiological mechanism and formation of other pathological respiratory sounds such as stridor, cough, and crackles (Pasterkamp et al., 1997; Larson et al., 2011). At times these sounds appear together on the same respiratory signal and their accurate detection and classification remain subjects of interest to many researchers (Ulukaya et al., 2015; Mazic et al., 2015; Uwaoma and Mansingh, 2015).

Bronchial asthma wheezes and VCD stridor are often confused in the preliminary diagnosis of airways obstruction during physical exercise (Irwin et al., 2013). Both sounds have been described as continuous, high-pitched musical sounds. They also exhibit periodicity in time domain given their sinusoidal waveforms. However, stridor is said to be louder and can be heard around the neck without the aid of a stethoscope. Dominant frequencies are between 100 - 1000Hz (Pasterkamp et al., 1997). Wheeze on the other hand, originates from the bronchia and it is mostly audible around the chest

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wall (Bohadana et al., 2014), with dominant frequencies around 600Hz (Uwaoma and Mansingh, 2014). Other respiratory sounds heard in the events of air passage obstruction or irritation include cough, throat clearing, sneezing and sniffle. Unlike wheeze and stridor, these categories of sounds are percussive, transient, and have quasi-periodic wave forms and short duration. Apart from audio information of the symptoms, there are other factors used in the differential diagnosis of exercised-induced asthma and VCD such as the respiratory phase of the sound occurrence (Inspiratory/Expiratory/Biphasic), and the reversibility of conditions (Pasterkamp et al., 1997; Irwin et al., 2013; Bohadana et al., 2014). However, these issues are not within the scope of this paper.

The study objective is to distinguish acoustic properties of respiratory symptoms that correlate with certain respiratory conditions induced by highly intensive physical activity; using smartphone as a platform for the analysis and classification of the sounds. The approach focuses on time-domain and frequency-domain analysis of these sounds. The machine learning algorithms exploit the differences in the energy content and variation, periodicity, spectral texture and shape as well as localized spectral changes in the signal frames. The extracted features from the audio data analysis are fed into classifiers - Random Forest, support vector machine (SVM), and k-Nearest Neighbor (kNN). The classification algorithms are performed on both individual domain and combined domain feature sets. A leave-one-out approach is used in the evaluation of the performance of the classifiers for objective comparison of their discriminatory abilities.

The next section of the paper describes the methods used in audio data acquisition, pre-processing and analysis techniques, and feature extraction. Section 3 highlights the classification algorithms and feature sets for the classifiers. In section 4, the classification results and performance evaluation are discussed. Section 5 is dedicated to further discussions on our study approach as it relates to existing work; while conclusion and application of the results are provided in the last section.

2 METHODS

2.1 Sound Recordings and Datasets

The recordings used in this study are obtained from different sources. The wheeze and stridor sounds are collected under licensed agreement, from R.A.L.E Lung repository (R.A.L.E Lung Sounds, n.d); with each record pre-labelled by an expert physician. The cough, throat clearing, and other sounds are retrieved from another database – creative commons licensed (FreeSounds n.d); while some of the sounds are direct recordings from healthy individuals and pathological subjects using the mobile phone microphone. The dataset comprises of five categories of sound including: wheeze, stridor, cough, throat clearing, and a mixed collection of other sounds. By visual inspection of the waveforms and audio verification, all distinct segments of the audio recordings containing the actual sounds are selected. Given the varying length and sampling rate of the recordings, the audios are down-sampled to 8000Hz and segmented into equal length to ensure uniformity and to lessen computational load on the mobile device.

2.2 Signal Pre-processing and Analysis

The signal pre-processing steps include windowing and digitization of each audio signal into frames of equal length (128ms) with 87.5% overlap. The signal frames are decomposed into spectral components using the Discrete Short-Time Fourier Transform (STFT) technique. Hamming window of size N = 1024 was used to reduce spectral distortion due to signal discontinuities at the edges of the frames. The windowing and overlapping techniques help to smoothen the spectral parameters that vary with time. Figure 1 shows the magnitude spectrum of wheeze and stridor sounds.

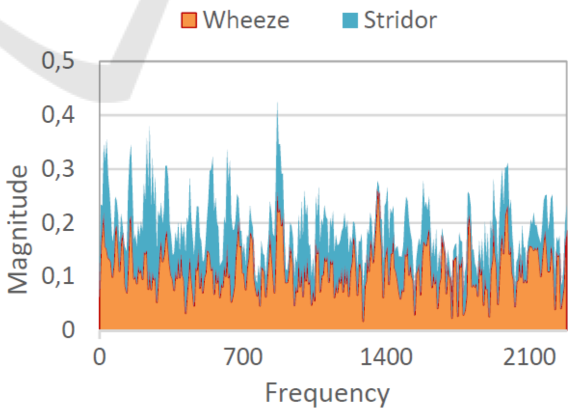


Figure 1: Magnitude Spectrum of Wheeze and Stridor.

2.3 Feature Extraction

In preparing the feature sets for classification, we employ two steps in the feature extraction. First, is the frame-level extraction, where the resulting coefficients from signal windowing and spectral analysis are used as parameters for calculating the temporal and spectral features of the audio signals. Time-domain features used include the RMS energy and Zero Crossing Rate (ZCR) of each frame in the audio record. The spectral features used in the classification are described as follows:

2.3.1 Spectral Centroid (SC)

This feature measures the spectral shape of individual frames and it is defined as the centre of spectral energy (power spectrum). Higher values indicate “brighter” or “sharper” textures with significant high frequencies, while lower values correspond to low brightness and much lower frequencies. Given P as the power spectrum of the frame f, and N being the Nyquist frequency with k as the frequency bins; SC is calculated as:

$$SC(f) = \frac{\sum_{k=0}^{N-1} k.P_k^2}{\sum_{k=0}^{N-1} P_k^2} \tag{1}$$

2.3.2 Spectral Bandwidth (SB)

Also known as ‘instantaneous bandwidth’ (Lerch, 2012), SB technically describes the spread or concentration of power spectrum around the SC. It is a measure of ‘flatness’ of the spectral shape. Higher values often indicate noisiness in the input signal and hence, wider distribution of the spectral energy; while low values show higher concentration of the spectral energy at a fixed frequency region. SB is calculated as follows:

$$SB(f) = \sqrt{\frac{\sum_{k=0}^{N-1}(k - SC(f))^2.|P_k|^2}{\sum_{k=0}^{N-1} P_k^2}} \tag{2}$$

2.3.3 Spectral Flux(SF)

Spectral Flux is an approximate measure of the sensation ‘roughness’ of a signal frame (Lerch, 2012). It is used to determine the local variation or distortion of the spectral shape and it is given by:

$$SF(f) = \frac{\sqrt{\sum_{k=0}^{N-1}\left(|P_f| - |P_{f-1}|\right)^2}}{N-1} \tag{3}$$

The window-level features or texture features are derived from the instantaneous features described above. These features are basically statistical functions of the frame-level features expressed in terms of rate of change, extremes, averages, and moments of grouped frames in the range of 2.5 seconds to 5 seconds of audio duration. Of particular interest among the derived statistical properties used in the audio discrimination is the *Above α-Mean Ratio* (AMR) (Sun et al., 2015). This metric is used to differentiate high-energy frames from low-energy frames in a signal window. It determines the ratio of the high-energy frames by setting the parameter α alongside the mean RMS of the signal window as threshold candidates; to separate different acoustic events – continuous signal, discrete signals and ambient noises. AMR is calculated as:

$$AMR(\alpha, w) = \frac{\sum_{j=1}^{n} ind[rms(f_j) > \alpha.\overline{rms}(w)]}{n} \tag{4}$$

where w is the signal window of the frames f_j (j = 1, 2... n), and $\overline{rms}$ is the mean RMS of the frames in the window. The indicator function $ind()$ is evaluated to 1 if the argument is true and 0, otherwise. Parameter α is empirically determined and can be set within the values between 0.5 and 1 (Sun et al., 2015). Table 1 provides a full list of the frame-level and window-level features used in the classification.

Table 1: Classification Features.

	Feature Group	**Descriptor**	**Classification Acronym**
Frame Level	Energy	Root Mean Square	RMS
	Periodicity	Zero Crossing Rate	ZCR
	Spectral Shape	Spectral Centroid	SC
		Spectral Bandwidth	SB
		Spectral Flux	SF
Window Level	Extremes	AMR of RMS window	amrRMS
		Relative Max RMS [15]	rmrRMS
	Averages	Mean of RMS window	meanRMS
		Mean of SC window	meanSC
		Mean of SB window	meanSB
		Mean of SF window	meanSF
	Moments	Variance of RMS window	varRMS
		Std. of ZCR window	stdZCR
		Mean Crossing Irregularity [7]	mciZCR
		Variance of SC window	varSC
		Variance of SB window	varSB

3 CLASSIFICATION ALGORITHMS

In the experiment, three classifiers – Random Forest, kNN, and SVM are used to investigate the performance of the extracted input parameters in differentiating the audio sound patterns. Each of the classifiers represents a category of classification algorithms often used in Machine Learning. Whereas the SVM is a non-probabilistic binary classifier that favours fewer classes, k-NN is an instance-based algorithm that uses the similarity measures of the audio features to find the best match for a given new instance; while Random Forest is an ensemble algorithm that leverages the desirable potentials of 'weaker' models for better predictions. We compare the discrimination abilities of the classifiers using both individual domain feature set and combined domain feature set. The classification process involves the following steps:

3.1 Feature Selection

Best of the discriminatory audio features were selected using two attribute selection algorithms namely – Correlation Feature Selection (CFS) and Principal Components Analysis (PCA). The original feature set consists of 13 attributes as highlighted in Table 1. However, the best first three features selected by CFS were varRMS, stdZCR and varSB; while the highest-ranking features according to PCA were meanRMS, armRMS, meanSF, stdZCR and varSF. This gives a total of 7 attributes in the selected feature set. It is interesting to note that the three features selected by CFS were good representation of the audio properties we considered earlier in the study. Whereas varRMS provides information on the energy level of the audio signal, stdZCR shows the periodicity, while varSB represents the spread or flatness of the audio spectral shape in terms of frequency localization.

3.2 Training and Testing

A smartphone-based classification model was built for recognition and discriminating of respiratory signals with related sound features. The experimental processes – STFT, Feature Extraction and Classification were carried out on Android Studio 1.5.1 Integrated Development Environment (IDE). With embedded Weka APIs, the classifier models were programmatically trained on the mobile devices running on Android 4.2.2 and 5.1.1, which were also used to record some of the audios used to evaluate the performance of the algorithms in real-time. We opted to train the models directly on the mobile devices rather than porting desktop-trained models, due to serialization and compatibility issues with android devices. Moreover, the response time of building the model on the smartphone is faster compared to the performance on the desktop. The machine learning algorithms are trained by using the statistical window-level features obtained from the audio signal frames. Due to limited datasets, a 'leave-one-out' strategy for **10-fold cross validation** was used in the training and evaluation of the performance of the classifiers and the selected features. Statistical metrics used in the performance evaluation were *precision*, *recall* and *F-measure*.

4 RESULTS

In this section, we discuss the results and performance of the machine learning algorithms in different scenarios. We also benchmark the real-time performance of the mobile device in terms of CPU and memory usage as well as execution/response time of each of the modules in the entire process.

4.1 Performance of the Classifiers

In the evaluation of the classification process, we presented different scenarios of the problem to the classifiers, to understand the mechanisms of their performances. First, we used two categories of datasets – 2.5 seconds length and 5 seconds length of the audio symptoms. The 2.5s length dataset has a total of 163 records (Wheeze = 49, Stridor = 33, Cough = 27, Clear-Throat = 26, Other = 28), while the 5s dataset used in the classification consists of 99 instances in total. Though there were fewer instances in the 5s datasets, the algorithms performed better on this category than in 2.5s datasets as shown in Table 2. This implies that longer audio durations rather than the number of instances provided the classifiers with more information to learn about the audio patterns.

Scaling the number of classes used in the classification and adjustment of the algorithms' parameters also had much impact on the performance of the classifiers. From Table 2, we observed that the SVM classifier performed much better when we reduce the number of symptom classes to two; and by increasing the complexity parameter *C*, from 1.0 to 3.0, the classifier performance improved by 4.6%. The kNN algorithm on the other hand, performed poorly with increased number of classes but the performance improved with higher number of features. For instance, setting the parameter *k* to 1, gives an accuracy of 88.88 % but drops to 53.98% when k is set to 5. In other words, kNN does very well with fewer classes and more features, as expected.

We examined two groups of classes whose elements are often conflated given the high level of their resemblance. These are: *Wheeze* vs. *Stridor* and *Cough* vs. *Clear Throat*. The comparisons are shown in Figure 2 and Figure 3 respectively. We noticed that the classifiers generally found it difficult differentiating between cough and throat clearing. However, when presented with only time-domain features, the discrimination became clearer as shown in Figure 3. In benchmarking the overall performance, we considered an ideal pathological case, where it is assumed that the symptoms -cough, wheeze and stridor are observed in an individual at the same. According to medical experts, these respiratory sounds are very common in exercise-induced VCD and bronchoconstriction or bronchial asthma. Figure 2 indicates that though wheeze and stridor signals relatively have uniform oscillation (periodicity), stridor has a ‘flatter’ spectral shape given its wide frequency range.

Table 2: Overall Performance of the Classifiers in Different Scenarios.

Classifiers	All Classes with all Features	
	5s Dataset	*2.5s Dataset*
Random Forest	86.86%	66.2%
SVM	75.75%	57.6%
k-NN	88.8%	65.0%
	Wheeze & Stridor with all Features	
Random Forest	87.5%	80.48%
SVM	80.35%	73.17%
k-NN	89.28%	86.6%

We can adduce from the results in Figure 4, that kNN classifier has the overall best discriminating ability among the three algorithms used in the study. RF maintained its robustness by averaging the predictions of other classifiers, while SVM was weak in recognizing stridor sound. However, we used the RF algorithm for the real-time implementation of the classification tool.

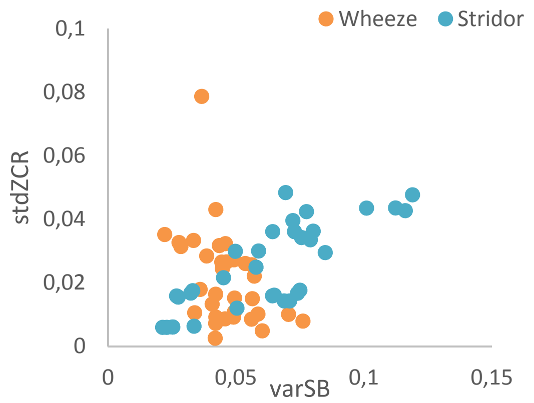


Figure 2: Discriminating ability of time-frequency domain features – stdZCR and varSB on wheeze and stridor.

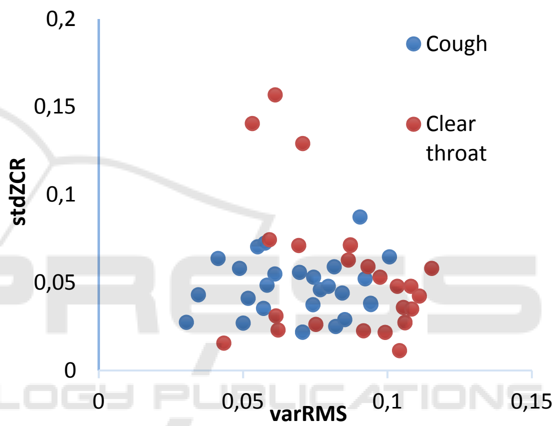


Figure 3: Discrimination of cough from throat clearing by time-domain features – stdZCR and varRMS.

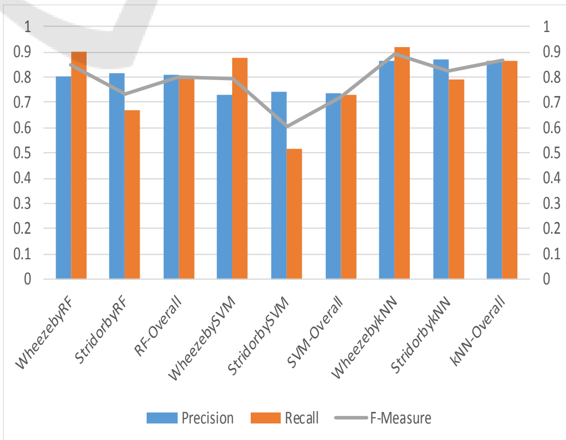


Figure 4: Performance measures for all classifiers – RF, SVM, and kNN on wheeze vs. stridor discrimination.

As we were unable to get real-time access to clinical respiratory sound symptoms such as wheezes and stridor at the time of writing this paper; we performed a pilot test on the discriminatory ability of the classification tool in real-time, using records of common sound symptoms – cough and clear throat volunteered by healthy individuals and those with pathological conditions. Figure 5 shows correct detection of different cough sounds on two android phones (Huawei p6 Ascend and Samsung Galaxy J3). The tool was also able to predict correctly an offline recorded wheeze sound that was not used in the training of the classifiers, as shown in Figure 6. Figure 7 also shows a correctly detected stridor sound. By mere visualization, we can observe that the waveforms and the spectrograms of these sounds are different from each other. This may as well serve as a clue to physicians in the differential diagnosis of the underlying respiratory illnesses.

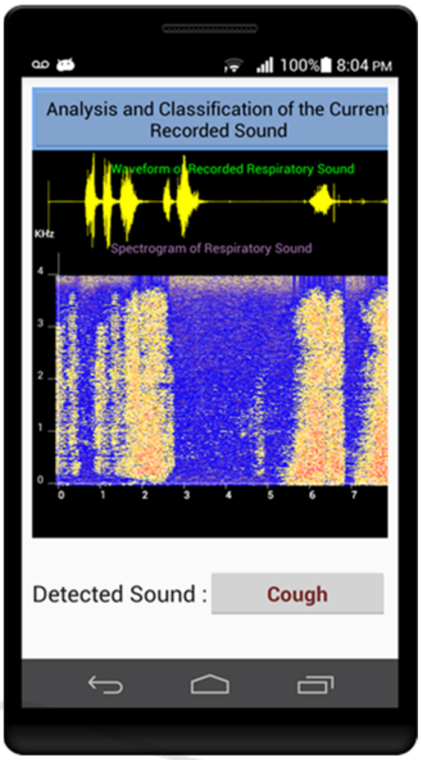
4.2 Device Performance on Resource Usage

We evaluate the smartphone performance on the utilization of the system resources when executing the major modules in real-time. The modules include audio pre-processing (framing and FFT), feature extraction, and the classification. Table 3 shows the measurements on the consumption of the device resources during the application run-time. The execution time in milliseconds (ms) is profiled in the android code. As expected, the response time for the pre-processing module was a bit long due to FFT metrics which are numerically intensive on the resources.

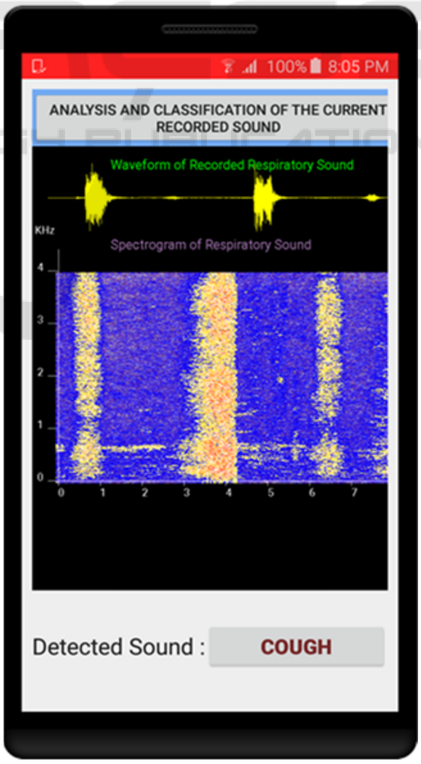
In measuring the power consumption by the application, we used an installed app known as *Power Tutor* which estimated the average power as 315mW (mill Watts) for one-minute processing.

Table 3: Benchmarks on Device Resource Usage by Major Operations.

Module	CPU	Memory	Exec. Time
Pre-processing	27%	2.2MB	1404 ms
Feature Extraction	25%	8MB	556 ms
Classification	0.02%	2MB	722 ms



(a) Cough Detection on Huawei Ascend.



(b) Cough Detection on Galaxy J3.

Figure 5: (a) and (b): Detected cough sounds in real-time.

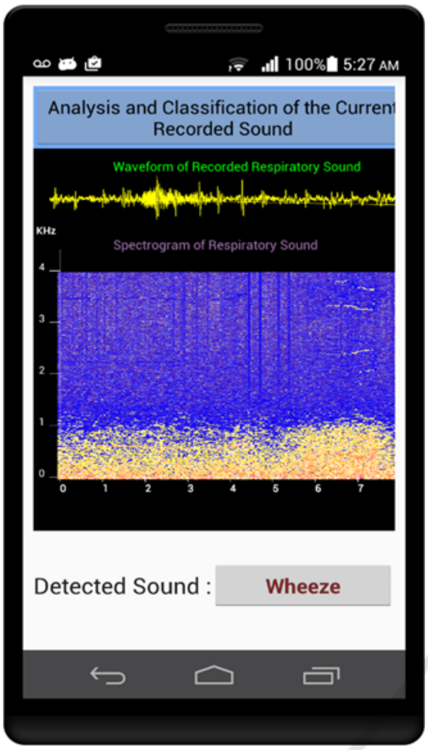


Figure 6: Detected wheeze sound recorded offline.

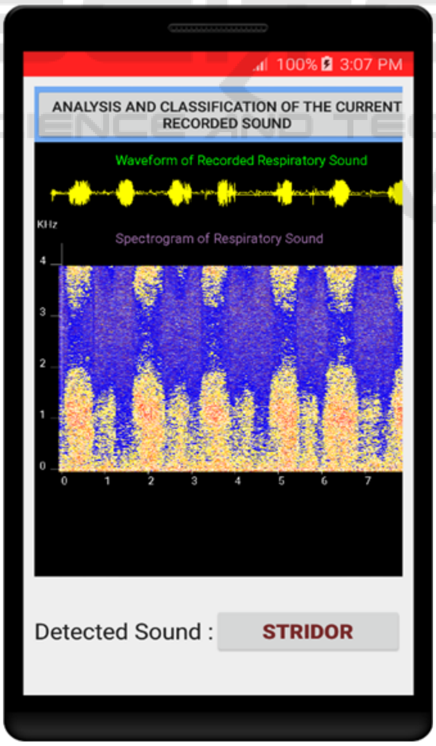


Figure 7: Detected stridor sound recorded offline.

5 DISCUSSIONS

In this section, we relate our study to existent work, and compare different designs and techniques used in selected studies to our own approach. Recent studies have focused on audio-based systems for continuous monitoring and detection of vital signs relating to management and control of long-term respiratory conditions. Aydore et al. (2009) in their work performed a detailed experiment on the classification of wheeze and non-wheeze episodes in a respiratory sound, using linear analysis. Though the approach they adopted yielded an impressive success rate of 93.5% in the testing; the study was not specific about the non-wheeze category of sounds such as rhonchi and stridor which mimic wheeze, and are reportedly misdiagnosed as wheeze in clinical practice. The work however, was extended by Ulukaya et al. (2015) on the discrimination of monophonic and polyphonic wheezes using time-frequency analysis based on two features – mean crossing irregularity (MCI) in the time domain, and percentile frequency ratios in the frequency domain. The authors considered MCI as the best discriminating feature with a performance accuracy of 75.78% when combined with image processing. We implemented MCI in our feature sets and discovered that it has strong correlation with stdZCR window-level feature. The stdZCR is one of the prominent features we used in our classification task and it is less computationally intensive than MCI.

There are on-going research efforts towards the design of monitoring and detection systems for respiratory conditions based on mobile platforms. The overall aim of these studies is to increase the awareness and compliance by individuals in managing their conditions, and to improve the efficacy of treatment procedures and therapies by health professionals. In the study (Larson et al., 2011), mobile phone was used as a sensing platform to track cough frequency in individuals and across geographical locations. The embedded microphone in the mobile phone serves as audio sensor to record cough events, with the phone placed in the shirt or pant pockets or strapped on the neck of the user. According to the authors, results obtained from the study could be channelled to further diagnosis and treatment of diseases such as pneumonia, COPD, asthma, and cystic fibrosis. Automated Device for asthma Monitoring (ADAM) was developed by Sterling et al. (2014) to monitor asthma symptoms in teenagers. The system design involves the use of lapel microphone attached to the mobile and worn by the user to capture audio signals. It uses Mel-frequency cepstral coefficients (MFCC) and multiple Hidden Markov Model (HMM) for feature extraction and classification, to detect the 'presence' or 'absence' of cough in the recorded sounds. The sensitivity of the detection algorithm is 85.7%. *BodyBeat*, proposed by Rahman et al. (2014), is another mobile sensing system for recognition of non-speech body sounds. Like ADAM, it uses a custom-made microphone attached to an embedded unit (Micro controller) for audio capturing and pre-processing. The embedded unit connects to the mobile phone through Bluetooth for feature extraction and classification of the audio windows. Sun et al. (2015) in their study, proposed *SymDetector*, a mobile application for detection of acoustic respiratory symptoms. The application samples audio data using smartphone's built-in microphone and performs symptom detection and classification using multi-level coarse classifier and SVM.

These novel designs appear quite elaborate and plausible; nonetheless, common issues with them include the ease of use of the system, and the reproducibility of the algorithms used in the detection process. There could be concerns about the setup and cost of deployment by the user for systems that utilize external audio sensors and other devices connected to the mobile phone. Also, running multiple level classification for the detection algorithms may impact on the response time of the applications when deployed in real-time. In addressing these issues, our study uses a standalone mobile platform with no external gadgets connected to the smartphone. In other words, all the major operations – audio sampling, pre-processing, feature extraction, and classification are performed on the mobile phone. This will not only enhance the usability but will to an extent, ensure user's privacy since there are no networked devices nor any processing performed at the backend.

Though we experimented with three classifiers, we settled for only one - Random Forest, given its robustness in different scenarios. The classifier has a reasonable response time in the real-time testing as highlighted in Table 3. And since the major operations run in the background on the smartphone, the concern about the classification tool hogging device resources is ruled out. Table 4 shows a comparison of different approaches from selected studies based on design platform configuration, type of audio sensor, and classification steps involved in the sound recognition.

Table 4: Design Approaches for Smartphone-based Detection of Respiratory Sounds.

Study	**Monitoring Platform Configuration**	**Audio Sensor**	**Classifier**
ADAM	Distributed mobile	Lapel Mic.	Multiple HMM
Body-Beat	Distributed mobile	Custom-built Mic.	Linear Discrimi-nant Classifier (LDC)
Sym-Detector	Standalone mobile	Smartphone Embedded Mic.	Multi-Level Coarse-classifier and SVM
Our Work	Standalone mobile	Smartphone Embedded Mic.	RF, kNN, SVM

6 CONCLUSIONS

The study focused on differentiating between respiratory sound patterns using spectral and temporal parameters. The parameters are believed to correlate approximately with auditory perceptions used in the evaluation of pathological respiratory sounds. The ability of a mobile phone to perform the sophisticated algorithms involved in the audio signal analysis and classification, makes it selectable as an assistive tool in providing real-time clinical information on certain respiratory ailments. The information obtained from the process can aid physicians in further diagnosis of the suspected respiratory conditions.

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