

AsthmaGuide: An Asthma Monitoring and Advice Ecosystem

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Abstract—Recently, there has been an increased use of wireless sensor networks and embedded systems in the medical sector. Healthcare providers are now attempting to use these devices to monitor patients in a more accurate and automated way. This would permit healthcare providers to have up-to-date patient information without physical interaction, allowing for more accurate diagnoses and better treatment. One group of patients that can greatly benefit from this kind of daily monitoring is asthma patients. Healthcare providers need daily information in order to understand the current risk factors for asthma patients and to provide appropriate advice. It is not only important to monitor patients' lung health, but also to monitor other physiological parameters, environmental factors, medication, and subjective feelings. We develop a smartphone, sensor rich, and cloud based asthma system called AsthmaGuide, in which a smartphone is used as a hub for collecting comprehensive information. The data, including data over time, is then displayed in a cloud web application for both patients and healthcare providers to view. AsthmaGuide also provides an advice and alarm infrastructure based on the collected data and parameters set by healthcare providers. With these components, AsthmaGuide provides a comprehensive ecosystem that allows patients to be involved in their own health and also allows doctors to provide more effective day-to-day care. Using real asthma patient wheezing sounds, we also develop two different types of classification approaches and show that one is 96% accurate, the second is 98.6% accurate and both outperform the state of art which is 87% accurate at automatically detecting wheezing. AsthmaGuide has both English and Korean language implementations.

I. INTRODUCTION

With the integration of wireless sensor networks and smartphones in hospitals and homes, healthcare providers are able to provide more accurate and personalized patient care. For example, devices such as EarlySense are being developed to accurately collect patient information in hospitals and relay this information to clinicians [13]. One group of patients that should greatly benefit from intensified daily monitoring is asthma patients. In the latest surveys by the Centers for Disease Control and Prevention, about 25 million people in the United States have asthma [9]. As of 2011, of these 25 million, 53% of these people suffered from acute asthma attacks [9]. Because there is currently no cure for asthma, the NIH states that the priority for doctors is to assess and monitor these patients as there are usually clear symptoms that indicate an oncoming asthma attack [26]. While it is obviously essential to monitor patients' lung health, per se,

environmental factors also trigger and exacerbate asthma symptoms. These factors include extreme temperatures, extreme humidity or dryness, pollen, smoke, and mold [10]. The effect of these environmental factors differs from patient to patient.

Currently, there is no effective way for doctors to monitor asthma patients at home on a day-to-day basis. Most patients visit their doctors monthly, but once they go home there is a lack of communication between the two parties. Since the course of asthma is dependent on dynamic factors, this loss of daily information is potentially costly. There have been attempts to detect wheezing via machine learning or to make peak-flow measurements convenient [4], [33], [15], [19], [11], [22], [7], [16], [3], [20], [21]. However, none of these systems analyzes these factors in an integrated fashion, and they do not consider environmental factors in conjunction with lung health.

We develop "AsthmaGuide", a sensor rich asthma ecosystem that monitors asthma patients comprehensively. A smartphone is used as a hub for collecting physiological, environmental, human input, picture, and video information. Physiological information includes lung sounds, peak flow values, and blood oxygen level. This information is then pushed to the cloud where doctors and patients interact with this information. One feature of the cloud web application is the automatic analysis of lung sounds: they are further analyzed and classified as either normal or wheezing. Subsequently, this lung health "diary", as well as the captured environmental information, is available in essentially real time to the healthcare providers and patients in the form of a web application. Beyond the display of information, AsthmaGuide uses the data to provide specific patient advice. Although there are many potential asthma triggers, they are not applicable to all patients. Thus AsthmaGuide use the data to act as a personalized coach for the patient. This system in no way replaces the doctor and we are actively working with doctors to better understand the kinds of advice that are appropriate.

The first technical contribution of AsthmaGuide is the development and assessment of two different approaches to detect wheezing lung sounds. The first approach uses features based on edge detection. This novel resultant classifier solution is, on average, more accurate than the current state of the art classifiers [27]. The classifier uses a combination

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of Support Vector Machine (SVM) and Random Forest classifiers, which leads to a more robust system than previous models. Overall accuracy is measured at 96% as compared to 87% in the state of art. The second approach is based on acoustic verbal features. The evaluation of the second approach determines the effective features and the best classifier (random forest) with the result of 98.6% accuracy.

The second contribution is the full implementation of an overall system which is the first highly automated comprehensive sensor based monitoring and advice system for asthma patients. By providing information about lung health and the environment, patients and healthcare providers have a more complete understanding of the state of pertinent health issues. Note that this general infrastructure can be used beyond monitoring asthma patients. Most of these factors used in AsthmaGuide are important for any lung disease, (e.g. COPD), and also could be of potential interest even for healthy individuals.

A third contribution is the design, implementation, and use of a patient lung sound collection system that is easy to use for physicians and serves as ground truth in our experiments. Collecting real patient data is one of huge challenges in the process of designing a practically working classification system. We address this issue by developing an application that can be used by physicians to collect data from patients.

It is important to note that full assessment of the utility of this system in terms of its impact on long term use by asthma patients requires long term studies and FDA approval. These studies are beyond the scope of this paper; instead this paper demonstrates and evaluates the underlying technical solutions. For these solutions real patients were used to collect wheezing sounds and five MDs, three of whom are co-authors, were used as consultants to identify all the features, sensors, and feedback of interest, and then these were all incorporated into AsthmaGuide.

II. RELATED WORKS

Although there are many ways to evaluate the health of asthma patients, one of the major indicators of deteriorating lung health is wheezing lung sounds. Many existing wheeze detection methods are based on frequency and durations of acoustic signals or location of peaks successive spectra [4], [33], [15], [19]. Some of these studies work with empirically fixed discriminative threshold to identify peaks and therefore, the accuracy of detected wheeze is easily affected by noise. Certain classification models have thus been combined with algorithms [11], [22], [7], [16], but most of these studies work with a limited number of coefficients that are available online. In contrast to these studies, AsthmaGuide works with a much larger wheeze sound dataset which we actually collected from real asthma patients.

Other attempts have been made to automate the wheezing detection process via machine learning by using features such as Mel Frequency Cepstral Coefficients [11], AR model [20], and wavelet coefficients [21]. However, these features are not robust enough to create an accurate classifier accuracy and result in high computational complexity.

Other than wheeze detection, there are also recent studies that have utilized mobile devices to provide users with feedback about the environmental factors they are exposed to. Methods accounting for personal movement include PEIR [24] and iMAP [12], which predict exposure to environmental pollution based on a user's mobile phone location history. ENVIROFI [31] allow users to use a mobile phone based application to receive air quality predictions for their current location based on GPS coordinates supplied by the user's phone. These solutions are not directed to asthma.

There are previous works that aim to monitor asthma patients at home by employing self-monitoring [17] or home-management [1] plan either in written or electronic form. However, these monitoring techniques require manual recordings and regular visits to the hospital for patients to receive review by the physicians. On the other hand, Air Sonea [3] and Finkelstein et al. [14] also provide a mobile application, and LinkMedica [23] provides a web-based application where patients log information and view data from previous days.

There are other products that attempt to automate the collection and display of physiological information. MySpiroo allows for patients to measure their lung capacity and view this information on their smartphones [25]. Another device called Propeller allows patients and doctors to track the time and place patients use their inhalers [28]. Like Air Sonea, both are not as comprehensive as AsthmaGuide. Despite this, both MySpiroo and Propeller may be integrated into AsthmaGuide in the future.

III. SYSTEM OVERVIEW

AsthmaGuide consists of four main components: an extensive sensor suite, the smartphone hub, the cloud web application, and the advice infrastructure. The sensor suite is where data collection occurs (Figure 1-Part A). Environmental data are collected from Sensordrone, which is a sensor platform, and sent to the user's smartphone via a physical connection or wirelessly via Bluetooth. Information such as physiological data, medication, and exercise cannot be obtained via sensors, so users enter these information manually into the phone. Patients also have an option to take a photo or video of themselves with the in-phone camera, which is useful in helping healthcare providers understand their health via this built-in telemedicine modality. Moreover, we provide a way to record patient lung sounds using an electronic stethoscope.

Once all of this data is collected, it is then pushed to the cloud where the data is stored and further analyzed (Figure 1-Part B). First, the lung sounds are classified via a machine learning classifier as either normal or wheezing. Next, all of this information is displayed in a coherent fashion for patients and healthcare providers to view. Patients and healthcare providers have the option to drill down to see more details about a specific category, or they can view the data over time to look for trends. The web application also accesses information from the internet such as temperature, allergen, and air quality predictions. With this information

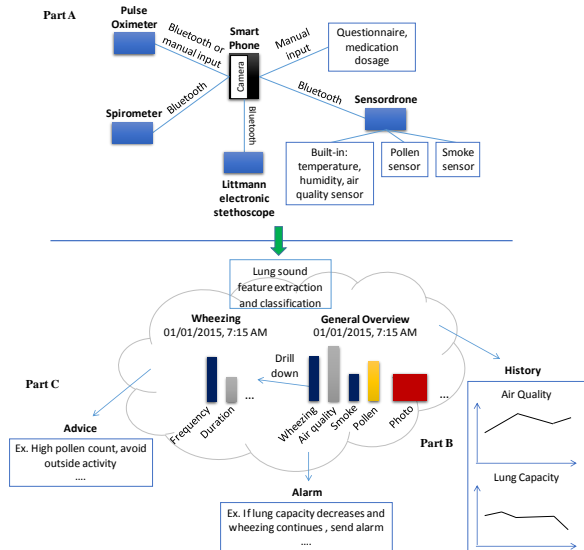


Fig. 1. AsthmaGuide overview.

organized in a cohesive manner, the patients and healthcare providers have the option to customize the normal delivery of reports. This allows both parties to specify how often and how much information the healthcare provider view on a daily basis. Alarms and alerts are also specified and are sent to healthcare providers if certain dangerous events occur. Overall, the delivery of these reports and alarms is highly customizable and can be adjusted based on the severity of a patient’s asthma.

The last part of our system is the advice given to patients (Figure 1-Part C). Currently, the advice that we provide follows an asthma action plan approved and used by the medical community.

The following use case illustrates how patients and healthcare providers collaboratively employ AsthmaGuide. A patient wakes up and at his bedside are a smartphone, the AsthmaGuide sensor suite, and an electronic stethoscope. The patient opens the AsthmaGuide smartphone application which prompts the user to collect lung sounds and measure lung capacity; to use the pulse oximeter (for oxygen and heart rate information) and spirometer (for lung volume); to take a ‘selfie’ picture and video; to answer questions about how they are feeling; and allows entry of his administered medication dosage from the previous day. At the same time, the sensor suite is collecting environmental data and sending it to the smartphone. At the end of the process, the patient clicks a button which sends the lung and environmental data to the cloud. Once in the cloud, the lung sounds are classified as normal or wheezing. Then based on specifications by the patient, the appropriate subset of the information is sent to the healthcare provider. The patient can also access this web application and view all their lung and environmental information and advice, if any.

IV. SENSOR SUITE

The sensor suite is the first component of our system. Our system uses the sensor suite to collect both physiological and environmental data. To collect patient lung sounds,



Fig. 2. Sensor suite: a) Littmann 3200 electronic stethoscope, b) Sensor drone, c) Contec SP10W spirometer, and d) Nonin Medical pulse oximeter.

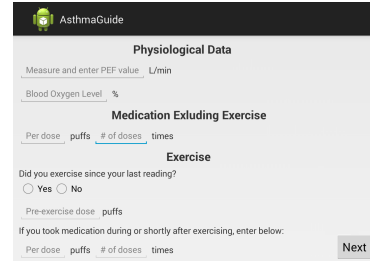


Fig. 3. Patient data collection application: a) questionnaires that patients fill out manually and b) physiological and environmental information are displayed on the application for review.

AsthmaGuide uses the Littmann 3200 electronic stethoscope shown in Figure 2a. This device has built-in Bluetooth technology which is capable of recording patient body sounds and appending them to medical experts for further analysis.

Collecting environmental data such as temperature, humidity, and various gases, such as carbon monoxide, ozone, nitrogen dioxide, and chlorine is important for asthma patients. To collect these data, we use a device called Sensor drone [29] shown in Figure 2b. Sensor drone is an open platform for many different sensors and Bluetooth peripheral devices, which makes it convenient for the users to portably carry around in indoor and outdoor settings to collect environmental information. We also use Contec SP10W spirometer as shown in Figure 2c to measure lung air capacity and Nonin Medical finger pulse oximeter as shown in Figure 2d to measure blood oxygen level.

V. SMARTPHONE HUB

The smartphone hub sits in-between sensors and cloud. Its main functionality is to post aggregated data to the cloud. In the process of aggregation, sensing data is automatically sampled and physiological information is surveyed by manual input. Considering that these are non-technical users, the user interface conveys a simple design as shown on Figure 3. Behind the user interface, seamless interaction between different libraries and collection phases has been implemented.

The first phase of the smartphone hub is the process of collecting lung sounds from patients. We first instruct a patient to sample lung sound by placing the stethoscope on the front of the individual’s torso. Using the SDK library provided by Littmann 3200, our application first connects to the pre-paired electronic stethoscope through Bluetooth and requests the patient to turn on the stethoscope. The patient can thereafter start collecting four different lung sound samples from the second intercostal space mid-clavicular line to the sixth intercostal space mid-axillary line of the patient’s chest. From each of the four different location, of

the patient's chest, 10 seconds auscultation wave file is saved to memory. The wave file header format specifies the 10 seconds with 64 kilobits per second bitrate. The sampling period is fixed to avoid insufficient or overloaded data for detecting wheeze sounds.

The second phase of smartphone hub is collecting physiological data, specifically questionnaires that patients fill out manually as shown on Figure 3. It consists of 10 items, where each item requires a number or a multiple choice answer. One of the example entry is administered medication dosage from the previous day. The answers from these items are used to predict the severity of the patient's lung condition. Test results are displayed in a color format, specifically, green, yellow, and red. Green or yellow color suggest good to moderate condition, where as red indicates that the patient should visit their doctor. Besides physiological data, a patient photo and video are also taken for further analysis of their health via appearance. Note that taking a photo or recording a video is optional and the system proceeds with any data that are available.

While the electronic stethoscope is connecting, the pre-paired Sensordrone is also connected to the application. Similar to the stethoscope connection, the system uses the SDK from Sensordrone for retrieving sensing data. As mentioned above, the user interface requests the patient to take the physiological questionnaires after lung sound sampling. The reason for this is to allow enough sampling period for Sensordrone to measure accurate information of the patient's surrounding such as temperature, humidity, and air quality. The Sensordrone connects and transmits data via Bluetooth to the smartphone.

For outdoor environmental data, we use National databases to gather information of air quality [2], pollen count [34], and asthma index [6]. These data are retrieved by using a patient's zipcode saved during the registration of the patient. The zipcode can be modified accordingly to the patient's preference in location. After retrieving physiological data, surrounding environmental data, and outdoor environmental data, these information are displayed on the application for review.

In order to upload information to the cloud, sampled data from each phase needs to be aggregated. The application implementation is built with 4.4 KitKat SDK with several activities and each collection phase represents an activity. Between activities, the previous activity pushes sampled data to intent which holds onto the data with hashmap, and this continues until the upload activity phase. At this phase, all the data stored on the intent is fetched and aggregated for submission. After the patient clicks on the submit button, data is uploaded to the cloud and a brief summary of the information is displayed on the smartphone. If any of this data triggers an alarm, a high priority notification is sent to the healthcare provider and to the patient. If any of the data triggers advice that does not reach the level of alarm, the content is displayed on the patient's smartphone. This process should take a minimal amount of time and can be repeated multiple times a day.

VI. CLOUD WEB APPLICATION

For doctors and patients to review collected data and observe daily lung health patterns, we developed a user interface. The interface is accessible by a web browser which is a cloud web application as shown in Figure 4. For privacy purposes, we have secured patients data with password protection. Patients and doctors need input their ID and password in order to access information. The doctor's lists of patients are presented with an overview of daily patient data. When a patient is selected, a summary of the latest health and environmental factors is displayed including: patient face image, video clip, physiological data, environmental data, and severity of the patient are presented in a form of numbers or image. For an advanced search, doctors select a start time and an end time: all the data collected from a selected patient between these two dates are presented to that doctor. Additionally, doctors select or deselect particular health or environmental factors to see or not see them in the presented summary as shown in Figure 4a. Moreover, when doctors select two of these any health or environmental factors, a correlation graph is generated to show the correlation between these two selected factors as shown in Figure 4b.

VII. ADVICE INFRASTRUCTURE

The last part of our system is to present recommended advice to the patient. The advice infrastructure is an especially challenging part of our system because we do not want to give any advice that endangers patients. Thus, we only provide very general and expert advice from existing asthma standards such as Asthma Action Plan from American Lung Association [5]. In addition, after retrieving outdoor environmental data, a patient also receives an alert notice when the air quality or asthma index is unhealthy, or pollen count is too high in the user's area. This advice infrastructure is extensible and allows for medical experts to extend the rule set as they continue to use AsthmaGuide. In general, the advice mostly considers non-pharmacological strategies which assist patients to reduce risks and sustain health conditions until a patient receives medical treatment from a doctor.

VIII. LUNG SOUND CLASSIFIERS

A. Data Overview

For any machine learning problem, it is important to first understand the data to be classified. There are two basic types of lung sounds: normal, wheezes. The characteristics of these types of lung sounds is shown in Table I. For these sounds, both frequency and time features are important. Normal lung sound features are located at lower frequencies, as there is a drop off in power below 200 Hz [8]. On the other hand, wheezing-type sounds usually have features from 200 to 1000 Hz [8].

In order to train a lung sound classifier, a source of normal and wheezing lungs sounds is required. There are three repositories of lung sounds: Marburg Repository of Sounds [18], R.A.L.E. repository [32], and CORSA [30]. There are many difficulties that come with the current data set. First of all, there are a limited number of clips available.

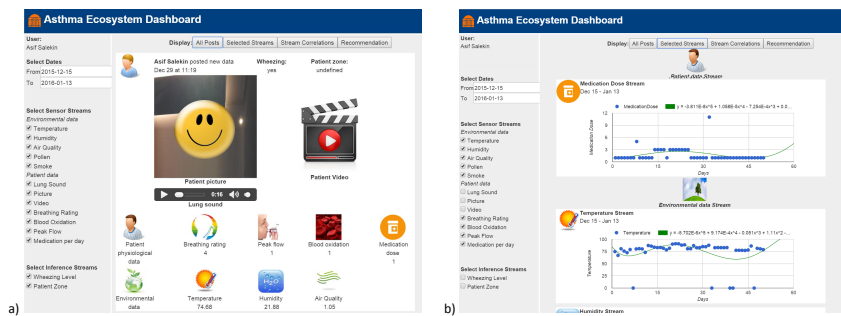


Fig. 4. Cloud web application: a) Overview of daily patient data and b) Scatter graph on physiological and environmental data.

| Auscultation Type | Typical Frequency | Duration (msec) |
|-------------------|--|-----------------|
| Normal | 100-1000 Hz (Drop of energy at 200 Hz) | N/A |
| Wheezing | 100-5000 Hz | 100 |

TABLE I

CHARACTERISTICS OF NORMAL, WHEEZE LUNG SOUNDS.

In addition, the data is not always well labeled. Some of the clips are collected from different parts of the lung, but many times this is not specified. Also, clips come from patients of different ages and this is not always specified. This is potentially problematic because it is unclear whether the lung sounds of a child should be used to train a classifier for an adult. Lastly, different recording strategies were used for the clips online, but the exact strategy is not specified. Thus, there needs to be a way to normalize these clips.

Unfortunately, of the three repositories of lung sounds, only R.A.L.E is publicly available and it contains 32 wheezing clips and 8 normal clips. This number is not enough for training and testing our system. Thus, our group used an electronic stethoscope to collect lung sounds. We collected 32 additional normal lung sounds from (healthy) members of our research group and 31 wheezing lung sounds from real patients.

B. Data Collection

One of the main challenges in designing a practical working classification system is the process of collecting real samples for learning and acceptable evaluations. We address this issue by developing a smartphone-based data collection application. This application collects normal and wheezing sound data, i.e., auscultation data, from real asthma patients by healthcare providers. Specifically, for this work, hospital doctors, without difficulty, collected 64 kilobits per second bitrate wav data from patients, which include auscultation recordings from 4 different locations around the torso. In total, 31 sound clips were recorded. Note that this application asks healthcare providers to fill out brief questionnaires regarding the patient's gender, age, torso location, and estimated health condition that can be used for any possible future studies.

C. Data Preprocessing

The following are the steps taken to preprocess the lung sounds.

- 1) Given lung sound recordings from online sources or the stethoscope, normalize these with respect to root-mean-square energy. Resample the clip to 4000 Hz, as this is the sampling rate of the stethoscope.
- 2) Apply a high-pass filter at 200 Hz as this eliminates many of the features of normal lung sounds. Apply a low-pass filter at 1990 Hz in order to satisfy the Nyquist sampling criterion.

D. Two Classification Approaches

We have explored two different approaches to detect wheezing from preprocessed lung sound clips. The idea is to determine if classification based on spectral edge detection or the more classical acoustic signals such as MFCC is better. The following two sections describe these two approaches and their evaluations.

1) Approach 1 - Classification Based on Edge Features:

The first approach is based on the methods of [22]. The strategy is to extract edge features from spectrogram of lung sound. All of the code was written in Matlab and the audio analysis used the MIRtoolbox library.

Feature Extraction using Spectrogram Edge Detection:

- 1) Calculate the short-time Fourier transform with a window of length 256. Examples of the generated spectrograms are shown in Figure 5a. It is clear that most of the features are filtered from the normal lung sound, but bands of sounds are seen in the wheezing sound.
- 2) Apply a Laplacian mask to filter noise and make edge features more prominent. The effect of this is shown in Figure 5b and Figure 5c.
- 3) Apply a threshold to the spectrogram so all data below $0.5 * \text{MaximumPower}$ is set to 0.
- 4) Extract the following edge features: the mean power, the orientation/slope of the edge, the length in terms of time, the frequency at the centroid. Pick the two edges whose length in terms of time and frequency sum to the greatest value.

After this process is complete, a total of 8 features for each lung sound is extracted.

Machine Learning Classifier: In order to develop an accurate classifier using features based on edge detection, we focused on three types of models: C4.5 Decision Trees,

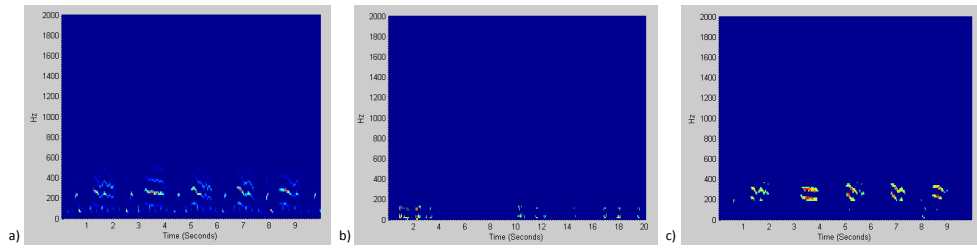


Fig. 5. Example of lung sound spectrograms: a) wheezing sound after calculating the short-time Fourier transform, b) normal sound after applying a Laplacian mask, and c) wheezing sound after applying a Laplacian mask.

| Classifier | Sensitivity (Wheezing Accuracy) | Specificity (Normal Accuracy) | Overall Accuracy |
|--------------------------|---------------------------------|-------------------------------|------------------|
| SVM | 58/63 (92%) | 28/40 (70%) | 90/103 (87%) |
| Decision Tree (C4.5) | 58/63 (92%) | 25/40 (62%) | 88/103 (85.4%) |
| Random Forest Classifier | 60/63 (95%) | 34/40 (85%) | 96/103 (93%) |
| Combination | 62/63 (98.4%) | 38/40 (95%) | 99/103 (96%) |

TABLE II

RESULTS OF APPROACH 1 USING DIFFERENT TYPES OF MODELS AND COMBINATION OF CLASSIFIERS.

Random Forest models with C4.5 trees, and Support Vector Machines (SVM). For the Random Forest model, we ran 100 iterations with 3 features considered for each decision split. For the SVM, we used a linear kernel, quadratic kernel, Gaussian radial basis kernel, and a polynomial kernel of order 3. We also used various combinations of features to see which yield the most accurate classifier. We used the Matlab implementation of each of these classifiers and tested the accuracy with 10-fold cross validation.

Using the 63 wheezing clips and 40 normal clips from the R.A.L.E. repository and data that we collected, we first evaluate the performance of detecting wheeze and normal sounds. The first three rows of Table II show the results for these three classification models. We only show the result for the quadratic kernel because this yielded the best result. The results show that of the three models, the Random Forest classifier performed the best with an accuracy of 93%.

In order to build a more accurate classifier, next we combined the results of multiple classifiers in order to take advantage of their strengths. After trying different combinations of features and different kernel functions, we developed the following three classifiers:

Classifier 1 : A SVM with a Gaussian radial basis kernel function which used all 8 features. This classifier generally could identify normal lung sounds with high accuracy, but had some false positives for wheezing.

Classifier 2 : A SVM with a linear kernel function which used the mean power, the length in terms of time, and the frequency of the centroid for 2 edges. Thus there are a total of 6 features. This classifier generally could identify wheezing sounds with high accuracy, but had some false positives for normal sounds.

Classifier 3 : A Random Forest model with 3 features considered for each decision split run for 100 iterations. This used the same features as Classifier 2. The classifier had about 90% accuracy with equal numbers of

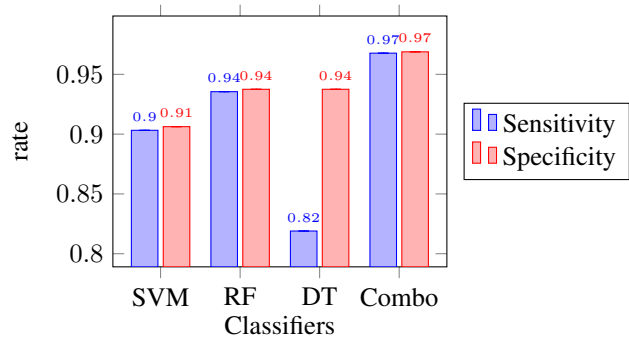


Fig. 6. Performance comparison between classifiers on sound clips collected by AsthmaGuide.

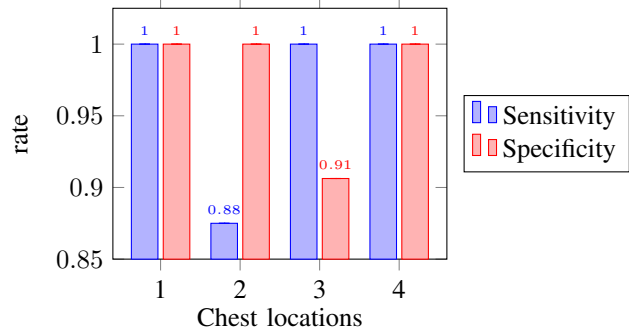


Fig. 7. Performance comparison between different chest positions for approach 1.

normal and wheezing misclassifications.

The following are the steps to use these three classifiers:

- 1) Run clip on Classifier 1 and Classifier 2.
- 2) If both label as normal, label as normal. If both label as wheezing, label as wheezing. Else, go to step 3.
- 3) Run clip on Classifier 3 and return label.

The result using this combination of classifiers is shown in the fourth row of Table II. It achieves the best result for sensitivity and specificity with a best accuracy of 96%.

We have evaluated the performance of our combination of classifiers approach on all 4 chest positions. Figure 7 shows the sensitivity and specificity on sound clips from 4 chest positions. Both sensitivity and specificity are 1 for chest position 1 and 3, where sensitivity decreases for chest position 2 and specificity decreases for chest position 4.

We also have evaluated our algorithm only using sound clips that we collected from real patients and healthy volunteers. We have collected 31 wheezing sound clips and

| Classifier | Sensitivity (Wheezing Accuracy) | Specificity (Normal Accuracy) | Overall Accuracy |
|---------------|---------------------------------|-------------------------------|------------------|
| SVM | 62/63 (98.4%) | 37/40 (92.5%) | 99/103 (96.1%) |
| Decision Tree | 59/63 (93.6%) | 33/40 (82.5%) | 92/103 (89.3%) |
| Random Forest | 63/63 (100%) | 38/40 (95%) | 101/103 (98%) |

TABLE III

RESULTS OF APPROACH 2 USING DIFFERENT TYPES OF MODELS FROM THE R.A.L.E. LUNG SOUND REPOSITORY DATA

32 normal sound clips from 4 chest positions. A leave-one-out cross validation on these 63 sound clips were performed and the performance is compared with different classification models. Figure 6 reports the performance on sound clips collected by AsthmaGuide. In both performance metrics sensitivity and specificity, our combination of classifiers approach outperforms conventional algorithms and achieves 97% for both metrics.

2) **Approach 2 - Using MFCC and Other Acoustic Features:** Approach 2 explores the acoustic signal processing features such as Mel-Frequency cepstral coefficients, loudness, logarithmic power of Mel-frequency bands 0 – 7 (distributed over a range from 0 to 8 kHz), LPC coefficients, fundamental frequency, zero crossing rate, etc. Through our evaluation we find that logarithmic power of Mel-frequency bands and the loudness as the normalised intensity raised to a power of 0.3 are good predictive features and adding any of the rest of the features does not increase accuracy.

Feature Extraction Based on Acoustic Features:

- 1) Segment each preprocessed lung sound clip into 40 ms frames with 10 ms overlapping.
- 2) Extract the logarithmic power of Mel-frequency bands 0 – 7 (distributed over a range from 0 to 8 kHz) and the loudness as the normalised intensity raised to a power of 0.3 from each of these small frames. To each of these features, the delta coefficients are also computed.
- 3) Next the 12 functionals: mean, standard deviation, kurtosis, skewness, minimum and maximum value, relative position, and range as well as two linear regression coefficients with their mean square error (MSE) are applied on all the features extracted from small frames in a lung sound clip. These are the resulting features for wheezing detection.

Machine Learning Classifier: Three types of models: C4.5 Decision Trees, Random Forest models with C4.5 trees, and Support Vector Machines (SVM) are evaluated with the extracted features of *Approach 2*. For the Random Forest model, we ran 100 iterations with 10 features considered for each decision split. For the SVM, we used a linear kernel, quadratic kernel, Gaussian radial basis kernel, and a polynomial kernel of order 3. We also used various combinations of features to see which yielded the most accurate classifier. Matlab implementation with 10-fold cross validation is used for the evaluation.

Using the 63 wheezing clips and 40 normal clips from the R.A.L.E. lung sound repository, we first evaluate the performance of detecting wheezing and normal sounds. Table III

| Classifier | RMSE | Overall Accuracy |
|---------------|------|------------------|
| SVM | 0.17 | 97 |
| Decision Tree | 0.31 | 92 |
| Random Forest | 0.12 | 98.6 |

TABLE IV

RESULTS OF APPROACH 2 USING DIFFERENT TYPES OF MODELS ON REAL DATA

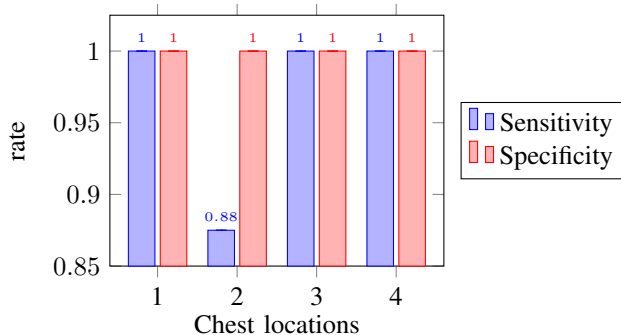


Fig. 8. Performance comparison between different chest positions for approach 2.

shows the results for the classification models. The results show that of the three models, the Random Forest classifier performed the best with an accuracy of 98%.

Also, Table IV shows the evaluation of our classification models on 31 wheezing and 32 normal sound clips that we collected. According to this evaluation the Random Forest classifier performed the best with an accuracy of 98.6% and 0.12 root mean square error.

For *Approach 2* we also have evaluated the performance of our random tree classifier on all 4 chest positions. Figure 8 shows the sensitivity and specificity on sound clips from 4 chest positions. According to this evaluation, specificity is 1 for all chest positions, where sensitivity decreases for chest position 2.

Both of our proposed approaches miss-classify one particular wheezing lung sound clip from chest position 2. This particular clip is an outlier in our collected wheezing data which can be addressed and corrected with more training samples.

3) **Evaluation Conclusions:** From our extensive experiments the performance of classification based on spectral edge detection (approach 1) versus the more classical acoustic features (approach 2) we find that the latter is slightly more accurate (96% versus 98.6%, respectively). Note that to obtain this accuracy requires careful choice of features and classification algorithms. For example, to achieve 96% accuracy for the spectral edge detection requires a novel combination of classifiers while the more classical approach which achieves 98.6% accuracy requires identifying the effective features and a random forest classifier. Consequently, because of its better overall performance we use approach 2 for AsthmaGuide.

IX. DISCUSSION AND LESSONS LEARNED

To develop AsthmaGuide, we interviewed 5 medical experts, multiple times each. For each of these interviews we

presented the current state of the design including a demo. At each step, feedback from the medical professionals informed the next version of AsthmaGuide. We give one example to illustrate this process. In the penultimate version we had all the physiological and environmental sensors mentioned in this paper. We then asked the doctors if anything else is needed or what do they do to make a final diagnosis. They answered that they just look at the patient and can see how badly off they are by how they appear. We then added both static photos and video clips. The final result is the comprehensive collection of data as described in this paper. Feedback also emphasized the need for the simplest user interface possible, simpler than our original notions of what was simple. One aspect of this is the idea to combine all the sensor devices into one device, plus the stethoscope. In the end, experts deemed this final version as extremely useful.

Other lessons learned include: (i) In collecting external knowledge on air quality, it was found that different countries have different definitions and techniques for reporting air quality. AsthmaGuide has implemented solutions for both U.S. and S. Korea. (ii) Medical device companies were unwilling to provide APIs for external users to develop Android applications. We had to use their interfaces. (iii) It is important to know when the stethoscope sounds are on the chest and recording properly. It cannot be assumed that all sounds from the stethoscope are lung sounds. (iv) Doctors also suggested that AsthmaGuide can easily be used for other lung problems such as COPD.

Several future steps are required or planned. One, long term pilot studies are needed to assess if patients would actually use the system, for how long, and whether better asthma outcomes result. As mentioned in the introduction, these pilot studies are outside the scope of this paper. Two, the classifiers can be extended to detect crackling. Three, asthma attack predictions can be added to AsthmaGuide. Four, once enough data is collected very useful longitudinal studies can be conducted for understanding the triggers of attacks for an individual and the effectiveness of treatments.

X. CONCLUSIONS

AsthmaGuide is a comprehensive asthma ecosystem that helps patients become involved in their own health and allows healthcare professionals to provide up-to-date care. By collecting both physiological and environmental data, AsthmaGuide provides a complete view of a patient's health. It also contains a state-of-the-art wheezing detector that utilizes wheezing characteristics such as frequency, power, and duration. The patient data allows for personalized advice and alarms that are specific to a patient's reaction to different triggers. This infrastructure is extensible and customizable which allows for healthcare providers to set parameters as they learn more about their patient's asthma triggers. It is also important to point out that the development of AsthmaGuide was a truly collaborative effort between technical and medical experts as reflected in the author list.

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