An mHealth System for Monitoring Medication Adherence in Obstructive Respiratory Diseases Using Content Based Audio Classification

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ABSTRACT Asthma and chronic obstructive pulmonary disease are obstructive respiratory diseases that affect negatively the quality of life for patients and their families worldwide. Despite the significance of these diseases, their management has been considered suboptimal around the world, whereas the improper inhaler use has been underlined as one of the main causes. Toward this direction, this paper presents an integrated mHealth system that provides real-time personalized feedback to patients for assessing the proper medication use and educating them and helping them avoid common mistakes. The identification of proper inhaler use is based on conventional and data-driven feature extraction and classification methods employed for the identification of four events (inhaler actuation, inhalation, exhalation, and background noise). The proposed scheme reaches 98% classification accuracy significantly outperforming recent and relevant state-of-the-art approaches. Finally, intuitive feedback interfaces were implemented in the form of a virtual guidance agent integrated with the mobile application, which can help patients follow their action plan and assess their inhaler technique in a more engaging manner. Extensive simulation studies, carried out using 12 subjects, demonstrated the efficiency of the proposed approaches in both indoor and outdoor environments.

INDEX TERMS Asthma, COPD, mHealth, medication adherence, pMDI correct usage, Gaussian mixture models, time-frequency analysis, classification.

I. INTRODUCTION

Asthma and COPD (Chronic Obstructive Pulmonary Disease) are chronic inflammatory conditions of the airways affecting over 235 million people worldwide [1] with more than 30 million living in Europe [2]. Inflammatory lung diseases significantly deteriorate the quality of life for patients and their families while affecting the overall efficiency of the healthcare system [3]. The diversity of obstructive respiratory diseases [4] reveals the importance for new and innovative approaches that can help patients cope with their condition and avoid dangerous exacerbation events [5].

The adherence of patients to their medication, both in terms of following the doctor prescription and using the inhaler device correctly, is one of the most important factors for the effective management of their condition. Reduced medication adherence has been already associated with asthma attack incidents and patient hospitalizations [6]. It is important to underline that 24% of asthma exacerbation and 60% of hospitalizations are related to poor medication adherence [7]. Furthermore, a recent comprehensive review of modern inhaler devices has underlined important monitoring features that are expected to enhance the experience of patients with obstructive respiratory diseases and help them manage their condition more effectively, indicating the assessment of inhaler technique as one of the most promising fields for further study [8]. Figure 1 demonstrates the correct usage of a pressurized Metered Dose Inhalers (pMDI) according to clinical practice and forms the basis for the separation of the four classes of events that are assessed in the current study, namely: pMDI inhaler actuations, inhalation sounds, exhalation sounds, and background/environmental sounds.

More specifically, proper inhaler use includes the following steps [9]: a) Remove the cap b) Breathe out, away from your inhaler c) Bring the inhaler to your mouth. Place the
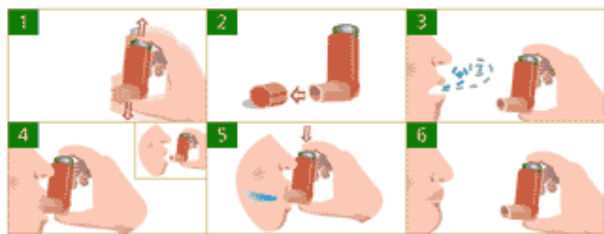
FIGURE 1. pMDI Usage described in [24]. 1) Shake the pMDI 2) Remove the cap 3) Exhale 4) Place the pMDI inside your mouth 5) While inhaling press the pMDI drug actuation button 6) Hold your breath for 10 seconds and breath out.

inhaler in your mouth between your teeth and close your mouth around it. d) Start to breathe in slowly. Press the top of you inhaler once and keep breathing in slowly until you have taken a full breath. e) Remove the inhaler from your mouth, and hold your breath for about 10 seconds, then breathe out. According to [10], 77.3% of patients performs at least one step of the inhalation technique incorrectly.

Recently, there has been increasing interest from researchers, system designers, and application developers on wearable and remote health monitoring approaches [11]–[19]. Several of these works are related to personalized management services for obstructive respiratory diseases aiming to provide methodologies for medication adherence monitoring. Specifically, these studies either focus on device integrated solutions, using pressure activated switches [17], [20], [21] or on ambient sound analysis approaches [18], [19], [22]. Despite their inherent differences, both approaches allow the detection of drug actuations, while the latter could be also employed for identifying inhalation or exhalation events.[1] Moreover, it is worth mentioning that none of the studies achieves classification accuracy higher than 94%, being incapable of differentiating accurately inhalation and exhalation sounds. Finally and more importantly, none of them provide an integrated application that can transform the mobile phone into a personalized agent which will help the patient to follow the prescribed action plan and use the inhaler correctly.

In this paper, motivated by the aforementioned open issues, we introduce a novel approach for identifying and evaluating the proper use of pMDIs. The process exploits the high separability of the Cepstrogram based features and achieves very high classification accuracy, reaching 98.7%, with the utilization of Gaussian Mixture Models. Additionally, the proposed processing pipeline demonstrates higher noise robustness that other approaches presented in this study. The dataset consists of 495 audio recordings per class, generated using 12 subjects.

The exploitation of a relevance feedback scheme allows the adaptation of the trained models to the user, aiming towards the improvement of the classification accuracy on a patient-specific basis.

[1] A preliminary version of this work has been reported in [23].

Moreover, the aforementioned approaches are implemented on a system comprised of a sensor device, a mobile application, and a cloud server. The user has access to the aforementioned functionalities and to statistics related to self-management of asthma and COPD through a graphical user interface (UI). The UI offers different information visualization approaches so as to present the information in a user-friendly manner in both patients and researchers.

A vocal oriented virtual guidance agent has been implemented in order to allow the support of patients during the use of the inhaler. Furthermore, the proposed guidance functionalities have been integrated with electronic calendar and action plan functionalities that allow the real time monitoring of medication adherence of patients by their responsible doctor and the easy change of the medication plan when considered necessary without the need for time and costly visits and the requirement of subjective patient feedback related to medication adherence.

The contributions of the proposed methods compared to current state of the art approaches can be summarized in the following points.

1) We propose a novel content based audio classification approach for monitoring pMDI medication adherence, which exploits the separability of the Cepstrogram features using a GMM classifier.
2) We propose the utilization of a relevance feedback scheme enabling the patient or the researcher to correct misclassified results and resubmit them allowing the personalization of the trained model in a user-oriented manner, thus increasing accuracy and personalization.
3) We propose the enhancement of the inhaler usage experience through intuitive interfaces of patient guidance including a virtual agent providing significant advice to the users regarding their medication.

Finally, extensive simulation studies with indoor and outdoor measurements, demonstrate that the proposed approach identifies correctly the four different events and the improved management of the obstructive respiratory diseases by providing user-friendly tools to increase the awareness of the effectiveness of medical treatment.

The rest of the paper is organized as follows: Section II provides an insight of the related work. The overall architecture of the system, the information visualization and the patient support interfaces are described in Section III. The proposed methods feature extraction and classification methods are analyzed in Section IV. The results and the system evaluation is presented in Section V. Finally, findings and contributions are concluded in Section VI.

II. RELATED WORK

The efficient and effective management of asthma and COPD is strongly connected with the patient adherence to the prescribed action plan and the correct use of the inhaler. It is worth mentioning that reduced adherence has been linked with significant indicators of health degradation [6], e.g.,

24% of asthma exacerbation and 60% of hospitalizations are attributed to poor adherence [7]. Towards this direction, mHealth monitoring systems can provide personalized guidance to patients allowing them to manage their own health.

Within this scope, the recent related studies can be categorized into the following groups: 1) works that focus on clinical outcomes of suboptimal medication adherence, 2) studies that present medication adherence monitoring devices, 3) energy-efficiency approaches, that focus on minimizing the processing and the power consumption either on the sensor or on the mobile device side of the mHealth system, 4) feature extraction and classification based approaches, 5) virtual agents for patient guidance.

A. CLINICAL OUTCOMES OF SUBOPTIMAL MEDICATION ADHERENCE

This is a group of studies, that outlines the importance of following a personalized action plan and a prescribed medication. D'Arcy *et al.* [25] validated that the inhaler technique errors have an impact on the clinical outcomes of asthma management. Pritchard and Nicholls [26] emphasized in the clinical terms of ''adherence'', ''inhaler competence'' and ''true adherence'' and aimed to define how non-adherence to medication affects patients.

Finally, Van Boven *et al* [27] focused on the optimization of adherence and on the management of non-adherence in Asthma.

B. MEDICATION ADHERENCE MONITORING DEVICES

Howard *et al.* [17] performed a review of electromechanical and electronic devices based on pressure activated switches. These approaches are capable of identifying inhaler actuation, while they completely ignore actions related to inhalations and exhalations. Furthermore, a recent comprehensive review of inhaler-based monitoring devices has underlined the clinical importance of accurate assessment of inhaler technique and provides a comparative analysis of the very few research and commercial attempts towards this direction [8].

C. ENERGY-EFFICIENCY MONITORING OF MEDICATION ADHERENCE

Provided that the monitoring system is mostly based on wearable devices and smartphones, the energy efficiency of the proposed processing, transmission and decision making tasks is of crucial importance. Lalos *et al.* [28] investigated efficient monitoring of pMDIs enhancing the benefits of conventional compressed sensing (CS) schemes taking into account specific characteristics of the audio features, using as recovery algorithm DG LASSO and integrated it with state of the art classifiers allowing high levels of accuracy (98%). Moreover, Oletic *et al.* [29] and Oletic and Bilas [30] employed CS framework in the context of a medical system for monitoring the respiratory system, consisting of a body-worn acoustic sensor and a smart-phone.

D. FEATURE EXTRACTION AND CLASSIFICATION APPROACHES

Taylor *et al.* [18] used the continuous wavelet transform to detect pMDI actuations, in order to perform a quantitative assessment of patients inhaler technique, focusing only on the detection of inhaler actuation sounds. Holmes *et al.* [19], [22] employed mean power spectral density to detect inhaler actuations, while for breath detection and for the separation of exhalation and inhalation sounds they defined decision rules employing an approach based on Mel-Frequency Cepstral Coefficients (MFCC) and zero-cross rate (ZCR). For each sound category, they used a predefined threshold and achieved a classification accuracy ranging from 91.7% for inhalations up to 93.7% for exhalations. However, even if the aforementioned studies aim towards audio content based medication adherence, they achieve classification accuracy up to 94% without taking into account noisy environments.

E. VIRTUAL GUIDANCE AGENTS

Fields of medical research, such as psychology, have devoted significant efforts to the development of conversational agents, that can support patients and accurately assess their condition [31]. This progress has paved the way for the utilization of such technologies in many areas of medical support [32] including some recent applications in the field of respiratory conditions [33].

To the best of our knowledge, this is the first work that provides an integrated mHealth solution, that utilizes commercially available BT microphones integrated with novel prediction models. This system aims to provide real-time personalized feedback to patients, to educate them and promptly to intervene with advices. Ultimately, this work aims to prevent common mistakes, leading to potential upcoming dangerous events, such as exacerbations and hospitalizations.

III. DESIGN AND DEVELOPMENT
This section consists of two parts. The first is dedicated to the presentation of the overall system architecture, while the latter presents the user interface and visual features part of the mobile application.

A. SYSTEM ARCHITECTURE
Figure 3 presents a diagram of the overall architecture. The system consists of three parts: 1) The monitoring device consists of a commercial Bluetooth microphone attached in a 3D printed inhaler case, as shown in Figure 2. The microphone's sensitivity and frequency response range are 105dB-SPL and 20Hz - 20kHz respectively. 2) The smartphone application part and 3) The cloud processing server part. The smartphone application receives audio samples from the audio sensor and performs a feature extraction process. Then the extracted audio samples are uploaded to a cloud server for classification, based on a pre-annotated dataset stored in a database. The result is downloaded to the mobile device for visualization and user interaction. Moreover, a relevance
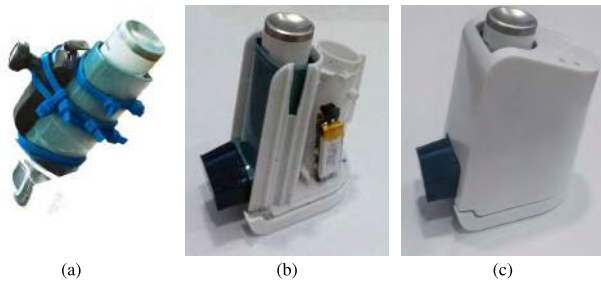
FIGURE 2. a) Experimental setup of the pMDI. The Bluetooth microphone is firmly locked on the device. b) Inhaler prototype without casing. The pMDI is placed within a cavity. c) Inhaler prototype with casing.

feedback functionality, described in subsection IV-C, allows the user to evaluate and correct the inhaler usage results and, thus, to improve the system towards a patient-specific perspective.

### 1) PROCESSING TASKS EXECUTED AT THE MOBILE DEVICE

The smartphone application has the following major objectives: a) Communicates with the inhaler device. b) Extracts features from the received audio samples c) Provides the interface to the user and d) serves as a data manager. e) Moreover, the application introduces a set of options to the user, allowing the modification of the feature extraction process by employing different type of window, different feature extraction algorithm or different classifier. f) Uploads the extracted audio features to the cloud server for processing. g) On completion, the classification result is downloaded and visualized to the user through intuitive visualizations. The application provides a relevance feedback feature, where the user corrects his/her inhaler usage results allowing the personalization of the trained models.

2) PROCESSING TASKS EXECUTED AT THE SERVER SIDE

Motivated from [28] and in order to optimize the energy efficiency of the mobile application, the classification of the uploaded audio features is performed on the cloud. Figure 3 shows the processing pipeline. The uploaded features and the stored training dataset are fed into the classifier. The response containing the classification result is downloaded to the smartphone application for visualization purposes.

B. USER INTERFACE, VISUALIZATION, AND PATIENT SUPPORT

The user interface consists of a detailed advanced view, to be used by researchers, and a simplified view, to be used by patients. In the researcher oriented view, the inhaler usage result is visualized with colored rectangles placed one next to another (Figure 8). Each rectangle corresponds to a window with a duration of 0.5 seconds. Afterwards, the relevance feedback capability is activated. The patient can click on any rectangle assumed be a misclassified entry, activating a selection menu. After the correct class is chosen, the result can be resubmitted to the cloud so as to be stored in a separate database table reserved for user-defined
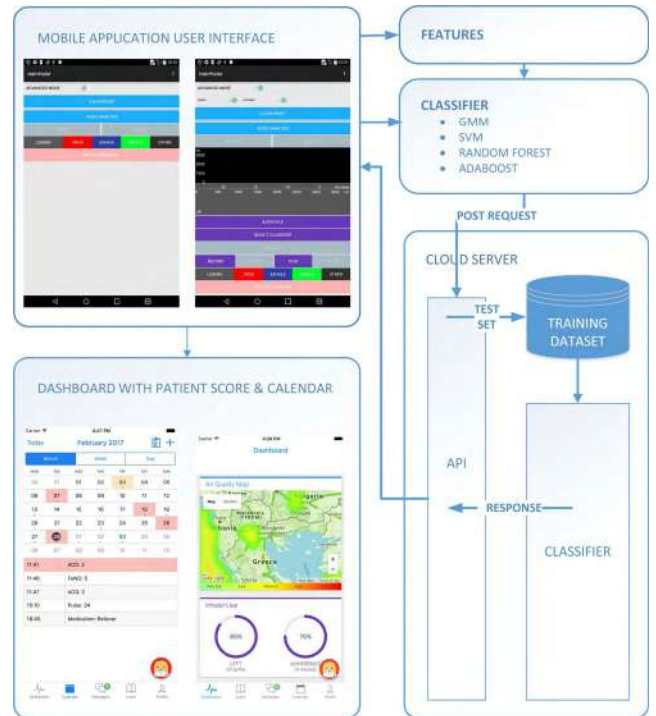
FIGURE 3. Overview of system architecture. The mobile application and submits the extracted features and the user options to the cloud server and receives the response.

entries. Figure 9 shows the relevance feedback user interface. Figure 4a illustrates the dashboard of patient support view containing information about the average adherence score of the user along with the number of doses currently remaining in the inhaler. The Virtual Guidance Agent on the bottom of the screen is activated when the patient uses the inhaler in order to collect real time feedback and notify the responsible health care professional when appropriate. Furthermore, the dashboard screen combines environmental measurements collected from the EU Copernicus system [34] for the calculation of the Common Air Quality Index [35] in the location of the patient, which are then visualized on a map for a complete support of the patient. Figure 4b illustrates the implementation of asthma diary, as integrated into the same mobile application, and provides an overview of the patient's respiratory health and medication uses comprising from asthma related questionnaires (e.g. ACD, ACQ) and the integration of commercial sensors (e.g. smart health watch, sensors of fractional exhaled nitric oxide).

IV. CONTENT BASED AUDIO CLASSIFICATION APPROACH

This section describes the audio feature extraction approach, the classification algorithm used for medication adherence assessment and the relevance feedback functionality.

A. AUDIO FEATURE EXTRACTION

There are several feature extraction methods based either on well-known classical approaches or on latest sophisticated
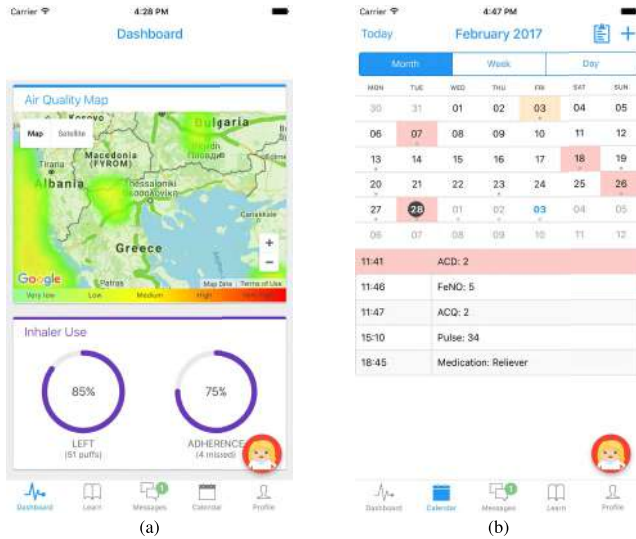
FIGURE 4. Mobile Application for the support of patients. a) Main dashboard. b) Patient calendar.
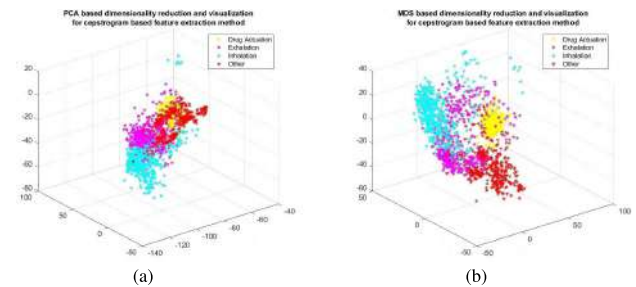

FIGURE 5. Dimensionality reduction and visualization for cepstrogram based feature extraction. The colors correspond to: Yellow for drug actuation, magenta for exhalations, cyan for inhalations and red for other types of noise. (a) PCA based. (b) MDS based.
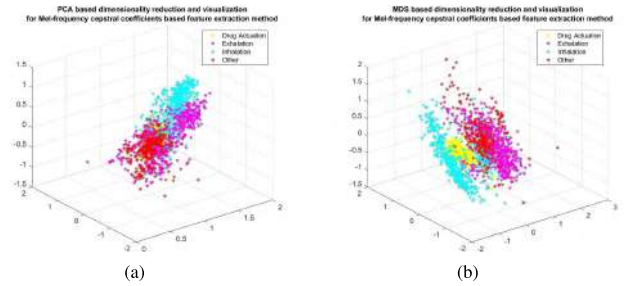

FIGURE 6. Dimensionality reduction and visualization for Mel-frequency cepstral coefficients based feature extraction. The colors correspond to: Yellow for drug actuation, magenta for exhalations, cyan for inhalations and red for other types of noise. (a) PCA based. (b) MDS based.

FIGURE 7. Dimensionality reduction and visualization for spectrogram based feature extraction. The colors correspond to: Yellow for drug actuation, magenta for exhalations, cyan for inhalations and red for other types of noise. (a) PCA based. (b) MDS based.
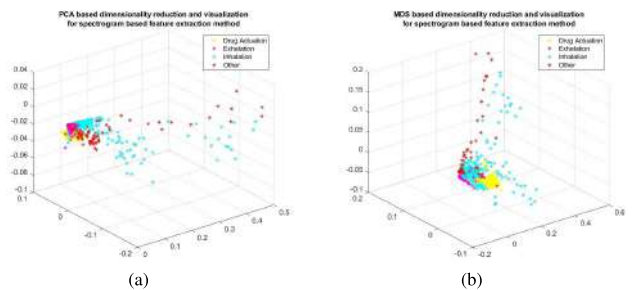
data-driven methods. The first include methods such as the MFCC feature extraction method, the Spectrogram and Cepstrogram approaches, while the latter include Fisher Kernels [36], and Fisher Kernel Learning (FKL) [37] methods. In order to examine the feature separability for the aforementioned approaches, we visualize the feature space by employing two separate methods: a) principal component analysis (PCA) method and b) multi-dimensional scaling (MDS) [38]. Figures 5 to 7 depict the visualization of the feature vectors in the three dimensional feature space for each of the dimensionality reduction methods. As it can be observed, the Cepstrogram based features demonstrate higher separability than the other approaches, which is later verified by the classification accuracy results presented in subsection V-B.

The Cepstrogram $C(m, k)$ is formulated as

$$C(m, k) = \left| \sum_{n=0}^{N-1} log|X(m, n)|^2 \cos(\frac{2\pi}{N}kn) \right|^2 \quad (1)$$

where $X(m, n)$ is the short time Fourier transform, m denotes the $m - th$ temporal component and k the $k - th$ cepstral coefficient and n the $n - th$ frequency component.

The audio feature vector $\mathbf{v} = [v_1 \; v_2 \; v_3 \ldots v_k]$ is derived by summing up the quefrency magnitude for every temporal window for each quefrency component.

$$\mathbf{v}_k = \sum_{m=1}^{M} C(m, k) \quad (2)$$

The feature vector $\mathbf{v}$ is then sub-sampled to 40 features.

B. FEATURE CLASSIFICATION FOR MEDICATION ADHERENCE WITH GAUSSIAN MIXTURE MODELS

Following feature extraction, classification is performed in order to differentiate the sound samples into the four aforementioned classes. GMMs are statistical models used in many pattern recognition applications. They can be employed to approximate any probability density function (pdf) given a number of components. Moreover, they have demonstrated to yield sufficiently good results in audio processing [39]. Our aim is to employ the GMM approach for feature classification [40]. Thus, for each class a separate model is trained by fitting the corresponding feature vectors to a GMM with parameters $\{a_i, \mu_i, \mathbf{C}_i\}, i \in K$, where K is the number of components, a_i is the mixture weight of component i, μ_i is the d-dimensional vector, containing the mean values for each feature, and $\mathbf{C}$ is the covariance matrix. The Gaussian mixture density $p(\mathbf{v}|\lambda_n)$ is modeled as a linear combination of multivariate Gaussian PDFs, where $\mathbf{v}$ is a feature vector and λ_n is the GMM corresponding to class n. In order to classify a test feature vector, we derive the $P(\mathbf{v}|\lambda_n)$ for each class. The test feature vector is assigned to the class n with the
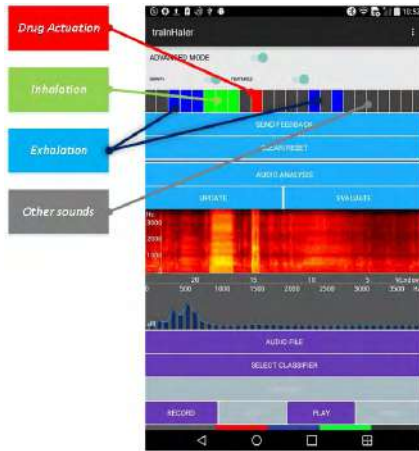
FIGURE 8. Classification result. The red color corresponds to drug actuation, the green color corresponds to inhalations, the blue color corresponds to exhalations and the gray to other sounds. Each colored area of the classification result corresponds to a segment of the spectrogram right below.

greatest likelihood $P(\mathbf{v}|\lambda_n)$. An expectation maximization (EM) approach is utilized to derive the parameters K_n, $\{a_i, \mu_i, \mathbf{C}_i\}_n$ for the GMM λ_n corresponding to class n that best fit the input data. The Gaussian mixture density of each feature vector $\mathbf{v}$ is modeled as a linear combination of multivariate Gaussian PDFs with the general form:

$$p(\mathbf{v}|\theta_i) = \frac{1}{(2\pi)^{\frac{d}{2}}|\mathbf{C_i}|^2} e^{[-\frac{1}{2}(\mathbf{v}-\mu_i)^T \mathbf{C_i}^{-1}(\mathbf{v}-\mu_i)]} \quad (3)$$

where: $\theta_i = (\mu_i, \mathbf{C_i})$, $\mathbf{v}$ is the d-dimensional feature vector, μ is the d-dimensional vector, containing the mean values for each feature, $\mathbf{C}$ is the $d x d$ covariance matrix and $|\mathbf{C}|$ is the determinant. The complete set of parameters for a mixture model with K components is $\Theta = \{a_1, \cdots, a_K, \theta_1, \cdots, \theta_K\}$. Each GMM model λ_n for class n is parameterized as follows:

$$\lambda_n = \{a_k^n, \mu_k^n, \mathbf{C}_k^n\} \quad (4)$$

where $k = 1, \cdots, K$

At this point we analyze the expectation-maximization (EM) algorithm [41] employed to compute the GMM parameters in eq.(4). The membership weight of data point $\mathbf{v}$ in component k given parameter Θ is defined as:

$$w_{ik} = \frac{p_k(\mathbf{v}_i, \theta_k) \cdot a_k}{\sum_{m=1}^{K} p_m(\mathbf{v}_i|\theta_m) \cdot a_m} \quad (5)$$

for all components k, $1 \leq k \leq K$ and all data samples i, $1 \leq i \leq N$. In each iteration of the EM algorithm for Gaussian Mixtures we deploy an E-step and an M-step.

1) E-STEP
We compute w_{ik} presented in eq.(5) for all feature vectors $\mathbf{v}_i$ and all mixture components k

2) M-STEP
We calculate the new parameters. Given $N_k = \sum_{i=1}^{N} w_{ik}$ the sum of membership weights for the $k - th$ component we get

the mixture weights:

$$a_k^{new} = \frac{N_k}{N}, \quad 1 \leq k \leq K \quad (6)$$

The updated mean:

$$\mu_k^{new} = \frac{1}{N_k} \sum_{i=1}^{N} w_{ik} \cdot \mathbf{v}_i, \quad 1 \leq k \leq K \quad (7)$$

and the updated covariance:

$$\mathbf{C}_k^{new} = \frac{1}{N_k} \sum_{i=1}^{N} w_{ik}(\mathbf{v} - \mu_i)^T (\mathbf{v} - \mu_i) \quad (8)$$

3) TERMINATION CRITERIA
The termination criteria for the EM is the following:

$$\log l(\Theta)_{t+1} - \log l(\Theta)_t \leq \epsilon \quad (9)$$

where the log-likelihood, defined as $\log l(\Theta) = \sum_{i=1}^{N} \log p(\mathbf{v}_i|\Theta)$ and ϵ is a small user-defined scalar value.

In order to find the best fit for the data, we compute the GMM for 1 to $d = 40$ components iterating over full and diagonal covariance matrices, where d is the size of each feature vector $\mathbf{v}$. With the generation of each model we estimate the Bayesian Information Criteria(BIC) [42]. The model with the lowest BIC best fits the input data.

After the optimal parameters for the GMMs have been computed and given d the number of features, K the number of components of the ith feature vector $\mathbf{v}_i$, λ_n the GMM of class n we get:

$$P(\mathbf{v_i}|\lambda_n) = \sum_{i=1}^{K} a_i^n p_i^n(\mathbf{v}) \quad (10)$$

where a_i^n are the mixture weights to satisfy the constraint:

$$\sum_{i=1}^{M} a_i^n = 1, a_i^n > 0 \quad (11)$$

Finally, and after the $P(\mathbf{v}|\lambda_n)$ for the test feature vector $\mathbf{v}$ and for each class n is estimated, the test feature vector is assigned to the class n with the greatest likelihood.

C. RELEVANCE FEEDBACK
This section describes the proposed relevance feedback approach for personalization of the trained models. The importance of the relevance feedback mechanism lies in the assumption that the initial dataset was compiled by a small group of people. This means that it may not contain the unique frequency patterns, related to the way that different end-users exhale, inhale or activate the drug. Thus, a relevance feedback mechanism should allow the personalization of the trained models and the compilation of patient-specific datasets. Initially, it is assumed that the patient has submitted a set of personal feature vectors annotated to the corresponding class using the relevance feedback functionality depicted in Figure 9. Each complete user submission includes $N = 24$
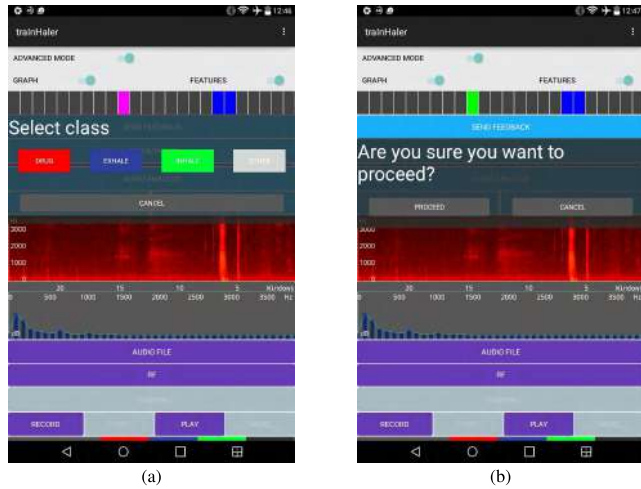
FIGURE 9. a) Relevance feedback functionality selection menu. The user taps a classification result and activates the selection UI. b) After the result is corrected, it can be resubmitted.

FIGURE 10. Annotation toolkit UI. The user inspects the audio graph, selects a segment corresponding to a certain class, and attaches the proper annotation.

TABLE 1. Classification accuracy (%) for the 4-class problem.

	MFCC	Spectrogram	Cepstogram
SVM	97.026	86.615	**98.718**
RF	96.205	97.282	**97.744**
ADA	96.205	**98**	**98**
GMM	96.718	94.769	**98.513**
	MFCC FKL	**SPECT FKL**	**CEPST FKL**
SVM	93.128	86.308	**95.744**
RF	92.41	**97.179**	94.615
ADA	92.821	**97.333**	96
	MFCC GMM FKL	**SPECT GMM FKL**	**CEPST GMM FKL**
SVM	96.718	94.821	**98.513**
RF	96.308	95.026	**98.513**
ADA	95.487	95.333	**98.205**

feature vectors corresponding to 12-seconds of audio recording. The dataset used to train the models consists of $M = 1980$ feature vectors, with 495 feature vectors per class.

Given the set of feature vectors $\mathcal{F}$ we perform kNN search with $k = 1$ in the dataset $\mathcal{D}$ for each feature vector $\mathbf{v}_{Fn}$. The result is denoted as $\mathcal{D}_{Fn}$. The new personalized dataset $\mathcal{D}_F$ is the union of $\mathcal{F}$ with each $\mathcal{D}_{Fn}$. At this point, it is important to remove all the duplicate vectors. Algorithm 1 presents a more detailed overview of the procedure.

Algorithm 1 Relevance Feedback Algorithm

Require:
1: User defined entries $\mathcal{F} = \{\mathbf{v}_{F1}, \cdots, \mathbf{v}_{Fn}, \cdots, \mathbf{v}_{FN}\}$
2: Dataset $\mathcal{D} = \{\mathbf{v}_{D1}, \cdots, \mathbf{v}_{Dm}, \cdots, \mathbf{v}_{DM}\}$
3: **Initialize:** Personalized dataset $\mathcal{D}_F = \{\}$ as an empty set
4: **for each** $\mathbf{v}_{Fn} \in \mathcal{F}$ **do**
5:     $\mathcal{D}_{Fn} \leftarrow$ k nearest neighbors of $\mathbf{v}_{Fn}$ using $\mathcal{D}$
6:     $\mathcal{D}_F = \mathcal{D}_F \cup \mathcal{D}_{Fn}$
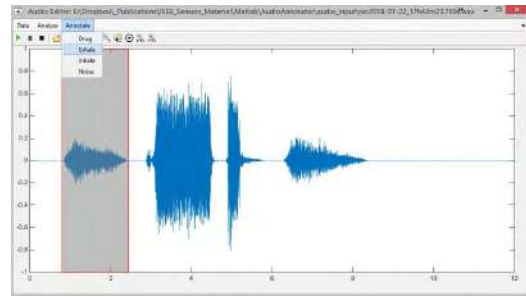7: **end for**
8: $\mathcal{D}_F = \mathcal{D}_F \cup \mathcal{F}$
Ensure: Each element of $\mathcal{D}_F$ is unique.

V. EVALUATION

This section focuses on the overall system evaluation methodology. More specifically, the following subsections describe the data collection and annotation approaches, present the classification accuracy results and provide a more detailed insight via the confusion matrices.

A. DATA COLLECTION AND ANNOTATION

We recorded several sound signals in indoor and outdoor environments. The sounds were categorized into inhaler actuations, exhalations, inhalations, and noise referring to environmental or other sounds. Twelve healthy subjects used the same inhaler device depicted in Figure 2 loaded with full

placebo canisters. For each subject a different canister was used. They recorded 495 sounds per class reaching the total of 1980 sounds. Each sound sample has a total duration of 0.5 seconds, sampled with 8 kHz sampling rate and 16-bit depth. To compile the initial training dataset, an annotation toolkit was employed. A user interface visualizes the audio samples while the user selects parts of the audio files and assigns a class. The annotated part is stored in a separate audio file. Figure 10 shows the user interface of the annotation toolkit.

B. ADHERENCE MONITORING ACCURACY

This section presents the adherence monitoring accuracy results for the Cepstogram feature extraction method compared to classical approaches, namely Spectrogram and MFCC based features and data-driven approaches, namely FK [36] and FKL [37]. Regarding the feature classification scheme, we compare GMMs with well-established classification algorithms, namely SVMs [43], Random Forests [44], ADABoost [45]. The classification results are presented in Table 1 and in Figure 11. 10-fold cross validation for evaluation of the classifiers has been employed.

In order to compare the proposed method with FKL approach we utilized the publicly available implementation of [37]. FKL receives time series as input and generates as output new vectors. Thus, we utilize two approaches: In the first approach, we use the extracted features of MFCC, Spectrogram and Cepstrogram as input time series. This way the FKL is used as preprocessing step. The results of this approach are presented in the blocks named MFCC FKL,
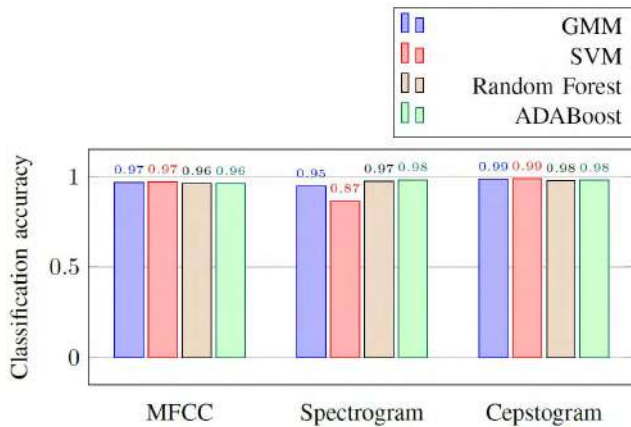
FIGURE 11. Classification accuracy for the 4-class problem. Three feature extraction algorithms are compared: i) MFCC ii) Spectrogram iii) Cepstogram.

TABLE 2. Classification accuracy (%) vs added noise factor.

		Added noise and environmental sounds factor			
		0.00	0.10	0.20	0.50
MFCC	GMM	96.718	93.13	87.778	79.899
	SVM	97.026	93.59	87.0202	79.4444
	RF	96.205	93.23	86.2626	78.333
	ADA	96.205	92.93	85.9091	72
SPECT	GMM	94.768	92.83	88.384	78.485
	SVM	86.615	85.35	83.2323	78.68687
	RF	97.282	95.66	91.8182	83.28283
	ADA	98	95.15	92.0202	81.71717
CEPST	GMM	98.513	**96.47**	**96.414**	82.879
	SVM	**98.718**	95.81	91.9192	**83.93939**
	RF	97.744	95.91	92.7778	83.8889
	ADA	98	96.11	91.6667	81.9697
MFCC GMM FKL	ADA	96.718	91.364	87.172	78.131
SPECT GMM FKL	ADA	94.821	93.384	87.727	77.121
CEPST GMM FKL	ADA	98.513	94.242	94.444	81.162

SPECT FKL, CEPST FKL in Table 1. In the second approach, we use the output of the GMM probability function as input time series. The results are presented in the blocks named MFCC GMM FKL, SPECT GMM FKL, CEPST GMM FKL blocks of Table 1. As it can be observed, the classification accuracy reaches 97% for all feature extraction methods.

Furthermore, to provide a comparison with Continuous Wavelet Transform (CWT) based approaches we utilized the CWT with Morlet wavelet as a feature extraction method [18]. Table 4 presents the confusion matrices for SVM, Random Forest and AdaBoost classifiers for the 4-class problem and for the Drug vs other sounds 2-class problem. Our results agree with the results provided in [18] yielding a 99.18% sensitivity, 99.73% specificity and 99.45% accuracy in the identification of drug actuation sounds.

Finally, as it can be observed in Table 1 GMM yields the best results reaching 98% in the case of Cepstogram features, while SVM seems to be a good classifier for MFCC and for Cepstogram but not for Spectrogram features. Considering the MFCC based feature extraction, GMM reaches 96%, SVM reaches 97%, Random Forest reaches 96%, and ADABoost 96%. For the spectrogram-based feature extraction method, the classification accuracy is 94.7% for GMM, 86% for SVM, 97% for Random Forest, and 98% for ADABoost. Finally, for the Cepstrogram, the classification accuracy reaches 98% in the case of GMM classifier, 98% in the case of SVM classifier, 97% for the Random Forest approach, and 97% for ADABoost. The utilization of the FKL preprocessing step does not provide better results than the corresponding features used as input time series. e.g. CEPST FKL with RF has yielded worse results than CEPST RF.

C. NOISE ROBUSTNESS ASSESSMENT

To assess the robustness to noise and other sounds, assuming that the initial dataset was created under ideal conditions, we compiled noisy datasets by adding background and environmental sounds [46], collected from freesound.org [47], by superposing dataset audio segments $\mathbf{x}$ and noise $\mathbf{n}$ in the

following manner:

$$\mathbf{x}' = \mathbf{x} + k * \mathbf{n} \qquad (12)$$

The classification accuracy for different values of factor k is shown in table 2.

As it is made obvious, the classification accuracy of each method drops below 85% as added noise factor reaches 0.5. Table 2 demonstrates that in noisy conditions, Cepstrogram based GMM approach yields the best results.

D. CONFUSION MATRICES

Table 3 presents the confusion matrices of each feature extraction method, for all classification algorithms performed in the current study. As it can be observed, the classification accuracy reaches 99% is some cases but, it is as low as 58% in the case of support vector machines when accessing exhalations in spectrogram-based feature extraction. Finally, an important observation is that the Cepstrogram feature based extraction method demonstrates the lowest misclassification rate in comparison to other approaches, which supports our initial assumption that this feature extraction approach yields the most separable feature representation.

E. EMPLOYING RELEVANCE FEEDBACK TO IMPROVE CLASSIFICATION ACCURACY

In order to validate the relevance feedback functionality, we employed the relevance feedback of a second group consisting of five subjects. It is important to note that subjects of the first group,that provided the audio samples, were not included in the second group. Each person provided 20 sets of annotated submissions with each submission to contain 24 annotated feature vectors. In the validation, process we assume that one of the 20 sets is not annotated and derive the classification accuracy for this set by employing the following cross-validation approach: At first, we include only two annotated sets for the compilation of the relevant dataset, performed using the process described in subsection IV-C, and derive the classification accuracy. Then, in each iteration, one more set is included, the relevant dataset is recompiled and the classification accuracy is recalculated. The process

TABLE 3. Normalized % confusion matrix for MFCC, spectrogram and cepstrogram feature extraction approaches.

|			Reference											
			\multicolumn{4}{c}{MFCC}	\multicolumn{4}{c}{SPECT}	\multicolumn{4}{c}{CEPST}					
			Drug	Exhale	Inhale	Noise	Drug	Exhale	Inhale	Noise	Drug	Exhale	Inhale	Noise
Prediction	SVM	Drug	**97.54**	0.00	0.21	0.21	**97.54**	0.00	0.00	0.00	**99.38**	0.41	0.00	0.41
		Exhale	0.41	**96.14**	1.23	2.89	2.46	**58.94**	1.43	3.73	0.41	**98.16**	1.43	0.41
		Inhale	0.00	0.00	**97.74**	0.20	0.00	0.41	**94.88**	0.83	0.00	0.20	**98.57**	0.41
		Other	2.05	3.86	0.82	**96.70**	0.00	40.65	3.69	**95.44**	0.21	1.23	0.00	**98.77**
	RF	Drug	**97.13**	0.20	0.21	0.00	**97.74**	0.20	0.00	0.00	**98.97**	0.41	0.00	0.62
		Exhale	1.44	**95.93**	2.26	4.33	0.00	**96.95**	2.05	2.69	0.82	**97.35**	1.64	1.65
		Inhale	0.41	0.00	**96.71**	0.62	0.62	0.61	**97.95**	0.83	0.00	0.61	**98.16**	1.24
		Other	1.02	3.87	0.82	**95.05**	1.64	2.24	0.00	**96.48**	0.21	1.63	0.20	**96.49**
	ADA	Drug	**97.54**	0.00	0.00	0.41	**98.77**	0.41	0.00	0.00	**99.18**	0.20	0.20	0.21
		Exhale	1.03	**96.75**	1.65	4.95	0.41	**96.95**	1.43	1.45	0.62	**97.35**	1.84	1.03
		Inhale	0.00	0.20	**96.91**	1.03	0.00	0.20	**98.36**	0.62	0.00	0.61	**97.54**	0.82
		Other	1.43	3.05	1.44	**93.61**	0.82	2.44	0.21	**97.93**	0.20	1.84	0.42	**97.94**
	GMM	Drug	**96.71**	0.00	0.00	0.00	**99.18**	0.41	0.00	2.69	**99.38**	0.00	0.00	0.62
		Exhale	0.82	**96.14**	1.23	2.68	0.62	**93.29**	1.64	6.00	0.41	**99.18**	1.43	2.27
		Inhale	0.21	0.00	**97.74**	1.03	0.20	3.46	**98.16**	2.90	0.00	0.41	**98.57**	0.21
		Other	2.26	3.86	1.03	**96.29**	0.00	2.84	0.20	**88.41**	0.21	0.41	0.00	**96.90**
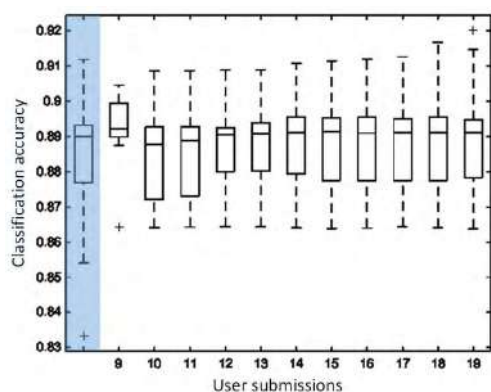
(a)
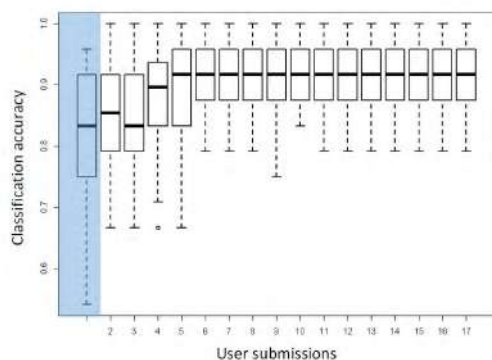
(b)

FIGURE 12. Relevance feedback of Cepstrogram based features. (a) Classification accuracy box plot as a function of included user submissions for the **CEPST-GMM** approach. (b) Classification accuracy box plot as a function of included user submissions for the **CEPST-SVM** approach.

is repeated until all remaining 19 sets are included. The process evaluates the improvement of the classification accuracy score relatively to the number of user submissions.

The results of the evaluation process are presented in Figure 12. The first column represents the classification

TABLE 4. Normalized % confusion matrix for continuous wavelet transform.

			Reference			
			CWT			
			Drug	Exhale	Inhale	Noise
Prediction	SVM	Drug	**97.11**	0.20	0.20	0.00
		Exhale	1.44	**98.16**	27.72	85.66
		Inhale	1.03	0.82	**71.66**	6.56
		Other	0.42	0.82	0.42	**7.78**
	RF	Drug	**98.97**	0.40	0.20	0.20
		Exhale	0.00	**94.10**	1.64	8.60
		Inhale	1.03	0.81	**95.70**	2.67
		Other	0.00	4.69	2.46	**88.53**
	ADA	Drug	**99.18**	0.00	0.41	0.41
		Exhale	0.00	**95.91**	1.64	6.56
		Inhale	0.20	0.61	**96.31**	1.64
		Other	0.62	3.48	1.64	**91.39**
	ADA 2-Class		\multicolumn{2}{c}{Drug}	\multicolumn{2}{c}{Other}	
		Drug	\multicolumn{2}{c}{**99.18**}	\multicolumn{2}{c}{0.27}	
		Other	\multicolumn{2}{c}{0.82}	\multicolumn{2}{c}{**99.73**}	

accuracy result without relevance feedback, while the next columns represent the classification accuracy for the corresponding number of user submissions. CEPST-GMM shows the slowest improvement rate but appears to be more robust, since the first column that represents the classification results without relevance feedback are concentrated around 89%. CEPST-SVM shows low classification accuracy without relevance feedback but appears to have great improvement as user submissions increase.

VI. DISCUSSION AND CONCLUSION

In this work, we have implemented and presented a novel mHealth system for monitoring medication adherence in obstructive respiratory diseases. The proposed system consist of a BT acoustic sensor, a mobile application and a cloud processing module. The smartphone application receives audio samples from the audio sensor and extracts Cepstogram features. The extracted features are then uploaded to a cloud

server, where GMM classifiers are executed for identifying exhalation, inhalation drug usage and ambient sound events. The smartphone application, enhances the inhaler usage experience through intuitive interfaces of patient guidance including a virtual agent, which can help patients follow their action plan and assess their inhaler technique in a more engaging manner. The extensive performance assessment has revealed the efficiency of the proposed approaches in both indoor and outdoor environments, significantly outperforming other state of the art approaches. Furthermore, the proposed relevance feedback scheme enables the patient or the researcher to correct misclassified results and resubmit them allowing the personalization of the trained model in a user-oriented manner, thus increasing even more the accuracy and personalization of the system. As a future step, a number of feedback sessions will be organized with the participation of the MyAirCoach Advisory Patient Forum, in order to evaluate the usefulness of the implemented functionalities, suggest future extensions and optimize the implemented user interfaces on the basis of actual patient needs.

REFERENCES

[1] World Health Organization. (2013). *Asthma*. Accessed: Mar. 2, 2018. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs307/en/

[2] European Lung White Book. (2013). *Adult Asthma*. Accessed: Mar. 2, 2018. [Online]. Available: https://www.erswhitebook.org/chapters/adult-asthma/

[3] M. Masoli, D. Fabian, S. Holt, and R. Beasley, "The global burden of asthma: Executive summary of the GINA dissemination committee report," *Allergy*, vol. 59, no. 5, pp. 469–478, 2004.

[4] M. I. Asher *et al.*, "Worldwide time trends in the prevalence of symptoms of asthma, allergic rhinoconjunctivitis, and eczema in childhood: Isaac phases one and three repeat multicountry cross-sectional surveys," *Lancet*, vol. 368, no. 9537, pp. 733–743, 2006.

[5] L. J. Akinbami *et al.*, "Trends in asthma prevalence, health care use, and mortality in the United States, 2001–2010," *NCHS Data Brief*, vol. 94, no. 94, pp. 1–8, 2012.

[6] A. C. Murphy *et al.*, "The relationship between clinical outcomes and medication adherence in difficult-to-control asthma: Table 1," *Thorax*, vol. 67, no. 8, pp. 751–753, Aug. 2012.

[7] C. B. Bårnes and C. S. Ulrik, "Asthma and adherence to inhaled corticosteroids: Current status and future perspectives," *Respiratory Care*, vol. 60, no. 3, pp. 455–468, 2015.

[8] D. Kikidis, V. Konstantinos, D. Tzovaras, and O. S. Usmani, "The digital asthma patient: The history and future of inhaler based health monitoring devices," *J. Aerosol Med. Pulmonary Drug Del.*, vol. 29, no. 3, pp. 219–232, 2016.

[9] Asthma Society Canada. (2009). *Metered Dose Inhaler*. Accessed: Mar. 2, 2018. [Online]. Available: https://www.asthma.ca/get-help/asthma-3/treatment/metered-dose-inhaler/

[10] C. Pothirat, W. Chaiwong, N. Phetsuk, S. Pisalthanapuna, N. Chetsadaphan, and W. Choomuang, "Evaluating inhaler use technique in COPD patients," *Int. J. Chronic Obstructive Pulmonary Disease*, vol. 10, p. 1291, Jul. 2015.

[11] M. Alhussein, "Monitoring Parkinson's disease in smart cities," *IEEE Access*, vol. 5, pp. 19835–19841, 2017.

[12] A. Yassine, S. Singh, and A. Alamri, "Mining human activity patterns from smart home big data for health care applications," *IEEE Access*, vol. 5, pp. 13131–13141, 2017.

[13] Q. Zhang, D. Zhou, and X. Zeng, "HeartID: A multiresolution convolutional neural network for ECG-based biometric human identification in smart health applications," *IEEE Access*, vol. 5, pp. 11805–11816, 2017.

[14] Z. Ali, G. Muhammad, and M. F. Alhamid, "An automatic health monitoring system for patients suffering from voice complications in smart cities," *IEEE Access*, vol. 5, pp. 3900–3908, 2017.

[15] E. Villeneuve, W. Harwin, and W. Holderbaum, "Reconstruction of angular kinematics from wrist-worn inertial sensor data for smart home healthcare," *IEEE Access*, vol. 5, pp. 2351–2363, 2017.

[16] N. Vemishetty *et al.*, "Low power personalized ECG based system design methodology for remote cardiac health monitoring," *IEEE Access*, vol. 4, pp. 8407–8417, 2016.

[17] S. Howard, A. Lang, M. Patel, S. Sharples, and D. Shaw, "Electronic monitoring of adherence to inhaled medication in asthma," *Current Respiratory Med. Rev.*, vol. 10, no. 1, pp. 50–63, 2014.

[18] T. E. Taylor *et al.*, "An acoustic method to automatically detect pressurized metered dose inhaler actuations," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2014, pp. 4611–4614. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/25571019

[19] M. S. Holmes *et al.*, "Automatic identification and accurate temporal detection of inhalations in asthma inhaler recordings," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBS)*, Aug. 2012, pp. 2595–2598.

[20] J. Pilcher *et al.*, "Validation of a metered dose inhaler electronic monitoring device: Implications for asthma clinical trial use," *BMJ Open Respiratory Res.*, vol. 3, no. 1, p. e000128, 2016.

[21] B. Aggarwal and J. Gogtay, "Use of pressurized metered dose inhalers in patients with chronic obstructive pulmonary disease: Review of evidence," *Exp. Rev. Respiratory Med.*, vol. 8, no. 3, pp. 349–356, 2014.

[22] M. S. Holmes, S. D'Arcy, R. W. Costello, and R. B. Reilly, "Acoustic analysis of inhaler sounds from community-dwelling asthmatic patients for automatic assessment of adherence," *IEEE J. Transl. Eng. Health Med.*, vol. 2, Mar. 2014, Art. no. 2700210.

[23] S. Nousias *et al.*, "Monitoring asthma medication adherence through content based audio classification," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Dec. 2016, pp. 1–5.

[24] Asthma Society of Canada. (2009). *Metered Dose Inhaler*. Accessed: Mar. 2, 2018. [Online]. Available: https://www.asthma.ca/get-help/asthma-3/treatment/metered-dose-inhaler/

[25] S. D'Arcy *et al.*, "A method to assess adherence in inhaler use through analysis of acoustic recordings of inhaler events," *PLoS ONE*, vol. 9, no. 6, p. e98701, 2014.

[26] J. N. Pritchard and C. Nicholls, "Emerging technologies for electronic monitoring of adherence, inhaler competence, and true adherence," *J. Aerosol Med. Pulmonary Drug Del.*, vol. 28, no. 2, pp. 69–81, 2015.

[27] J. F. Van Boven, J. C. Trappenburg, T. Van Der Molen, and N. H. Chavannes, "Towards tailored and targeted adherence assessment to optimise asthma management," *NPJ Primary Care Respiratory Med.*, vol. 25, p. 15046, Jul. 2015.

[28] A. S. Lalos, J. Lakoumentas, A. Dimas, and K. Moustakas, "Energy efficient monitoring of metered dose inhaler usage," *J. Med. Syst.*, vol. 40, no. 12, p. 285, 2016. [Online]. Available: http://link.springer.com/10.1007/s10916-016-0642-y

[29] D. Oletic, M. Skrapec, and V. Bilas, "Prototype of respiratory sounds monitoring system based on compressive sampling," in *Proc. Int. Conf. Health Inform.*, 2014, pp. 92–95.

[30] D. Oletic and V. Bilas, "Energy-efficient respiratory sounds sensing for personal mobile asthma monitoring," *IEEE Sensors J.*, vol. 16, no. 23, pp. 8295–8303, Dec. 2016.

[31] S. Provoost, H. M. Lau, J. Ruwaard, and H. Riper, "Embodied conversational agents in clinical psychology: A scoping review," *J. Med. Internet Res.*, vol. 19, no. 5, p. e151, 2017.

[32] T. W. Bickmore, D. Utami, R. Matsuyama, and M. K. Paasche-Orlow, "Improving access to online health information with conversational agents: A randomized controlled experiment," *J. Med. Internet Res.*, vol. 18, no. 1, p. e1, 2016.

[33] R. Rammohan, N. Dhanabalsamy, V. Dimov, and F. J. Eidelman, "Smartphone conversational agents (apple siri, google, windows cortana) and questions about allergy and asthma emergencies," *J. Allergy Clin. Immunol.*, vol. 139, no. 2, p. AB250, 2017.

[34] European Commission. (2013). *Copernicus, the European Earth Observation Programme*. Accessed: Mar. 2, 2018. [Online]. Available: http://www.copernicus.eu/

[35] *CiteairII Project*. Accessed: Mar. 2, 2018. [Online]. Available: http://www.citeair.eu/

[36] T. Jaakkola and D. Haussler, "Exploiting generative models in discriminative classifiers," in *Proc. Adv. Neural Inf. Process. Syst.*, 1999, pp. 487–493.

[37] L. van der Maaten, "Learning discriminative fisher kernels," in *Proc. 28th Int. Conf. Mach. Learn. (ICML)*, 2011, pp. 217–224.

[38] T. F. Cox and M. A. A. Cox, *Multidimensional Scaling*. London, U.K.: Chapman & Hall, 2001. [Online]. Available: https://www.crcpress.com/Multidimensional-Scaling-Second-Edition/Cox-Cox/p/book/9781584880943

[39] D. A. Reynolds and D. C. Rose, "Robust text-independent speaker identification using Gaussian mixture speaker models," *IEEE Trans. Speech Audio Process.*, vol. 3, no. 1, pp. 72–83, Jan. 1995.

[40] Y. Huang, K. B. Englehart, B. Hudgins, and A. D. C. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 11, pp. 1801–1811, Nov. 2005.

[41] G. McLachlan and T. Krishnan, *The EM Algorithm and Extensions*, vol. 382. Hoboken, NJ, USA: Wiley, 2007.

[42] G. Schwarz, "Estimating the dimension of a model," *Ann. Statist.*, vol. 6, no. 2, pp. 461–464, 1978.

[43] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining Knowl. Discovery*, vol. 2, no. 2, pp. 121–167, 1998.

[44] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

[45] J. Zhu, H. Zou, S. Rosset, and T. Hastie, "Multi-class AdaBoost," *Statist. Interface*, vol. 2, no. 3, pp. 349–360, 2009.

[46] D. Kikidis, K. Votis, and D. Tzovaras, "Utilizing convolution neural networks for the acoustic detection of inhaler actuations," in *Proc. e-Health Bioeng. Conf. (EHB)*, Nov. 2015, pp. 1–4.

[47] MTG. (2015). FreeSound: A collaborative database of audio data. Pompeu Fabra University. [Online]. Available: https://freesound.org/

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