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Detecting Symptoms of Chronic Obstructive Pulmonary Disease and Congestive Heart Failure via Cough and Wheezing Sounds Using Smart-Phones and Machine Learning

Anthony Windmon
University of South Florida

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Detecting Symptoms of Chronic Obstructive Pulmonary Disease and Congestive Heart Failure via Cough and Wheezing Sounds Using Smart-Phones and Machine Learning

by

Anthony Windmon

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
Department of Computer Science and Engineering
College of Engineering
University of South Florida

Major Professor: Sriram Chellappan, Ph.D.
Ponrathi R. Athilingam, Ph.D.
Kenneth Christensen, Ph.D.
Tansel Yucelen, Ph.D.
Alfredo Weitzenfeld, Ph.D.

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Dedication

This dissertation is dedicated to my siblings Adam, Antonio and Antavious Windmon; And, Tiara Allen and Kyle Samuel. The five of you are very special to me, and you all inspired me to keep going. I’d also like to dedicate this dissertation to my parents for never allowing me to quit, and my Grandmother for her constant prayers. I am very excited and honored to share and celebrate this victory with you all.
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Abstract

Chronic Obstructive Pulmonary Disease (COPD) and Congestive Heart Failure (CHF) are progressive disorders, and major health concerns among today’s aging population. COPD causes a large mucus buildup in the lungs, leading to chronic cough and difficulty to breathe. CHF causes fluid buildup in the lower lungs due to the failing heart, causing cough and difficulty to breathe. People who are clinically diagnosed with COPD or CHF are expected to regularly monitor their symptoms and follow complex medical recommendations in an effort to prevent exacerbation. In this dissertation, we elaborate upon three different machine learning based techniques that we developed for early signs of exacerbation of COPD or CHF symptoms by detecting worsening cough and wheezing.

First, we present the feasibility of leveraging chronic cough samples, recorded using a smart-phone’s microphone, and processing the audio samples via machine learning algorithms, to differentiate COPD from normal (non-COPD) cough patterns. This is done using a cohort of 39 adult cough samples (23 with COPD; 16 healthy patients without COPD which we called "Controls"), evenly spread across both genders, and Random Forests classification algorithm. Next, we propose TussisWatch, a smart-phone system to identify cough episodes as early symptoms of COPD or CHF. TussisWatch consists of a two-level, Random Forests classification scheme. At level-one, cough episodes are distinguished as DISEASE (COPD
or CHF) or NO DISEASE. If the former is identified, the second-level classifier indicates if the disease is COPD or CHF. If the latter is identified, classification is complete since the user does not have COPD or CHF cough symptoms. TussisWatch was developed with 36 adults cough samples (9 with COPD; 9 with CHF; 18 Controls). Lastly, we consider proper inhaler use among COPD patients, to evaluate the effectiveness of the inhaler in relation to the severity of their symptoms.

In this technique, we test using both cough and breath sound samples collected from 55 clinically diagnosed COPD patients who were hospitalized and were receiving inhaler to manage symptoms. Data was collected before and after proper inhaler administration to determine change using a Support Vector Machine classifier. In all techniques, we extracted commonly used audio features (i.e. Mel-frequency Cepstral Coefficients, Zero Crossing Rate, etc.), and achieved good system performances based on several metrics: Precision, Recall, F1-Scores, Specificity, and Sensitivity. We believe that our proposed systems have the potential to aid early access to healthcare, educate patients on clinically proven self care practices that they can perform at-home and reduce the rates of re-hospitalization caused by COPD exacerbation. In fact, at the end of this dissertation, we present details on the development and future plans on our forthcomin mobile application to assist COPD patients with at-home symptom monitoring.
Chapter 1: Introduction

1.1 Motivation and Problem Statement

Chronic Obstructive Pulmonary Disease (COPD) and Congestive Heart Failure (CHF) are progressive disorders and are often the terminal stage of pulmonary and cardiac disease. COPD is the fourth leading cause of death worldwide, and is estimated to become the third most common condition by 2020 [2]. The prevalence of COPD in the US is 24 million, however it is estimated that the number is actually much higher, since there are over 14 million undiagnosed people with impaired lung functions [3]. The most common cause of COPD is smoking, accounting for 85%, while non-smoking associated with occupational smoke/dust and genetic is related to the remaining 15% [3]. CHF affects 26 million people globally, 6.5 million in the US, and its prevalence is expected to increase 46% by 2030 [4]. Coronary artery disease, high blood pressure and previous heart attack(s) are the most common cause of CHF.

There’s no cure for COPD or CHF but there are several clinically supported methods that can be executed to slow disease progression and improve symptoms. These methods include, but are not limited to, early symptom detection and adherence to complex medication regimen (i.e. inhalers or water pills), healthy diets that limit salt/sodium, fluid intake, getting plenty of exercise, performing several clinically supported coughing and breathing
techniques (i.e. "huff cough" used by COPD patients to clear built-up mucus from their lungs), proper weight management, and blood pressure and heart rate tracking. In this dissertation, we describe three machine learning based methods that we developed to assist COPD and CHF patients with the detection and monitoring of their symptoms. In each development, we pre-process and filter all cough and breath audio samples, implement a one second windowing algorithm, extract several commonly used audio features and apply machine learning algorithms for supervised learning.

In Chapter 3, we developed a model capable of distinguishing cough patterns associated with COPD and without COPD [5]. For this model, we used nearly 30 audio features to extract data from our collected cough samples. To limit the amount of features used for our model, we implemented Information Gain Feature Selection Algorithm. This feature selection algorithm uses a ranker method to present the features with the highest discriminatory power. That is, the audio features that are the strongest and most relevant for the problem. Next, we develop a Random Forests classifier to enable supervised learning. More details on this design are covered in Chapter 3. In Chapter 4, we discuss the development of TussisWatch [6], a smart-phone based system to detect cough pattern associated with COPD and CHF compared to healthy adults’ cough sample, labelled “no disease". Similar to our previous project, we extracted a plethora a well-known audio features and applied feature selection to scope the best features for the problem. This system has two-levels and both are based on Random Forest classification. At the level one, the cough episodes as labelled as either “disease” or “no disease”. If “no disease” classification is done. However, if “disease”
is detected, then the second layer classification will determine if the disease in question is either COPD or CHF. Specific details on the data collection process, differences between COPD and CHF coughs, as well as results based on metrics like sensitivity and specificity are discussed in Chapter 4.

In Chapter 5, we examine how proper inhaler use among COPD patients can change the cough and breath sound with improved symptoms [7]. Using this change in breath sound, we develop a machine learning system, based on Support Vector Machine, that can determine the severity and improvement of one’s cough and breath sound, before and after proper inhaler use. People with COPD patients are required to self-administer inhalers to combat their symptoms. These inhalers do not cure COPD, but they do temporarily relieve patients of harsh symptoms of cough and difficulty breathing and relieve mucus buildup in the lungs. Unlike our previous systems[5][6], we did not incorporate a vast number of features or any feature selection. Instead we used the Mel-frequency Cepstral Coefficients (MFCC), which best capture the spectral envelope of the cough and wheezing sounds.

Collectively, these systems will help our team to collaborate in the development of a user-friendly mobile application, targeted towards helping COPD patients manage their symptoms at home. Using this algorithm, we propose to educate and demonstrate patients proper techniques use an inhaler and develop an action plan for worsening symptom, and ultimately reduce rehospitalization for COPD exacerbation. Future plans surrounding features and capabilities our mobile application will be discussed in Chapter 6.
1.2 Importance of Our Work

Modern day health-care is making a steady transition from traditional practices to more advanced smart-health approaches. Smart-health, according to Active Advice [8], is the use of Information and Communication Technology to improve the quality of health-care. Smart-health, more specifically, is defined by the advanced technology that leads to improvements in medical diagnostic tools (i.e. stethoscopes, blood pressure monitoring equipment, etc.), treatments plans and decisions made by health-care providers leading to an improvement in patient quality of life, as well as patient and doctor relationships. The advanced technology used in smart-health systems varies from robotics to artificial intelligence, and is usually dependent upon the specific tasks in question. The research presented in this dissertation is our contribution to the smart-health field. Our systems combine machine learning, smart-phone and digital signal processing technologies to detect early symptoms of COPD via cough and breath audio signals. Our work intends to enable health-care providers to make evidence based decisions for their COPD and CHF patients, while increasing convenience for their patients and introducing more efficient personalized health-care plans for patients. This is especially important for patients who lack health-care resources (i.e. insurance, close proximity to hospital facilities, etc.) but have access to smart-phone technology, which was 96% of Americans in 2019 according to Pew Research Center [9]. Our work is not intended to replace health-care providers, but to better aid them in decision making to increase their COPD and/or CHF patient’s quality of life.
Studies show that the life expectancy in most countries has significantly increased [10]. This is due to improvements made in the smart-health field, as well as the increase of education about health, nutrition and personal and environmental hygiene [10][11][12][13]. The World Health Organization (WHO) predicts that the senior citizen population (people over the age of 65) will outnumber the children under the age of 14 by 2050 [13]. Considering this staggering increase in the elderly population, we have to be prepared to provide a sufficient amount of health-care inevitably required to support this group of individuals. Our systems to detect early symptoms of COPD will be needed now and as the rise in senior citizens occurs in the near future. This especially true as COPD and CHF both majorly affect individuals of senior citizen age, or individuals closer to senior citizen age (55+ years old). Our system is important because it will bridge the gap in education (specifically education surrounding health, wellness and medicine) for patients, allow health-care providers to have constant communication with patients unable to visit the hospital (this includes patients with disabilities, patients unable to drive due to old age and those without a caretaker) and assist caretakers (family members, spouses, nursing home assistants, etc.) with the care of elderly living with COPD or CHF.

Currently, there are several systems discussed in the literature that aim towards COPD or CHF symptom detection using cough, breath and several other components. However, many of these applications, further discussed in Chapter 2, are not approaching the problems like we are and many of the systems are one dimension as they all only do specific tasks in relation to COPD and CHF symptom management or disease education.
1.3 The Significance of COPD and CHF

Chronic obstructive pulmonary disease (COPD) and congestive heart failure (CHF) are global epidemics incurring significant morbidity and mortality. The combination of these disease spectrums present many diagnostic challenges because clinical symptoms and signs frequently overlap with presence of cough and shortness of breath. Therefore, diagnosing these conditions require objective diagnostic tests and careful interpretation to avoid misdiagnosis and inappropriate treatment. In COPD, there is destruction of the alveolar walls leading to hyperinflation of the alveoli and airflow obstruction due to air not moving in and out causing cough and difficulty breathing. Whereas, in CHF, due to the failing heart, fluid backs up to the alveoli causing cough and difficulty breathing, as seen in Figure 1.1. A plethora of other upper and lower respiratory conditions can also produce cough and difficulty breathing such as a common cold, sinusitis, bronchitis, laryngitis, whooping cough/pertussis, and influenzas.
To some extent, based on cough and the type of sputum produced, physicians can differentiate the condition. However, to make a clear diagnosis, objective diagnostic test is warranted, such as, an echocardiogram for the diagnosis of CHF, and pulmonary function test using spirometry for COPD, and X-rays in both cases in order to make the diagnosis to determine damage to the lung parenchyma. Once diagnosed, these patients are prescribed complex medication and advised to monitor symptoms carefully to seek medical help promptly, which is often a challenge for these patients. Thus, we hypothesized that our approach will offer solutions for patients to monitor symptoms at home and seek medical help promptly to avoid hospitalization and worsening health outcomes.

The current systems in place do not allow patients to share their data on symptom monitoring with their health care provider. The use of mobile technology is proposed to develop an integrated system to overcome delay in seeking care for exacerbation of symptoms. We subsequently propose to develop a dashboard with patient data that allows sharing with their health care providers. This allows health care providers to make decision on the need for early treatment, thus improving health and avoid costly hospitalization. Thus, our system combines smart health ideas and machine learning to detect early symptoms of exacerbation of COPD and CHF from symptoms and audio signaling of cough and breath sound, which is discussed in this dissertation.
1.4 Contributions

This dissertation elaborates upon research using smart-phones and machine learning techniques to detect COPD and CHF via cough and breath sounds. Specifically, the contributions of this dissertation as follows:

· Chapter 2 – We present related works and systems in the domain of using audio signals (i.e., cough, breath, sniffling, swallowing, etc.) for detection of different chronic illnesses (i.e., COPD, asthma, pneumonia, etc.). We also present mobile applications available in the market, that are targeted towards COPD and CHF patients.

· Chapter 3 – We develop a Random Forests classification system capable to distinguishing between cough patterns associated with COPD and without COPD, which we labelled as Controls. Using 23 COPD and 16 Control subjects, and Information Gain to select our strongest audio features, this system achieves high accuracy.

· Chapter 4 – TussisWatch, a two-level Random Forests classification scheme to identify cough patterns as indicative of a Disease (COPD or CHF) or No Disease is presented. Here, we use a cohort of 9 COPD, 9 CHF and 18 Control subjects, and our system achieves good Sensitivity and Specificity at both classification levels.

· Chapter 5 – We investigate the effectiveness of a clinically diagnosed COPD patient using their inhaler to combat their symptoms, via cough and wheezing sounds, using a Support Vector Machine approach. This system was modelled using data collected from 55 clinically diagnosed COPD patients, and produced accuracies close to 80%.
Chapter 6 – We present the conclusion of our work, as well as our work’s limitations and future systems (i.e. our mobile application) and algorithms we plan to explore and develop.

1.5 Thesis Statement

Using smart-phone, digital signal processing and machine learning techniques, we are able to detect early symptoms of Chronic Obstructive Pulmonary Disease and Congestive Heart Failure via cough and breath sounds. In this dissertation, we elaborate upon the algorithms we have developed and data we have extracted from these cough and breath audio signals, and how our systems are essential to advancements made in health-care and smart-health.
Chapter 2: Related Work

In this chapter, we elaborate upon existing research conducted in the domain of using audio signals (i.e., cough, breath, sniffing, swallowing, etc.) for detection of different diseases. These projects are different based on the types of audio features extracted, data collection methods, amounts of subjects incorporated into study, technology used to collect data, machine or deep learning algorithm used, type of disease classified, etc. There are several categories in which we can divide these topics into to completely grasp the diversity. These categories include basic cough and breath identification systems, finer grained cough and breath systems to detect diseases (i.e., COPD, pneumonia, asthma, etc.), deep learning for health-care and mobile health using mobile applications to detect or monitor diseases.

2.1 Systems Developed for Detection of Basic Cough

In [14], a smartphone application has been developed to detect respiratory events like sneezing, coughing, sniffing and clearing the throat. Using a number of time and frequency domain features, followed by a Support Vector Machine based algorithm, the authors design a multi-level classifier (similar to our design in [7]) for classification. The accuracy achieved is 82% for respiratory events, and 99.1% for non-respiratory events. Similar results to classify only cough from other noises are presented in [15]. In related works, like [16],
[17] and [18], the problem is to classify wet cough from dry cough. The sources of data were external recording devices in [16] and [17], and a high fidelity data acquisition system in [18]. Features extracted include 1st, 2nd and 3rd order formant frequencies, mel-cepstrum, non-Gaussianity, bispectrum, pitch, zero crossing rates, peaks of cough spectrum envelopes, and power ratios of frequency bands. Subsequently, using standard machine learning algorithms, good classification accuracies are achieved in these works. Another work in [19], specifically focuses on classifying cough in pediatric settings. Using specialized instruments to record cough, features extracted include MFCC, formant frequency, ZCR, non-Gaussian score and Shannon entropy. Then, using Neural Net models, Sensitivity, Specificity, and Cohens Kappa, accuracies of 93%, 98%, and 0.65, respectively, were achieved during classification. These projects were merely for the detection of cough, and not finer grained research that we have done to differentiate between cough patterns associate with and without COPD in [5].

2.2 Deep Learning for Cough Detection

More recently, and with advances in deep learning via neural networks, there are some works that design convolutional neural network (CNN) based techniques in the domain of cough detection. Work in this domain include [20], [21] and [22]. In these papers though, the number of subjects recruited was relatively small (ranging from only 9 to 14), and accuracies close to 95% were achieved. A key difference in our research was the methodology used to collect data. Due to the University of South Florida’s IRB agreement, we were only
allowed to recruit a select number of patients (36-55) with COPD that met our criteria for recruitment (including age, gender, mental health conditions, approved for inhaler use etc.). And, it required nearly nine months of recruitment per project. Many patients did not consent to our study, and it is normal to do so. As such, in this dissertation, we do not attempt deep learning (i.e., featureless) techniques, due to non-availability of truly big data. But we are confident that our machine learning techniques in this dissertation are rigorous.

2.3 Finer Grained Systems for Detection of Diseases Using Cough

The work in [23] attempts to differentiate pneumonia from asthma using a sample of 18 child subjects and cough data recorded from a low noise microphone. Using features like MFCC, non-gaussianity score and Shannon entropy, the authors design Artificial Neural Net classifiers to achieve a Sensitivity, Specificity and Kappa of 89%, 100%, and 0.89, respectively in classification. In [24], the problem is to evaluate the airflow and sound characteristics of a voluntary cough to classify lung diseases, wherein specialized instruments were designed to record signals. Using a sample of around 100 subjects, and a relatively large number of features (more than 100 of them), the authors design a Principal Component Analysis model, wherein the classification accuracies were in the range of 94% and 97% for female and male subjects, respectively. In another paper [25], the problem is to detect pertussis in children. Classification was performed using publicly available audio sources from 38 children patients to achieve an accuracy of 92%. In [26], work has been done to diagnose and screen pulmonary disease via cough sounds, using a sample of 33 healthy subjects and 54 patients
having COPD, asthma, and allergic rhinitis. The source of data was a stethoscope to collect lung sounds data. Using 7 audio features (including kurtosis, variance, zero crossing rate, and rate of decay), and a logistic regression algorithm, classification accuracy of 80% was achieved.

In another project, researchers collected cough sounds from 38 subjects, 17 with tuberculosis and 21 without, to develop an algorithm capable of detecting symptoms of Tuberculosis [27]. Cough samples were recorded, voluntarily, from both infected and uninfected patients, using a Tascam DR-44WL hand-held audio recording device with a 44100Hz sampling rate. The features processed were log spectral energies and MFCC (similar to our system in these papers [5][6][7]), and the classifier combines decision trees and logistic regression methods. For this problem, the authors achieved an 82% accuracy, 95% sensitivity, 72% specificity, and an area under the curve (AUC) score of 0.95 [27]. Although these project are finer grained, none of them attempt a two-level classification scheme using cough to differentiate between COPD, CHF and no disease as we do in [6].

2.4 Finer Grained Systems for Detection of Diseases Using Breath

In [28] and [29], techniques are developed to analyze breath samples using gas chromatography and mass spectrometry to detect the presence of volatile organic compounds (VOCs) that are indicative of COPD. Accuracies, in range of 70% to 90%, have been reported in such studies using samples of around 80 to 120 subjects. Unfortunately, these techniques are quite expensive and un-suitable for periodic or in-home use. Machine Lear-
ing algorithms have been designed and implemented to analyze breathing techniques to differentiate patients with lung cancer from healthy patients, and from a mixed group of patients with other lung diseases (i.e., COPD, asthma, pneumonia, etc.) in works like [30]. Also, systems to detect various phases on breathing (without a specific disease context) have been developed in works like [31]. Other related work in the space of breath detection is [32], where algorithms are devised to measure lung function, including exacerbation, by processing breath sounds via a spirometer connected to a smart-phone. Our project in [7] dives deeper to evaluate breath sounds, specifically wheezing, before and after inhaler administration for the severity level of the users COPD symptoms. To the best of our knowledge, this problem is unique and has not been attempted in the literature.

2.5 Mobile Health Systems for Chronic Obstructive Pulmonary Disease

Mobile health for COPD is in its rudimentary form with emerging evidence. Particularly, researchers from Radboud University Medical Centre and Australian National University collaborated to develop an automated telephonic exacerbation assessment system (TEXAS) [33], while another set of researchers developed “The EXAcerbation of Chronic Pulmonary Disease Tool” (EXACT) [34][35], which are both tools used to quantify and measure exacerbations in COPD subjects. Additionally, the COPD Self-Management Activation Research Trial (SMART action) [36], a support tool for self-management of physical activities, was developed for COPD patients unable to attend a pulmonary rehabilitation center. This system consists of an education sector, which pairs users with a health coach, who
schedules weekly follow ups with the user. Furthermore, there is Self-Management Program of Activity, Coping and Education (SPACE) [37], developed to provide COPD education, with the intention to change user behavior for an improved method of COPD management. SPACE showed improvement in quality of life, endurance and mental health (i.e., depression). There are also several other COPD centered developments, such as M-COPD [38], a cost-effective system allowing users to directly communicate with health care providers, and COPD24 [39], a wearable body area network system which manages COPD symptoms with respect to the user’s environmental conditions. However, none of these current systems that are being tested are available in the mobile App stores for download. Once our system [5][6][7] is fully developed, we will make it available for use on all platforms.

The previously described applications each only cater to one component of COPD management and are not comprehensive with feedback for early symptoms. EXACT and TEXAS only measure COPD exacerbation, while SMART’s sole purpose is physical activity and SPACE specifically specializes in COPD education. Our systems, on the contrary, will be effective in early identification of COPD symptoms and target preventing COPD exacerbation. Our system will encourage deep breathing exercise to help loosen phlegm (sputum) and track six-minute walk test (6MWT), which are medically approved self-care techniques, and include COPD education. The system will offer reminders for medications and post-discharge follow-ups with the user’s healthcare provider, which are essential for proper maintenance of COPD. A built-in feedback feature, developed using machine learning algorithms, will offer feedback and warn the user when it is imperative that they seek medical
attention due to symptom exacerbation. Furthermore, our system also speaks to the needs of the current technology landscape, by ensuring an important user requirement, which is convenience. Individuals with COPD require a variety of assistance, and they need it swiftly to avoid rehospitalization. It will provide that assistance as an all-inclusive package, sparing users the time of having to download multiple applications, all of which performs only one task each. This prevents users, specifically elderly users whom will majorly utilize (since COPD occurs most frequently in the elderly population) from this development, from having to search through an app store to find, download, update and maintain enough phone storage to store several applications devices. We are certain that our multi-component systems [5][6][7] is innovative and includes all key aspects of self-care needs for patients with COPD.
3.1 Introduction and Contributions to Study

Chronic Obstructive Pulmonary Disease (COPD) symptoms often don’t appear until significant lung damage has occurred. However, daily cough and mucus (sputum) production at least three months to a year or two are reported by 90% of COPD sufferers [2]. Patients tend to find coughing the most embarrassing and disruptive of these symptoms. Coughing can interfere with social events, like going to the movies, and it can prevent patients from falling asleep at night. As annoying as coughing may be, it actually serves a useful function. Deep coughing clears the mucus clogging the airways, allowing individuals to breathe more easily [2]. The evaluation of chronic cough begins with a thorough history, including smoking status, environmental exposures, and medication use. Once the healthcare provider diagnoses that the coughing and trouble breathing are due to COPD, patients are told to quit smoking and are started on medications to control symptoms. For patients with COPD, coughing is due to mucus buildup. Therefore, patients are also taught to self-manage COPD symptoms at home and taught a coughing technique, called huff cough, to bring up mucus without wearing out. It is important however, for patients to understand their coughing patterns to know if their symptoms are getting worse due to superimposed infection, or if their

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1This work has been accepted into the 11th International Conference on Health Informatics (HEALTHINF 2018) as a short paper. Permission is included in Appendix A.
symptoms are more stable. The clinical criteria for assessment of COPD include a pulmonary function test and listening to lung sounds with a stereoscope for wheezing, rales, and other adventitious sounds by trained health care providers. But this is not possible to be done in patient homes, which imposes a serious challenge to care, which this system aims to overcome. In this chapter, we present the feasibility of leveraging cough samples recorded using a smart-phone’s microphone, and processing the associated audio signals via machine learning algorithms, to detect cough patterns indicative of COPD.

Between Fall 2016 and Spring 2017, we visited Tampa General Hospital in the Hillsborough County area of Downtown Tampa, Florida, USA to collect cough samples from patients diagnosed with COPD, and those without any history of COPD (Controls). The collection process was executed using a smartphone recording application developed in Android. While specific details are presented later, Table 4.1 summarizes the patient’s demographics. Our experiments resulted in collecting 82 seconds of cough samples from 23 COPD patients and 83 seconds of cough samples from 16 Controls. Then, we extracted several audio-related features from the cough samples and used an Information Gain approach to select a subset of 15 features, which were used to develop a cough detection model. Our model is based on the notion of Random Forests Classifiers, which are ideal for our problem, because they are one of the most accurate learners available, produce high classification accuracy, and reduce the likelihood of over-fitting [40]. Our performance evaluations, using a 10-Fold Cross Validation technique, yielded an accuracy of 85.45% with very good Precision, Recall and F-Measure.
Table 3.1: Subject’s Demographics Data

<table>
<thead>
<tr>
<th>Description</th>
<th>COPD</th>
<th>Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age: Mean/SD Range</td>
<td>59.85 ± 12.88</td>
<td>67.43 ± 14.32</td>
</tr>
<tr>
<td></td>
<td>30-86</td>
<td>30-89</td>
</tr>
<tr>
<td>Gender: Male</td>
<td>14</td>
<td>10</td>
</tr>
<tr>
<td>Female</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>Martial Status:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>15</td>
<td>7</td>
</tr>
<tr>
<td>Single, Divorced or Widowed</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>Race:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>African American</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Hispanic</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Education Level:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Graduate Degree or above</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>Some College</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>High</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>School/GED</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;High School</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>Smoking Status:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smoker</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>Quit Years Ago</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Non-Smoker</td>
<td>8</td>
<td>14</td>
</tr>
</tbody>
</table>

Figure 3.1: Amplitude (dB) and Length (sec) of COPD and Controls Cough
3.2 Experimental Design

In this section, we describe in detail the procedures of our experiment using a customized recording mobile application for data collection. The Institutional Review Board (IRB) of the University of South Florida approved the experimental procedures. The authors performed experimental procedures in accordance with the approved guidelines.

3.2.1 Data Collection

All cough samples, shown in Figure 3.1, were recorded using a custom voice recording android application, called VoiceRecorder, developed by the authors. This application was implemented on the Samsung Galaxy S5 smart-phone, which uses Android Operating System 5.1.1 Lollipop, used to record cough samples. This smart-phone devices also consists of a microphone with a sampling rate of 44100Hz. We present the graphical user interface (GUI) of this recording application in Figure 3.2. The recording applications works as follows:

1. When the application is opened, it immediately initiates a 30 second timer, and audio recording begins.

2. The Stop button is used to stop the audio recording. Otherwise, the application will automatically close and stop the audio recording upon reaching the 30 second limit.

3. Recording is saved in local device storage of smart-phone as 3GP file.
Figure 3.2: GUI of Mobile Application Used to Collect Cough Samples
3.2.2 Recording Cough Samples

Tampa General Hospital (TGH) in Downtown Tampa, FL was our primary source for data collection. With the expertise of nursing staff, we identified many patients with COPD, and many alternative subjects, of a similar age group, that did not have COPD and served as Controls. All subjects that gave us their cough samples consented to do so. Individuals with COPD and Controls were numbered traditionally, as we recorded their cough samples. Prior to recording each cough sample, the nurse would turn on the app, and state a unique identifying number for the patient, followed by stating whether or not the patient has COPD (stated as “COPD” or “Controls”). Then, the subject was asked to cough into the microphone of the Samsung Galaxy S5 smartphone for a maximum of 30 seconds. The duration of each cough ranged from 2 seconds to 14 seconds. The number of subjects were 23 with COPD and 16 without COPD. Table 4.1 presents demographics of the subjects.

3.3 Technical Approach

In this section, we discuss our approach to distinguish COPD from Controls cough, using smart-phone recorded cough samples. In our approach, we first remove irrelevant noises and pauses from each sample, tag each sample in the presence of medical professionals with COPD expertise, extract and select limited features from cough audio, and then design our algorithm for classification.
3.3.1 Remove Irrelevant Noise and Pauses

The first step is to remove irrelevant noise from each cough sample. Occasionally, during data collection, there were additional sounds picked up while recording cough samples. These sounds were derived from televisions, medical equipment, surrounding conversations, and dialog between the nurses and patients. Such noises were considered distractions from our main concern, which is the cough itself, and, therefore, were removed. Also, recall that nurses began each recorded cough sample stating a patient's number and cough association. Once we created individual files, separating COPD and Controls cough samples, the nurses recorded identification was no longer needed, so it was discarded.

Additionally, there were few instances of samples containing long pauses before, after and in between coughs. These occurrences, as well as previously mentioned ones, will cause inconsistencies in samples that could later become a problem while extracting features. Consequently, pauses were removed to ensure consistency. All noises, additional voices, and pauses were removed from cough samples using a publicly available online audio cutting application.

3.3.2 Data Tagging to Enable Learning

Once all noises were removed, we developed a one second windowing algorithm to partition each cough sample into one second segments. That is, for a cough duration of 10 seconds, we extract 10 segments each of one second duration. Then, our collaborators with COPD expertise listened to each second of each cough sample, to tag the segment
as indicative of COPD or otherwise. As a result of this step, we obtained a total of 82 seconds of COPD cough, and 83 seconds of Controls cough, which enabled subsequent model development.

3.3.3 Feature Extraction and Selection

The third step is feature extraction. We first chose 30 features to extract from each cough sample. Since, we partitioned each cough sample to multiple one second segments, these 30 features were computed for each one second segment for COPD and Controls cough. For example, suppose a COPD cough sample lasted for 10 seconds. Then in total, 300 features are computed for this sample. The same is done for Controls coughs. This process is depicted in Figure 3.3. After computing features for both cough classes, the accumulated numerical data from features was appended to a .csv file where each feature and class name (COPD or CONTROLS) was labeled to create a dataset, i.e., a collection of organized data.
After extracting features, the next step is to intelligently reduce the number of features to a select few that provides high discriminatory power among the two classes. We did this because processing too many features can lead to over-fitting and increased overhead. To do so, we employed an Information Gain feature selection approach [41]. In this approach, the entropy (or randomness) of each feature is computed to determine the feasibility of that feature for classification. More specifically, Information Gain of each feature is calculated as the difference between entropy of all features combined and entropy of the individual feature. A higher difference means more information contained in that feature for classification, and hence is more useful. The Information Gain $IG$ for a feature $F_i$ calculated is as follows:

$$IG(Tr,F_i) = H(Tr) - \sum_{t \in F_i} p(t)H(t),$$

where

$$H(Tr) = -\sum_{x \in m} p(x) \log_2 p(x)$$

Here, $Tr$ denotes the set of training samples containing all features extracted for all cough segments, and $F_i$ denotes the $i^{th}$ feature. The term $t$ denotes the number of unique values for the feature $F_i$, and $p(t)$ is the ratio of the number of cough segments for which the corresponding Feature $F_i = t$. Here, $H(Tr)$ and $H(t)$ are the entropy of the features in training set $Tr$ and the entropy of features in the subset $t$ respectively. The term $p(x)$ is the ratio of number of cough segments in one class $x$ (i.e., COPD or CONTROLS) to the total number of cough segments in training data set $Tr$ and $m$ is the total number of classes (in this case = 2).
This feature selection technique provides a good measure for deciding the relevance of a feature by quantifying the degree of utility (i.e., via entropy). For our problem scope, we attempted the use of the top 5, 10, 15, 20 and 25 features and selected the top 15 features, described in Section 3.4.4, which produced the highest classification accuracy. See Table 3.2 for definition of terms used for Section 3.4.4’s equations.

3.3.4 Selected Features Extracted from Cough Samples

1. Index Maximum (IM): Calculates the index where the maximum fast fourier transform (FFT) value can be found in each window. The Index Maximum is calculated as,

\[ im = \max|fft(x - \bar{x})| \]  \hspace{1cm} (3.3)

2. Variance (VAR): Calculates variance for time series signal of each window as,

\[ var(x) = \frac{\sum(x - \bar{x})^2}{L} \] \hspace{1cm} (3.4)

3. Standard Deviation (STD): Calculates standard deviation for time series signal of each window as,

\[ std(x) = \sqrt{\frac{\sum(x - \bar{x})^2}{L}} \] \hspace{1cm} (3.5)

4. Maximum Value (MX): Calculates the largest component for the time series signal of each window using, MATLAB’s max function, as,

\[ mx = \max(x) \] \hspace{1cm} (3.6)
5. Entropy (ENT): Calculates the entropy for the time series signal of each window using Equation 3.2.

6. Total Power (TP): Calculates the total power of signal in frequency domain of each window as,

\[tp = \sum \text{fft}(x) \ast \overline{\text{fft}(x)}\]  
(3.7)

7. Sound Pressure Level (SPL): Calculates sound pressure level of each window measured in decibel (dB) as,

\[\text{spl} = 20 \log_{10} \frac{x}{2.0 \ast 10^{-5} Pa} dB\]  
(3.8)

8. Zero Crossing Rate (ZCR): Counts the number of times that the sign of the signals amplitude changes in the time domain for each window as,

\[zcr(f) = \sum_{i=2}^{L} \frac{|\text{sgn}(S_i) - \text{sgn}(S_{i-1})|}{2(L - 1)}\]  
(3.9)

9. Mel-Frequency Cepstral Coefficients (MFCC): Evaluates cough audio performing the following steps: 1. Frame Blocking, 2. Windowing, 3. FFT, 4. Mel-frequency Wrapping, 5. Cepstrum, which produces mel cepstrum coefficients [42]. 4 out of the 13 mel cepstrum coefficients were selected features for our algorithm. The MFCC is calculated as,

\[C = \sum_{k=1}^{K} (logS_k)[x(k - \frac{1}{2})\pi]\] 
(3.10)

\[C = \text{mean of input value}\]

\[x = 1, 2, ...K\]

\[K = 44100\]
Table 3.2: Definition of Terms Used in Section 3.4.4

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x$</td>
<td>Number of samples = 44100</td>
</tr>
<tr>
<td>$\bar{x}$</td>
<td>Mean of $x$</td>
</tr>
<tr>
<td>$\text{fft}$</td>
<td>discrete Fourier Transform of $(x)$ using fast Fourier Transform algorithm</td>
</tr>
<tr>
<td>$L$</td>
<td>Length of samples in cough recordings</td>
</tr>
<tr>
<td>$f$</td>
<td>A frame consisting of $x$ samples</td>
</tr>
<tr>
<td>$\text{sgn}$</td>
<td>Signal function returning 1 for positive arguments, 0 for zero, and -1 for negative</td>
</tr>
<tr>
<td>$S_i$</td>
<td>Sign of the signals amplitude</td>
</tr>
<tr>
<td>$S_k$</td>
<td>Mel cepstrum coefficients</td>
</tr>
</tbody>
</table>

10. Root Mean Square (RMS): In cough samples, the signal value (amplitude) of each window is squared, averaged over a period of time, then the square root of the result is calculated as,

$$rms = \sqrt{\frac{1}{L} \sum_{i=1}^{L} x_i^2} \quad (3.11)$$

11. Energy (E): Calculates energy of signal in frequency domain of each window as,

$$e(x) = \sum \frac{|\text{fft}(x)^2|}{\text{fft}(x)} \quad (3.12)$$

12. Minimum Value (MN): Calculates the smallest component for the time series signal of each window, using MATLAB’s $\text{min}$ function as,

$$mn = \text{min}(x) \quad (3.13)$$
3.3.5 Random Forests Algorithm Design

The last step is design of our classification algorithm. In this chapter, we apply a Random Forest based technique for our problem. Random Forests creates random subsets of training samples from datasets by creating a congregation of decision trees. Each decision tree predicts a class, independently. The class prediction is based on a vote made by each decision tree and the class that earns the majority vote will be the final predicted class. For instance, let us denote our dataset $S$ as training samples of cough, each of which consists of $F$ cough features. RF constructs the training model by executing the following steps:

1. $C$ random samples are selected from the dataset $S$, to train model of a specific decision tree.

2. $G$ random features are chosen from the set of unused cough features $F$, where $G \ll F$.

3. Each decision tree will grow to its maximum size until it has reached its benchmark.

In our algorithm, the benchmark consisted of 100 decision trees which gave us the best classification accuracy. Once the forest has been ensembled, testing data specimen is labeled with one of the classes (COPD or CONTROLS) by taking the majority vote: i.e., it is labeled with the class which has been selected by maximum number of trees. To illustrate further, given an unclassified feature variable $z$, which is a variable extracted from the cough samples, conditional probabilities of both classes are calculated by taking the average of the conditional probabilities given by the trees constructing the forest.
The following describes how conditional probabilities are determined. Given decision
tree $R$, the unclassified input feature variable $z$, we can denote $v(z)$ as the leaf node where
$z$ is assigned when classified by $R$. The probability $P(e|z, R)$ that variable $z$ lies in class $e$,
where $e \in \{\text{COPD or CONTROL}\}$, is calculated as follows:

$$P(e|z, R) = \frac{w_e}{w}.$$  \hfill (3.14)

Here, $w_e$ represents the amount of cough training samples assigned to $v(z)$ after the
learning procedure and $w$ is the amount of cough training samples assigned to $v(z)$ by the
training procedure. The probability $P(e|z)$ that variable $z$ belongs to the cough class $e$ is
calculated as follows:

$$P(e|z) = \frac{1}{J} \sum_{i=1}^{J} P(e|z, R),$$  \hfill (3.15)

where $J$ is the number of trees present in the forest and $P(e|z, R)$ is the conditional proba-
bility of the decision tree $R$. The following output is given for the variable $z$ to be classified:

$$c = \{P(COPD|z), P(CONTROL|z)\}$$  \hfill (3.16)

The corresponding class (COPD or CONTROLS) of a decision tree containing the
maximum probability out of the two is selected. For our RF algorithm, the class which gets
the majority vote from the forest of decision trees is the final class. Algorithm 3.1 details the
work flow of the RF algorithm, which includes feature extraction, training and prediction.
Algorithm 3.1 RF-based Algorithm to differentiate between COPD and Controls cough patterns

Cough dataset = S, Cough Training dataset = ST, Cough Testing dataset= ST, Extracted Features from Cough Training dataset = FT, Extracted Features from Cough Testing dataset = FT, Classified Disease from Coughs = e, Probability that feature variable z ∈ e = P (e|z), Number of Decision Trees used during Random Forests = J

Step 1 Extraction:

1. Features FT and FT are extracted from dataset S, which consists of ST and ST

Step 2 Dimensionality Reduction:

1. Using Information Gain Equations 3.1 and 3.2, Features FTDR and FTDE are selected from Features FT and FT.

Step 3 Training:

Input: Training dataset FTDR
Output: Random Forest model to differentiate between COPD and Controls cough patterns

1. Select sample size from training dataset FTDR
2. Grow decision tree R by execution of these rules:
   (a) Select G random features from set of FTDR features
   (b) Choose best features (based on rank order) and split features, to be build decision tree, using Information Gain Equations 3.1 and 3.2
   (c) Split nodes until all subsets are pure
   (d) Grow decision tree to maximum size
   (e) Repeat these steps when constructing further decision trees (we constructed 100 decision trees for our algorithm)

Step 4 Prediction:

Input: Test FTDE and train RF model from previous step (Step 2)
Output: Final Disease prediction e

1. Select the testing feature set FTDE, which includes same features used for training the model.
2. Predict the disease e based on cough samples using the following equations:
   \[
   \text{for each } R \text{ in Forest do} \\
   P (e|F) = \frac{1}{J} \sum_{i=1}^{J} P (e|FTDE, R_i) \\
   \text{end for} \\
   e = \arg \max_{i \in \{1,2\}} \left( P (e_i|FTDE) \right),
   \]
   where e_i classified as either (1) COPD or (2) CONTROLS
3.4 Results

We now discuss the results of our system using 10-Fold Cross Validation as our testing method. The idea of 10-fold cross validation is to divide an entire dataset into 10 subsets, and evaluate them 10 times. Each time, nine subsets are used to train, or build a model, and one is used to test, or validate the built model. Finally, the average error across all 10 trails is calculated for reporting.

Precision, Recall, F-Measure and Confusion Matrix are the metrics used to test our system. Based on classification of True Positives (\(TP\)), False Positives (\(FP\)), True Negative (\(TN\)) and False Negatives (\(FN\)), we have

\[
Precision = \frac{TP}{TP + FP}, \tag{3.17}
\]

\[
Recall = \frac{TP}{TP + FN}. \tag{3.18}
\]

We then define the F-Measure, a metric that balances Precision and Recall, as

\[
F - \text{Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{3.19}
\]

and, Accuracy as

\[
Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{3.20}
\]
Finally, we also present the Confusion Matrix as,

\[
\begin{bmatrix}
TP & FN \\
FP & TN
\end{bmatrix}
\] (3.21)

which is a tabular representation of the performance of an algorithm. In our case, it presents the degree of our algorithm to correctly and incorrectly identifying instances of both classes.

Our analysis reveals that our system can differentiate between COPD cough and otherwise with high accuracy. Note that these results were achieved using Waikato Environment for Knowledge Analysis (WEKA), an open source machine learning software that houses various algorithms and data mining manipulation techniques. The average Precision produced was 85.63\%, the average Recall was 85.47\% and the average F-Measure was 85.44\%, as depicted in Figure 3.4, and the overall Accuracy was 85.45\%. These results are based on the Confusion Matrix shown in Figure 3.5.

Despite a certain degree of confusion in the performance of our system, we are confident in our overall results. First off, the results with a relatively smaller number of cough samples are still good. We plan to improve our system in three ways. First, we can certainly include many more cough samples from many more subjects to enable better learning and further improve accuracy. Secondly, we can include certain demographics, behavioral, and medical information of subjects like age, smoking history, other chronic conditions are more as features for classifying. With more orthogonal (i.e., non audio) features, we expect learn-
Figure 3.4: Precision, Recall and F-Measure Using 10-Fold Cross Validation

Figure 3.5: Confusion Matrix Using 10-Fold Cross Validation
Table 3.3: Comparing Performance of Different Machine Learning Algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forests</td>
<td>85.45%</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>81.82%</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>76.36%</td>
</tr>
<tr>
<td>One R</td>
<td>52.73%</td>
</tr>
</tbody>
</table>

...ing and accuracy to improve. Also, we believe that while our system certainly will recognize more intense COPD coughs, it could possibly make mistakes in classifying mild COPD cough as a non COPD cough. To circumvent this issue, we are planning for algorithms design that will classify COPD cough itself as severe, medium or mild. With more patients, this will also be feasible. With learning in this manner, accuracy of COPD detection will definitely improve. Finally, for comparison purposes, we show in Table 3.3, our results from implementing different machine learning algorithms for classification using the features extracted, and found that Random Forests performs the best, for the same reasons discussed earlier in Section 3.2.

3.5 Clinical Application

According to new estimates by the World Health Organization (WHO), COPD is predicted to become the third leading cause of death globally by 2030 [43]. Although death rates for COPD have declined in the United States, the prevalence of COPD varies considerably by state indicating the need for novel patient-centered symptom monitoring and education to combat the rising prevalence [44]. Monitoring symptoms related to COPD can be a difficult endeavor for patients living with this disease. The GOLD 2020 strategy [2]
classifies persons with COPD into four groups based on the severity of disease, as assessed by
the degree of airflow restriction, a patient symptom score, and the number of exacerbations
in one year. Therefore, we propose to use the COPD classification using patient symptom
score to help patients track COPD symptoms such as coughing and shortness of breath using
the system proposed in this chapter, which we will encode as an easy to use smart-phone
application.

The symptom score will be assessed by the frequency and intensity of cough and
shortness of breath (Dyspnea). GOLD recommends the use of the COPD Assessment Test
(CAT) or the modified Medical Research Council Dyspnea Scale. We propose to use the
modified Medical Research Council Dyspnea Scale [45], shown in Table 3.4, in combination
with our proposed system for cough analysis and prediction. Persons with mild or moderate
airflow restriction will be assigned to groups A or B, whereas those with severe or very
severe airflow restriction are assigned to groups C or D. Based on the data on symptom
score, our proposed mobile application will be designed to give feedback on use of inhalers
for relief. The app will be further expanded to enable oxygen saturation level and peak
flow monitoring from wearables and integration, offer reminders to take medication, keeping
step count for six-minutes and motivate to exercise. The application will provide health
education components such as medication, nutrition, exercise, and advice on coping with
emotions that affect individuals health overtime. These are the proposed future works based
on our contributions in this chapter.
Table 3.4: Modified Medical Research Council Dyspnea Scale Score

<table>
<thead>
<tr>
<th>Description of breathlessness</th>
<th>Score</th>
<th>Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>I get breathless only with strenuous exercise.</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>I get short of breath when hurrying on level ground or walking up a slight hill.</td>
<td>1</td>
<td>A or B</td>
</tr>
<tr>
<td>On level ground, I walk slower than other people my age because of breathlessness, or I have to stop for breath when walking at my own pace.</td>
<td>2</td>
<td>B</td>
</tr>
<tr>
<td>I stop for breath after walking about 100 yards or after a few minutes on level ground.</td>
<td>3</td>
<td>C</td>
</tr>
<tr>
<td>I am too breathless to leave the house, or I am breathless when getting dressed.</td>
<td>4</td>
<td>D</td>
</tr>
</tbody>
</table>

3.6 Conclusion

In this chapter, we presented a smart-phone based system to record cough, and then detect if the cough patterns are indicative of COPD. Our proposed system involves an application for recording cough, removing noise, an information gain approach for feature selection, followed by a Random Forests based algorithm for classification. We presented our results that demonstrated high accuracy with good Precision, Recall and F-measure. We presented practical ideas to further improve accuracy of classification of our algorithm. Towards the end, we presented important clinical applications of our proposed system for comprehensive in-home COPD monitoring by patients themselves.
Chapter 4: TussisWatch: A System to Identify Cough Episodes as COPD and CHF

4.1 Introduction and Contributions to Study

Cough is often regarded as a critical symptom of Chronic Obstructive Pulmonary Disease (COPD) and Congestive Heart Failure (CHF), and listening to cough is still an important mechanism for physicians to gauge disease onset and severity. In this chapter, we design TussisWatch, a smart-phone based system that is user friendly and low cost to enable self-diagnosis of COPD and CHF by patients. Specifically, our system consists of a) a simple and user friendly mobile application to record cough; b) noise cancellation techniques to filter out ambient noise; c) careful extraction of a small number of audio features that provide discriminatory power among classes; and d) a two-level Random Forest based classification technique, where the first-level identifies the recorded cough as symptomatic of DISEASE (COPD or CHF) or otherwise (CONTROLS); followed by a second level classification of the recorded cough as symptomatic of COPD or CHF, based on classification at the first-level. With a cohort of 9 COPD, 9 CHF and 18 CONTROLS subjects, spread across both genders, races and ages, we extensively evaluate our proposed system. We see good performance across Sensitivity, Specificity, Accuracy and Area under ROC curve, across multiple testing strategies, which demonstrates practical utility of our proposed system.

2This work has been accepted into IEEE’s Journal of Biomedical and Health Informatics (JBHI) in 2018, and published officially in 2019. Permission is included in Appendix A.
To summarize, the problem we address in this chapter follows the overall flavor of most related works. However, our problem, namely classification of cough symptomatic of COPD/CHF is unique and not explored yet, but very important. Naturally, the features we extract in this chapter, explanations of their relevance, and design of classification algorithms are unique in this chapter. Recall that in the previous chapter, we present results on detecting only COPD symptoms using cough recorded from smart-phones [5]. However, the system in [5] does not address the issue of classifying both CHF and COPD cough, which is a much more difficult problem. This necessitates new features and methods for classification, which are new contributions of the system proposed in this chapter.

4.2 Data Collection

With the help of nurses at Tampa General Hospital, located in Downtown Tampa, we identified patients who were clinically diagnosed, by a physician, with early stage COPD and/or CHF. We also identified subjects of a similar age group who did not have COPD or CHF, and they served as CONTROLS. All subjects who gave us cough data consented to do so.

In our study, a registered nurse asked each subject to cough close to the microphone of the Samsung Galaxy S5 smartphone, and would then turn on our app. The duration of each cough ranged from 3 seconds to 17 seconds per subject. In this manner, cough data was collected from 9 COPD, 9 CHF and 18 CONTROLS subjects. After recording a cough episode, the corresponding audio file in the phone was renamed with a unique subject
identifier appended with the subject type (i.e., “COPD” or “CHF” or “CONTROLS”). In our experiment, 40% of subjects were female, and 60% were male. The average age of subjects was 55 years, with a standard deviation of 7. Subject’s demographic information is presented in Table 4.1.

4.3 Technical Approach

Figure 4.1 presents the work-flow of TussisWatch. It is a two-level classification system, where at the first level, a cough segment is identified as either DISEASE or CONTROLS. In the case of the former, the second level of classification identifies the cough segment as symptomatic of COPD or CHF.
<table>
<thead>
<tr>
<th>Description</th>
<th>COPD</th>
<th>CHF</th>
<th>CONTROLS</th>
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<tr>
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<td>Non-Smoker</td>
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</table>
4.3.1 Removal of Pauses and Noise

The first step is to remove pauses and noise. Occasionally, during a cough recording, there were few instances of audio data containing long pauses before, after, and in between coughs. Such pauses were discarded using an online audio cutting application. Afterwards, we applied a band-pass filter to remove additional noises. The cut-off frequencies are 300 Hz and 1200 Hz, since cough related sounds are primarily in this range [46]. This design choice is also applied in other related works for extracting extract cough signals from noise [16].

As we can see, in any cough episode, only selected portions of the episode are indicative of COPD or CHF, and not the entire episode. The issue for us is how to partition a cough episode to only retrieve only those segments symptomatic of disease to enable learning. Fortunately, three authors of in our paper (i.e., the fifth, sixth and seventh authors) [6] have decades of combined experience in identifying COPD and/or CHF cough by listening, and they indicated that segmenting a cough episode into one second windows was optimum to catch the corresponding cough sounds of interest. A window size smaller than one second is too hard for the ear to process, and a window size larger than one second may contain data from more than one class, both of which are problematic.

As such, we partitioned each cough episode into multiple segments, each of one second duration. That is, for a cough episode of 10 seconds, we extract 10 segments each of one second duration. Then, our three COPD/CHF expert co-authors jointly listened to each (one second) segment of each recorded cough episode carefully, to agree and tag that segment as symptomatic of COPD or CHF or otherwise. At the conclusion of segmentation, we derived
a total of 82 segments of cough that were symptomatic of COPD and 47 segments of cough symptomatic of CHF from all the patients. The rest of cough segments from these cohorts, and those from the CONTROLS cohort were labeled as CONTROLS cough. In this manner, we labeled 81 cough segments as CONTROLS. Note that the duration of each cough segment across all classes was one second. Also, recall that since the sampling rate of the smart-phone in our case was 44100 Hz, each cough segment in our data set had that many data samples within. This dataset enabled subsequent model development.

4.3.2 Feature Extraction at First Level

Any learning algorithm is sensitive to the features on which it is trained. At the first level of our scheme, we identify whether a given segment of cough is indicative of DISEASE (either COPD or CHF) or CONTROLS. To do so, we extract 6 features that we carefully identified for our problem.

Each feature is computed for each (one second) segment of a cough episode in either class. The features are presented below:
1. Zero Crossing Rate (ZCR): Let $\text{sgn}(x)$ return $+1$ when $x$ is positive; return $0$ when $x = 0$; and return $-1$ when $x$ is negative. For a cough segment $f$, with $L$ samples, ZCR is

$$ZCR(f) = \sum_{i=2}^{L} \frac{|\text{sgn}(s_i) - \text{sgn}(s_{i-1})|}{2(L-1)}.$$ (4.1)

ZCR [14] is a measure of the number of times the amplitude of sample points $s_i$ in a segment $f$ of a given cough episode passes through a value of zero. Figure 4.2 demonstrates an instance of the significance of this feature for classification, where the DISEASE cough (COPD & CHF) has much higher ZCR’s compared to CONTROLS cough.

2. Sound Pressure Level (SPL): SPL is a logarithmic measure of the actual sound pressure of a cough segment, with respect to a fixed reference pressure. For a given cough segment $f$, the SPL, measured in decibels $dB$, is defined as

$$SPL(f) = 20 \log_{10} \frac{r}{r_{\text{ref}}} dB.$$ (4.2)

Here, $r$ denotes the average sound pressure of a cough segment and $r_{\text{ref}}$ denotes a reference value of $20\mu Pa$, which is lowest hearing threshold of a healthy ear. The DISEASE class, when compared to the CONTROLS class, showed consistently higher SPL values. This is depicted in Fig. 4.3.

3. Interquartile Range (IQR): To derive IQR, we divide the frequencies within each cough segment into quartiles, the $75^{\text{th}}$ percentiles (upper quartile) and the $25^{\text{th}}$ percentile (lower quartile), and determine their difference. Cough segments corresponding to
Figure 4.3: Sound Pressure Level of DISEASE and CONTROLS Cough Segments

DISEASE class have consistently lower frequencies, due to lower pitches. CONTROLS cough segments have frequencies fluctuating more, which usually start high (upper quartile) and end much lower (lower quartile). Hence, the differences between the two quartiles were higher for CONTROLS cough in comparison to DISEASE cough.

4. Percentiles (PER): To calculate PER, we extract all frequencies available in a cough segment, and sort them in ascending order. The PER value for this cough segment is that frequency, below which 40% (which is a tunable parameter) of all frequencies contained in that segment are present. For our dataset, the PER values computed as above were consistently higher for CONTROLS cough compared to DISEASE cough.

5. Mean Absolute Deviation (MAD): This parameter is the mean absolute deviation of the set of all frequencies contained within a cough segment. In our dataset, DISEASE cough had consistently higher MAD values in comparison to CONTROLS cough.
6. Standard Deviation (STD): This parameter is the standard deviation of the set of all frequencies contained within a cough segment. In our datasets, DISEASE cough had consistently higher STD values in comparison to CONTROLS cough.

4.3.3 Feature Extraction at Second Level

At the second-level of classification, recall that we want to classify a cough segment as symptomatic of COPD or CHF, if the first-level classifier identified the segment as belonging to the DISEASE class. To do so, we identify 11 features which we compute for each segment of cough in either class.

1. Spectral Centroid (SC): Let $p_i (i = 1, 2, \ldots n)$ represent the normalized magnitude of the $i^{th}$ frequency bin of a cough segment $f$ computed using Fast Fourier Transform (FFT). The Spectral Centroid is calculated as

$$SC(f) = \frac{\sum_{i=1}^{n}(i)(p_i)}{\sum_{i=1}^{n}(p_i^2)}.$$  \hspace{1cm} (4.3)

Here, SC represents the “brightness”, or loudness, of a cough segment. As shown in Fig. 4.4 (a) for a few instances, the SC is higher for the CHF class compared to COPD class. This is because CHF coughs contain crackles and fluids, which have higher sounds (i.e., volume) compared to COPD coughs that contain mucus, which produce lower, muffled sounds.

2. Spectral Roll-Off (SR): Consider the Total Energy of a cough segment, which is computed as $\sum_{i=0}^{n}(p_i)$, where $n$ and $p_i$ are defined above. In this case, SR is that frequency
below which 85% of the energy of the cough segment is contained. The SR for CHF cough was consistently higher compared to COPD cough as seen in Fig. 4.4 (b).

3. Spectral Flatness (SF): SF characterizes the audio spectrum of each cough segment by determining how “noise-like” a cough is versus how “tone-like” it is. It is determined as,

\[
SF(f) = \frac{\sqrt{\prod_{i=1}^{n}(p_i)}}{\sum_{i=1}^{n}(p_i)} dB.
\]  

(4.4)

COPD cough segments, considering their common mucus sounds, are more “noise-like” compared to CHF segments. Thus, SF for COPD segments were higher than that of CHF.
4. Mel Frequency Cepstral Coefficients (MFCC): Let $C$ denote the mean of the frequencies in a cough segment. Let $x = 1, 2 \ldots K$, where $K = 44100$ (the sampling rate of the smart-phone) and $S_k$ represent the Discrete Cosine Transform (mel cepstrum) coefficients. The MFCC is calculated via

$$C_x = \sum_{k=1}^{K} \left( \log S_k \right) \left[ x(k - \frac{1}{2}) \frac{\pi}{K} \right]. \quad (4.5)$$

The MFCC represents the spectral envelope of a given cough segment, and its computation requires a series of complex steps [42][47][48], which are further elaborated in Chapter 5, Section 5.4.2. For best performance of our cough classification scheme, only 2 of the 13 cepstrum coefficients were selected after analysis, which were the third and sixth coefficients. As seen in Figs. 4.4 (c) and (d) for a representative case, the third coefficient reflected a consistently higher MFCC for COPD cough, while the sixth coefficient reflected a consistently higher MFCC for CHF cough.

5. Short Time Energy (STE): Let $y_i$ denote the amplitude of the $i^{th}$ sample of a cough segment, and $h(w)$ denote impulse response of a linear filter of signal $w$. For a cough segment $f$,

$$STE(f) = \sum_{i=-\infty}^{\infty} y_i^2 \ast h(w - i). \quad (4.6)$$

The STE measures (in increments) energy increase of a cough segment. In our case, we set $w = 10\text{ms}$. We find that COPD cough segments had consistently higher values for STE as compared to CHF cough segments.
6. **Root Mean Square (RMS):** Let $L$ denote the number of samples in a cough segment $f$, and $n_i$ denote the normalized amplitude value of the $i^{th}$ sample in $f$. Then,

$$RMS(f) = \sqrt{\frac{1}{L} \sum_{i=1}^{L} n_i^2}.$$ (4.7)

RMS is used to characterize the energy contained in the sound waves of a given cough segment. We see a consistently higher RMS in COPD, compared to CHF cough segments, due to its higher averaged sound pressure.

7. **Maximum Value (MAX), Variance (VAR), Median (MED) and Mean (AVG):** These features denote the maximum value, variance, median and mean among frequencies contained in a cough segment. For each feature, values were higher for CHF cough compared to COPD cough.

4.3.4 **Data Balancing via SMOTE**

Recall that our dataset is imbalanced, containing 129 seconds of cough in DISEASE class (i.e., 82 seconds of COPD, and 47 seconds of CHF cough); and 81 seconds of CONTROLS cough. Classification on unbalanced datasets can create biased results. To alleviate this problem, we balance our datasets by oversampling the deficient classes, following the idea of Synthetic Minority Oversampling Technique (SMOTE) [49]. SMOTE is a widely used data balancing method in which feature values in the minority classes are oversampled.
by creating synthetic examples, rather than by replacement or creating copies \(^3\). We explain using Fig. 4.5.

Let us consider an arbitrary feature in the minority class. In the SMOTE technique, for this feature, an arbitrary feature point from the feature vector is picked as seen in Fig. 4.5 (a). Then, the distance to a randomly chosen neighboring feature point among 5 closest ones is computed \(^4\). This is shown in Fig. 4.5 (b). The difference (i.e., distance) is multiplied by a random number in the range \([0, 1]\) and this value is added to the initial arbitrary data point picked, and this resulting data point becomes a new entry in the corresponding feature vector for the minority class, as shown in Fig. 4.5 (c). The process repeats until the desired number of feature points are computed and added. The process naturally repeats for each feature. The SMOTE technique is widely used, and has been identified as a robust technique for over-sampling (by sometimes up to 200\% of the original data) to overcome class imbalance effects \([49]\).

\(^3\)Undersampling the majority class is not viable due to our limited amount of data. Also, balancing techniques, like Cost Matrix are better for larger datasets, and are shown to not work as well as SMOTE when datasets are small \([50][51]\), as is the case with our dataset.

\(^4\)Choosing 5 neighboring feature points gave us best results, and is also recommended in \([49]\)
In our proposed implementation for class balancing, each feature in the CHF class was increased from 47 to 82 (75%); and each feature in the CONTROLS class was increased from 81 to 162 (100%). As a result, we now have 164 data points for each feature in the DISEASE class (i.e., 82 for COPD cough, and 82 for CHF cough); and 162 data points for each feature in CONTROLS class resulting in a balanced dataset.

4.3.5 Random Forest Classifier

Finally, we design a Random Forests (RF) based classification algorithm at both levels. The RF algorithm creates a random subset of training samples from the cough datasets, for both classification levels by assembling a congregation of decision trees. Each decision tree predicts a class, based on a majority vote made by each individual tree. Then, the decision tree utilizes the majority vote to determine the final predicted class. The parameters of our RF model, that gave us best results for both classification levels are as follows: 121 decision trees, information gain as splitting criteria, 6 as the maximum depth of each decision tree, 5 as minimum number of samples to split the internal node, and bag size percent of 100. We found these parametric values optimal by applying grid search on wide range of parameters.

4.4 Results and Related Discussions

Results were calculated using Specificity, Sensitivity and Accuracy as metrics. Based on True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN), we have
\[ Sensitivity = \frac{TP}{TP + FN}, \]  
(4.8)

\[ Specificity = \frac{TN}{TN + FP}, \]  
(4.9)

and

\[ Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \]  
(4.10)

### 4.4.1 First Level Results

At this level, the classification of a cough segment was between DISEASE and CONTROLS. Employing 10-Fold Cross Validation, we achieved a Sensitivity of 82.31\%, Specificity of 79.01\% and an Accuracy of 80.67\%. Employing Leave-One-Out Cross Validation, we achieved a Sensitivity of 77.54\%, Specificity of 79.02\% and an Accuracy of 75.45\%.

### 4.4.2 Second Level Results

Here, the classification of a cough segment was between COPD and CHF. Employing 10-Fold Cross Validation, we achieved a Sensitivity of 71.95\%, Specificity of 84.14\% and an Accuracy of 78.04\%. Employing Leave-One-Out Cross Validation, we achieved a Sensitivity of 75.00\%, Specificity of 73.65\% and an Accuracy of 74.63\%.
4.4.3 Justification for our Two-level Classification Scheme

Note that both COPD and CHF related cough sound similar, even for experts. In our system, when we attempted a single level classification scheme to differentiate between COPD, CHF and CONTROLS cough, our system learns to recognize CONTROLS cough from the other two classes better, but there was significant confusion between COPD and CHF cough. This is because the features used to differentiate CONTROLS cough from DISEASE (i.e., either COPD or CHF) do not work well enough to isolate COPD cough from CHF cough. This is reasonable, since the differences between physiology of CONTROLS cough and DISEASE cough are more pronounced. Once we identify that the cough belongs to the DISEASE class, the separate set of features we designed to separate COPD cough from CHF cough perform much better, hence explaining our design choice.

4.4.4 A Note on Representativeness of our Dataset

It is vital for any machine learning system to train on sufficient sized datasets to avoid overfitting. We present insights on the representativeness of our datasets, by employing a variance based approach that is used in the literature [52][53]. In employing this approach, we randomized our entire dataset by dividing it into 10 non-overlapping subsets initially. We then classified cough using our technique for the first 10% subset of the dataset to get 10 numbers for classification accuracy for the case of 10-fold cross validation. Next, we quantify the variance among accuracies derived. Then, we do the same for 20% of datasets, and again we compute the variance in classification accuracies among the 10 values for 10-fold cross
Figure 4.6: Variance Trends for Different Subsets of Our Dataset

Table 4.2: Comparing Accuracy (%) of Different Machine Learning Algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>First Level</th>
<th>Second Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forests</td>
<td>80.67%</td>
<td>78.04%</td>
</tr>
<tr>
<td>Support Vector Machine</td>
<td>76.77%</td>
<td>75.60%</td>
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<tr>
<td>k-Nearest Neighbors</td>
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<tr>
<td>Naive Bayes</td>
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</table>

validation. We do the same for 30%, 40%, 50%, 60%, 70%, 80%, 90% and the entire 100% of our dataset. Fig. 4.6 plots the resulting variances. As we see, for small sized datasets, the variances are higher, but they start to decrease with more datasets. Beyond 70% of datasets, the variances are stable and very low as well. This, we believe, gives us confidence on representativeness of our datasets for our system at both levels.

4.4.5 Comparing Performance of Classification Algorithms

In Table 4.2, we show classification results from implementing different learning algorithms for our problem, and found that Random Forests performs the best. This is because Random Forests Classifiers are one of the most accurate learners available, and better reduce the likelihood of over-fitting [40].
4.5 Clinical Application

Monitoring symptoms related to COPD and CHF can be a difficult endeavor for patients living with these diseases. Breathlessness and cough are both increased during exacerbations in COPD and CHF. Studies have generally focused on quality of life during end-stage of these diseases, where breathlessness becomes dominant and cough less important. When COPD and CHF progresses to an advanced stage, there are many decisions to be made to manage worsening symptoms. Cough may be a marker for progressive disease. Therefore, ambulatory monitoring of cough using a mobile application will provide novel insights into the determinants of cough in COPD and CHF. [54] recommends coughing that produces white or pink blood-tinged mucus as an early warning sign of worsening CHF. Similarly, [2] classifies patients with symptoms of cough, but without airflow obstruction as Stage 0 disease. Therefore, suggesting that these patients are at risk of developing COPD and further progression of the stage of COPD due to a productive cough. This, in the presence of already established airflow obstruction, does predict FEV1 decline in COPD.

4.6 Conclusion

In this chapter, we designed *TussisWatch*, a smart-phone based system to record and detect cough patterns indicative of COPD, CHF or no disease, using a two-level classification scheme. We believe our system is the first to demonstrate the feasibility of a smart-phone based system for self-detection of cough symptomatic of COPD/CHF.
Chapter 5: Evaluating the Effectiveness of Inhaler Use Among COPD Patients

5.1 Introduction and Contributions

Chronic cough and wheezing from the lungs are main symptoms of COPD, due to excess mucus production. Pharmacological therapy for COPD includes regular self-use of an inhaler (to deliver medicine directly to the lungs to breakdown mucus), and is validated in several clinical trials [55][56]. However, it is a fact that a significant percentage of patients engage in sub-optimal inhaler techniques during self-care [57], which, as a consequence does not breakdown mucus enough, leading to worsened symptoms/health, and sometimes re-hospitalizations. Our Contributions: In this chapter, we propose an in-home smartphone based system to enable a COPD patient determine the effectiveness of inhaler use via processing cough and breath sounds. To do so, we recruited a cohort of 55 clinically diagnosed COPD patients, spread across both genders. Each subject was asked to cough and take deep breaths before inhaler use (to detect presence of mucus) and after correct inhaler use (to detect break-up of mucus and symptoms improvement). All data was recorded via a smartphone. After removing noise, three experts (one of them, our co-author) listened to each audio segment recorded, to classify the cough and breath sounds as symptoms of COPD (i.e., excess mucus build-up) or otherwise (i.e., mucus breakup due to correct inhaler use).
After appropriate pre-processing, a total of 430 seconds of cough audio, and 1161 seconds of breath audio were obtained, evenly spread before/ after inhaler use.

From this audio dataset, we then extracted Mel-frequency Cepstral Coefficients (MFCC) for post-processing. Very briefly, the mel-frequency cepstrum (MFC) is a representation of the short-term power spectrum of an audio signal, based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency. The Mel-frequency cepstral coefficients (MFCC) are those that together make up an MFC. MFCC provides a robust feature set for our classification problem (i.e., assess improvement in cough and breath due to inhaler use), as this feature performs best at capturing the spectral envelope of cough and wheezing sounds. As we present later in the chapter, the spectral envelope is a critical component in audio signal processing that best captures features unique to sounds like cough and breath.

We then designed a spectrum of machine learning algorithms to process the MFCC extracted in order to classify cough and breath of COPD patients. Specifically, we want to discern those cough and breath sounds that indicate absence of mucus (with correct inhaler use) compared to sounds that indicate presence of mucus. It is easy to see that if we are successful in achieving our goal, quick feedback can be given to patients indicating either a) they are correctly using the inhaler; or b) they are incorrectly using the inhaler (while also directing them to tutorials on correct inhaler use). To address our goal, we found that a Support Vector Machine (SVM) algorithm performed the best among k-Nearest Neighbors, Random Forests, and Logistic Regression in terms of standard metrics like Precision, Recall,
Sensitivity and Specificity. Our overall accuracies were close to 80% for both cough and breath. We believe that our system is the first to actually design an in-home smartphone based system to record and process cough breath to evaluate the effectiveness of inhaler use. We expect our system to have significant value to educate patients, improve health outcomes and reduce rehospitalization rates in relation to COPD.

5.2 Data Collection

5.2.1 Recruitment of Subjects with COPD

During Spring and Summer 2019, we collaborated with respiratory therapists at Tampa General Hospital in Downtown Tampa, FL. With their assistance, we identified 55 (34 Female and 21 Male) clinically diagnosed COPD patients. Each subject were asked to sign an Institutional Review Board (IRB) approved consent form, indicating their willingness to participate in our study. Additionally, subjects were asked to provide their demographic information (i.e. age, gender, martial status, etc.), documented in Table 5.1, and completed the COPD ABC and Leicester Cough Questionnaires. The COPD ABC Questionnaire measures the burden of COPD [58], and the Leicester Cough Questionnaire assesses the impact of cough on various aspects of life (i.e., personal, professional, etc.) [59].

5.2.2 Our Procedure for Recording Cough and Breath Sounds

Cough and breath sounds were recorded using a custom application developed by the authors. This application was installed onto a Motorola Moto E Smart-Phone device,
Table 5.1: Subject’s Demographic Information

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<th>Category</th>
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<td>Martial Status:</td>
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<td>16 (29.6%)</td>
</tr>
<tr>
<td></td>
<td>Never Married</td>
<td>11 (18.5%)</td>
</tr>
<tr>
<td></td>
<td>Windowed, Divorced or Separated</td>
<td>28 (51.9%)</td>
</tr>
<tr>
<td>Education:</td>
<td>&lt;High School</td>
<td>11 (18.5%)</td>
</tr>
<tr>
<td></td>
<td>High School or GED</td>
<td>16 (29.6%)</td>
</tr>
<tr>
<td></td>
<td>Some College Degree or Professional</td>
<td>12 (22.2%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>16 (29.6%)</td>
</tr>
<tr>
<td>Smoking Status:</td>
<td>Current Smoker</td>
<td>9 (16.7%)</td>
</tr>
<tr>
<td>Mean of COPD Burden Score:</td>
<td>Score on COPD ABC Questionnaire</td>
<td>29.5 ± 5.11</td>
</tr>
<tr>
<td>Mean COPD Severity Score:</td>
<td>Score on Leicester Cough Questionnaire</td>
<td>8.57 ± 3.59</td>
</tr>
</tbody>
</table>
containing Android version 4.4.4 KitKat, recording at a sampling rate of 16 (per second). This sample and bit rate is standard [60] and recommended [61]. In related studies, [62] samples cough at 8000Hz and [63] samples wheezing at 9000Hz, however sounds sampled below 11025Hz produces poor sound quality and are not sufficient enough for serious recording tasks [61] (i.e. cough/breath recording to diagnose a major chronic illness). Thus, to make sure that we are analyzing the best sound quality for cough and breath, which will affect our raw data and classification results, we used the standard sampling and bit rate.

We collected four samples from each subject: (1) cough and (2) breath sounds before inhaler use, and (3) cough and (4) breath sounds after inhaler use. To collect cough, each subject would simply cough into the phone’s microphone via our app. However, to collect breath sounds (i.e., wheezing), we developed a custom recorder using the diaphragm of an actual stethoscope. Connected it to is an Audio-Technica ATR-3350IS Omnidirectional Condenser Lavalier microphone, which records breath sound waves as audio files. The microphone, shown in Figure 5.1, connects to our smart-phone via wire and is available in the market.

The process of collecting data required care. Initially, before each subject was administered their inhaler medication, we recorded a sample of their cough. To do so, each subject was asked to cough directly into the microphone of our smartphone in which the sound was recorded. Recording breath required a series of steps. First, we started off using an actual stethoscope to manually listen to each subject’s wheezing sounds in their lungs, which indicate quality of breath sounds. The objective was to locate the clearest wheez-
Figure 5.1: The Audio-Technica ATR-3350IS Omnidirectional Microphone
Table 5.2: Number of Seconds (sec.), Before (BP) and After (AP) Processing

<table>
<thead>
<tr>
<th>Class</th>
<th>Sec. (BP)</th>
<th>Sec. (AP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>cough_before_inhaler_use</td>
<td>289 sec.</td>
<td>219 sec.</td>
</tr>
<tr>
<td>breath_before_inhaler_use</td>
<td>627 sec.</td>
<td>579 sec.</td>
</tr>
<tr>
<td>cough_after_inhaler_use</td>
<td>261 sec.</td>
<td>211 sec.</td>
</tr>
<tr>
<td>breath_after_inhaler_use</td>
<td>632 sec.</td>
<td>582 sec.</td>
</tr>
</tbody>
</table>

ing sounds being projected. Most often, wheezing sounds are best heard on four different areas of the subject’s front, mid-to-lower chest, where the lungs are located. Additionally, wheezing sounds can be heard on eight different areas of the subject’s mid-to-lower back. The best areas of auscultation, as depicted in Figure 5.2, vary by subject. Once we identify the best location where wheezing was heard, we used our stethoscope, Audio-Technica microphone and mobile application to record and store the clearest wheezing sound from that location for that subject. All recorded data was appropriately labeled (without any identifiable information).

In the second round of recording, the subject was required to take their inhaler medication, which was correctly administered by a respiratory therapist. About five minutes after inhaler use, the exact same cough and breath recording process was executed, and all data was labeled. This process was repeated for all subjects. Since all patients used the inhaler correctly, their cough and breath sounds sounded differently due to mucus break down after inhaler use (which can be gleaned by a trained ear). Automating the classification via this ground-truth data is our problem.
5.3 Data Pre-processing

5.3.1 Cough and Breath Data Before Pre-processing

In our data collection procedures, Cough sounds, on an average, lasted about 7 seconds each. Breath sounds, on the contrary, were collected for approximately one minute each, consisting of 5-7 deep breaths. Using this data, we developed four different classes: cough before inhaler use, breath before inhaler use, cough after inhaler use and breath after inhaler use. As shown in Table 5.2, the second column contains the duration of raw data before any pre-processing (denoted as BP). Data in the third column is after pre-processing (denoted as AP), and is discussed next.

5.3.2 Pause and Noise Removal

First, we identified unintentional pauses in our audio files post recording, and cut them using an audio cutting application. Next, we applied a band-pass filter to lower background...
noise in our cough data (i.e., noise due to surrounding conversations, medical equipment, etc.), with cut-off frequencies as 300Hz and 1200Hz because cough lies in-between those frequencies[16][46]. There was little to no noise in our breath data, because the stethoscope was placed tightly on the subject’s skin for recording.

5.3.3 One Second Window Algorithm

The next issue is accurate ground-truthing of data collected. This is a little tricky. Even if a patient is clinically diagnosed with COPD and chronic cough, it is still not the case that the entire cough episode indicates symptoms of COPD. It often happens that only a certain subset of their entire cough episode indicates COPD symptoms. Naturally, with proper inhaler use, subsequent cough segments will be completely devoid of COPD symptoms. Fortunately, the third co-author on this research [7] has decades of experience working with COPD patients, and she indicated that a one second segment of cough can indicate presence of COPD symptoms to a trained human ear. The same is true for breath also. As such, we split our entire dataset of cough and breath (after pause and noise removal) from all patients into one second segments and our third co-author, joined by other experienced nurses, listened to each cough and breath segment to tag it as indicative of concerning COPD symptoms (that necessitated inhaler intervention for that episode of cough/breath) or very mild/no discernible COPD symptoms (that does not necessitate any further inhaler use for that episode).

As a result of these procedures, we generated a new dataset containing 219 seconds of cough and 579 seconds of breath audio that indicated COPD symptoms necessitating inhaler
intervention; and 211 seconds of cough and 582 seconds of breath audio that demonstrated improved COPD conditions not warranting any further inhaler use for that episode. This data is shown in the third column in Table 5.2. This dataset is what we train and validate our machine learning algorithms on.

5.4 Feature Extraction and Classification Algorithms

We now elaborate on extraction of Mel Frequency Cepstral Coefficients (MFCC) from our dataset as features, and our Support Vector Machine based algorithm for classification.

5.4.1 Feature Overview

There are many features that can be derived from audio data during the design of a classification algorithm. These include, but not limited to, Zero Crossing Rate, Spectral Flatness, Spectral Centroid, Spectral Roll-off etc. However, it is important we extract only the right (and limited) set of features for processing to ensure accuracy and avoid overfitting. For our problem, we carefully identified that the Mel Frequency Cepstral Coefficients (MFCC) were ideal.

5.4.2 Mel Frequency Cepstral Coefficients

For sound recognition systems, a primary goal is to classify a sound (i.e., speech, singing, breath, cough, etc.) as produced by a human. Human sounds are produced via the larynx (voice box) and vibrations of vocal cords. This sound is then filtered by their vocal tract, which determines how the sound produced is, both, shaped and ejected from the
mouth. The vocal tracts for a human consists of the lips, nose, tongue, teeth and throat areas [64], as depicted in Figure 5.3. The corresponding shape of the sound is defined within the envelope of the short time power spectrum, which estimates loudness and timbre, also shown in Figure 5.3. The MFCC is the strongest audio feature capable of accurately defining that envelope [47][65], which inturn serves as robust features to classify sounds like cough and breath, since the shape of the vocal tract defines how these sounds emanate [66][67][68]. The MFCC accomplishes this by generating Cepstral Coefficients. The calculation to generate the Cepstral Coefficients, depicted for each of our four classes in Figure 5.4, is explained below and mapped out in Figure 5.5.

In Figure 5.4, the four images represent the lower 13 MFCC coefficients, which contain the highest quantity of information about the overall spectral shape produced by cough and breath sounds. For cough, there’s a difference in amplitude due to reduction of mucus build-up after inhaler use. For breath, there’s a difference in amplitude consistency, also due to reduction in mucus build-up after inhaler use. The figure is best viewed in color.
Figure 5.4: MFCC of Before & After Cough, and Before & After Breath Samples

Figure 5.5: The Steps Required to Calculate Mel Frequency Cepstral Coefficients
5.4.3 Computing MFCC Features

First, each audio (i.e., cough or breath) signal \( h \) is split into a small number of frames of duration 20 milliseconds (ms). We chose 20ms duration for frames. If the frame is shorter we do not have enough samples to get a reliable spectral estimate. If it is longer, the signal changes too much throughout the frame, making it highly non-stationary [47]. Since, our sampling rate to record the cough and breath audio signals is 44100Hz, the frame length \( s \) of each audio signal is now \( 0.020 \times 44100 = 882 \) samples. Next, from each frame, we extract one set of 13 MFCC coefficients.

To do so, we denote our pre-framed audio signal as \( h(s) \), and our framed audio signal as \( h_i(s) \). Then, we calculate the Discrete Fourier Transform (DFT) \( D_i(k) \) of each \( i^{th} \) frame as,

\[
D_i(k) = \sum_{s=0}^{S-1} h_i(s)w(s)x(s)e^{\frac{2\pi ks}{S}}. \tag{5.1}
\]

Here, \( w(s) \) represents the length of the hamming window function, where \( w(s) = 0.54 - 0.46\cos(\pi s/S) \). \( S \) is the length of the discrete-time signal \( x(s) \), which represents the quantity of signals in \( s \). Also, \( k \) is the sampling frequency of the DFT, where \( k = 0, 1 \ldots S - 1 \).

We then compute the Periodogram Estimate \( M_i(k) \) as,

\[
M_i(k) = \frac{1}{S}|D_i(k)|^2, \tag{5.2}
\]

to identify which frequencies are present in each frame, and decipher cough and breath sound frequencies analogous to the human ear [47].
Next, to produce the Mel-Filter Bank, we applied a Triangular Filter, depicted in Figure 5.6 [1]. The Triangular Filter, roughly, captures energy within the spectral envelope of a frequency bin. In other words, the filter provides an estimate of the given audio sample’s spectral envelope shape. The Triangular Filter is applied on a Mel-Scale to the power spectrum. The Mel-Scale imitates the linear frequency of the human ear’s perception to sound.

The Mel-Filter Bank contains 26 vectors, and 257 coefficients. We multiple each Filter Bank by the power spectrum, calculated using Equation 5.2, then add the coefficients. This results in 26 numbers, representing the amount of energy in each Filter Bank. The logarithm of these 26 numbers is calculated, which imitates what is heard by a human ear.

Finally, we take the Discrete Cosine Transform (DCT) of the 26 log numbers. This results in 26 cepstral coefficients. We only keep the lower 13 coefficient, as these coefficients contain the strongest quality of information about the spectral envelope’s shape [47].
discard the higher coefficients because they represent fast changes in the Mel-Filter Bank energies, which decrease cough and breath recognition performance. We see a small, but noticeable, increase in performance by dropping the higher coefficients.

After applying the DCT, the MFCC can be expressed as,

$$C_m = \sum_{k=1}^{K} (\log D_t(k)) [m(k - \frac{1}{2}) \frac{\pi}{K}], \quad (5.3)$$

where $C_m$ denotes the MFCC, $m = 1,2...13$, which equates to the 13 MFCC coefficients, and $K = 44100$ which is the sampling rate of our recording device.

5.4.4 Justification for MFCC Audio Features

As of today, health-care professionals listen to the sound of a patient’s cough and wheezing to determine the presence and severity of COPD [69]. The point of our study is to automate this process using machine learning processed on cough and breath. To do so, we need to capture the spectral envelope of cough and wheezing sounds. In the literature, it has been demonstrated various times that the MFCC audio features are most capable of capturing the spectral envelope [47][65][70]. The MFCC does so by converting sounds to a Mel-Scale which analyses those sounds at frequencies that humans speak, and are capable of hearing. The MFCC is an ideal feature for our problem for the following reasons: (1) MFCC uses the mel-scale to analyze sound in a manner similar to humans [47]; (2) It has been successfully used in several similar applications related to cough [5][6][7][71][72], breath [73], wheezing [74][75], music [76] and speech recognition systems [77]; (3) MFCC is considered
a classic front-end algorithm capable of significant and accurate performance in sound and speech recognition systems \[70\]|\[78\]. Lastly, there are several studies that suggest a significant relationship between the MFCC audio feature and Support Vector Machine classification combination (which were both utilized in this study), when used in the domains of cough \[22\] \[77\]|\[79\] and breath \[74\]|\[80\] analysis.

Other audio features, like Spectral Centroid, Spectral Flatness or Spectral Flux, could have been used to solve this problem. However, these features do not capture the spectral envelope’s perception as the MFCC does. Thus, we did not incorporate those features into this study. Furthermore, using a large number of features on our classification models can cause overfitting problems and also increased overhead. Hence, we stick with MFCC features alone for our problem, and are confident about our decision to do so.

5.4.5 Support Vector Machine

Based on MFCC features presented above, we briefly present our Support Vector Machine (SVM) based algorithm for classification, which performed the best among other techniques. Broadly speaking, SVM classifiers aim to find the best hyperplane between two classes. A hyperplane is a line which linearly separates the data points between the classes. In SVM, a hyperplane is considered “best” when it produces the largest margin between two classes. SVM uses Support Vectors, which are the classes’ data points closest to the hyperplane, to calculate margin maximization \[81\]. This can be seen in Figure 5.7. Recall again that our problem is to identify improvement in symptoms before and after inhaler
usage using cough and breath data in Table 5.2. We design two separate SVM classifiers to do so – one to process cough and the other to process breath.

Our classifiers for cough and breath were developed using the scikit-learn machine learning software, built into python programming language. The parameters for our SVM classification models, which produced best results were as follows:

For cough, the degree of the Radial Basis Function (RBF) kernel function is 7, the cache size is 120, the random state is 4 and the kernel is linear, regularization = 1.0, tolerance for stopping criterion = 1e-3, class weight = balance, decision function shape = one-vs-rest, maximum number of iterations = -1 (default), gamma = "scale" and shrinking = True.

For breath, the degree of the Radial Basis Function (RBF) kernel function = 5, the cache size = 215, the random state = 4, the kernel is linear, regularization = 1.0, tolerance for stopping criterion = 1e-3, class weight = balance, decision function shape = one-vs-rest, maximum number of iterations = -1 (default), gamma = "scale" and shrinking = True.

The RBF kernel was selected and works best for our study because (1) parts of our data has overlap making it difficult for SVM to find the right hyperplane to separate the data; (2) RBF provides better discriminative ability in a much higher dimensional subspace [81]; (3) RBF provided a much faster classification time in comparison to the Polynomial kernel.

5.5 Results

Classification results, presented below were measured using the following cross validation methods: 10-Fold (10-FCV) and Leave-One-Out (LOOCV). Metrics are Specificity,
Figure 5.7: Support Vector Machine for Cough Before & After Inhaler Data Points

Sensitivity, Precision, Recall and F1-Score. Results of our SVM classifier, as well as other machine learning algorithms are recorded in Tables III-VI.

For our cough classification scheme, testing the cough_before_inhaler and cough_after_inhaler classes, we achieved the following results. Employing 10-Fold Cross Validation, we averaged an accuracy of 79.00%, precision of 81.00, recall of 81.00%, sensitivity of 84.52%, specificity 77.61% and a F1-score of 81.00%. Employing Leave-One-Out Cross Validation, we averaged an accuracy of 80.69%, precision of 80.00, recall of 80.00%, sensitivity of 83.45%, specificity 78.02% and a F1-score of 80.00%.

For classification, testing the breath_before_inhaler and breath_after_inhaler classes, we achieved the following results. Employing 10-Fold Cross Validation, we averaged an accuracy of 84.49%, precision of 84.00, recall of 83.00%, sensitivity of 83.00%, specificity 93.30% and a F1-score of 82.00%. Employing Leave-One-Out Cross Validation, we averaged
an accuracy of 84.32%, precision of 83.00, recall of 83.00%, sensitivity of 82.00%, specificity 91.49% and a F1-score of 80.00%.

Tables 5.3-5.6 show classification results using several popular machine learning approaches (i.e. k-Nearest Neighbors, Random Forests, Logistic Regression and Multilayer Perceptron). As shown, Support Vector Machine (SVM) provided the best results for the majority of metrics. This is because SVM works best for binary classification problems, and also works well with linearly separable data [81], such as our data. Figure 5.8 illustrates the Receiver Operating Characteristic (ROC) curves for classification performance based on breath and cough data, with SVM performing the best with Area under the Curve (AUC) scores close to 94% for cough and 93% for breath, when applying 10-Fold Cross Validation. When applying Leave-One-Out Cross Validation, the AUC scores are 87.5% for cough and 88.4% for breath.

5.6 Conclusion

In this chapter, we design a system capable of discerning improvements in cough and breath symptoms for COPD patients as a result of correct inhaler use (due to reduced mucus build-up). Data from 55 patients was used to developed our model. Our ultimate goal is to improve health of the individual and reduce costly re-hospitalizations, by detecting and recommending correct health procedures in-home. Our results are very favorable. We also believe that our work is the first to address the issue of designing algorithms to automatically evaluate the effectiveness of prescribed interventions (in this case, inhalers) for COPD.
Figure 5.8: ROC Curves Using 10-Fold and Leave-One-Out Cross Validation
In the future, we propose to integrate our algorithm as an AI based in-home care system for patients with COPD. With immediate feedback upon symptoms monitoring, patients could be better notified of when to use an inhaler, and also offered tutorials on correct inhaler use which can definitely reduce re-hospitalizations. This system will also include the ability to inform patients when their cough symptoms have exacerbated enough for them to seek medical attention. Integrating these AI designs into current COPD care products in the market like [34][35][39][82][83] is our strategy.

Also, we are aiming to conduct a longer study to design gender based algorithms, since clinical studies suggests that women experience significantly harsher COPD symptoms than men, throughout their lifespan [84]. While in this chapter, we processed cough and breath separately, we are also looking into integrate both sounds and related features together to detect correctness of inhaler usage. Conducting longitudinal experiments to design personalized models for each patient is also part of our future work.

During our data collection, as previously discussed, each subject was asked to participate in both COPD ABC and Leicester Cough Questionnaires (LCQ). The ABC Questionnaire [58] measures burden associated with COPD, while the LCQ measure impact of chronic cough on various aspects of life (i.e., personal, professional, etc.) [59]. Results from the data collected, using these questionnaires, is shown in Table 5.7.

As shown, Almost 60% of our patients reported having history of cardiac condition and 90% had a formal diagnosis of COPD. Almost all patients (94.55%) were taking inhalers to treat their COPD, 50% were on an antibiotic, 59.3% were receiving steroids, 25.9% were on
a diuretic, 24% on a beta-blocker, 33.3% on statin and only 11% on Angiotensin converting enzyme (ACE) inhibitors or Angiotensin receptor blocker (ARB). And, only 64.8% reported having smoked, but we had a missing data on 35.2% of their smoking statuses.

The following data is crucial, as we plan to implement this system, and our previous systems [5][6], into a user-friendly mobile application enabling COPD patients to self-monitor their symptoms, via cough and wheezing. Our system will enable users to become educated on proper self-medication techniques, which will reduce their likelihood for exacerbation, as well as enable monitoring of their daily symptoms and provide feedback on the appropriate or mandatory time to seek early medical attention. This system will also include tutorials for proper use of medications, medically approved self-care techniques (i.e. deep breathing exercises), reminders of post-discharge appointments and analysis of cough, which will inform the user when their cough symptoms are showing improvement, and when they’ve exacerbated enough for the user to seek medical attention.
<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
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<td>81.00%</td>
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### Table 5.7: COPD ABC and Leicester Cough Questionnaire (LCQ) Results

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</tr>
<tr>
<td>Diastolic Blood Pressure (mm/hg)</td>
<td>65.50 ± 19.28</td>
</tr>
<tr>
<td>Heart Rate</td>
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<td>Temperature (Fahrenheit)</td>
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<td>Height (inches)</td>
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<tr>
<td>Weight (lbs.)</td>
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<td>LCQ. Physical Effect of Cough</td>
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<td>Psychological Effect of Cough</td>
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</tr>
<tr>
<td>Social Effect of Cough</td>
<td>2.99 ± 1.31</td>
</tr>
<tr>
<td>LCQ Total Score on Cough</td>
<td>8.57 ± 3.59</td>
</tr>
<tr>
<td>COPD Burden on Symptoms</td>
<td>6.12 ± 1.09</td>
</tr>
<tr>
<td>COPD Burden on Physical Function</td>
<td>6.02 ± 1.58</td>
</tr>
<tr>
<td>COPD Burden on Mental Health</td>
<td>5.02 ± 1.50</td>
</tr>
<tr>
<td>COPD Burden on Emotional</td>
<td>5.71 ± 1.86</td>
</tr>
<tr>
<td>COPD Burden on Fatigue</td>
<td>6.6 ± 1.0</td>
</tr>
<tr>
<td>COPD Burden Total Score</td>
<td>29.5 ± 5.11</td>
</tr>
</tbody>
</table>
In this dissertation, we discussed three machine learning systems that we developed to assess cough and wheezing as early symptoms of Chronic Obstructive Pulmonary Disease (COPD) or Congestive Heart Failure (CHF). In Chapter 3, we developed a model capable of distinguishing between cough patterns associated with COPD and without COPD [5]. For this model, we used nearly 30 audio features to extract data from our collected cough samples. To limit the amount of features used for our model, we implemented Information Gain Feature Selection Algorithm. This feature selection algorithm uses a ranker method to present the features with the highest discriminatory power. That is, the audio features that are the strongest and most relevant for the problem. Next, we develop a Random Forests classifier to enable supervised learning. The average Precision produced was 85.63%, the average Recall was 85.47%, the average F-Measure was 85.44% and the overall Accuracy was 85.45%.

In Chapter 4, we developed TussisWatch [6], a smart-phone based system to detect cough pattern associated with COPD, CHF or neither disease. Similar to our previous project, we extracted a plethora a well-known audio features and applied feature selection to scope the best features for the problem. This system has two-levels and both are based on Random Forest classification. At the level one, the cough episodes as labelled as either
“disease” or “no disease”. If “no disease” classification is done. However, if “disease” is detected, then the second layer classification will determine if the disease in question is either COPD or CHF. We also applied a Synthetic Minority Oversampling Technique (SMOTE) to combat challenges associated with data imbalances amongst the classes. This system achieved Specificities, Sensitivities and Accuracies, using both 10-Fold Cross Validation, ranging from 71.95-84.14%.

In Chapter 5, we examined how proper inhaler use among COPD patients can change the sound of their cough and wheezing [7]. Using this change in sound, we develop a machine learning system, based on Support Vector Machine, that can determine the severity of one’s cough and wheezing, before and after proper inhaler use. Many COPD patients are required to self-medicate with inhalers to combat their symptoms. These inhalers do not cure COPD, but they do temporarily relieve patients of harsh symptoms like mucus buildup in the lungs which make breathing difficult and chronic cough which often wears affects many areas of a patients life (i.e. personal, professional, etc.). Unlike our previous systems[5][6], we did not incorporate a vast number of features or any feature selection. Instead we used the Mel-frequency Cepstral Coefficients (MFCC), which best capture the spectral envelope of the cough and wheezing sounds. This system achieved accuracies close to 80%.

6.1 Interpreting Results of this Dissertation

We now provide important clarifying discussions on the practical utility of our contributions in this paper. At the outset, diseases like COPD and CHF, of interest in this
dissertation affect millions of Americans, and millions more across the globe. In order to protect patients from worsening symptoms, in-home care is vital. There are some practical considerations here. First is the issue that we are not making any clinical diagnosis in this paper, but rather, we provide a service to monitor progression of symptoms over time for a patient (diagnosed by a clinician), by monitoring their cough patterns. In very simple terms, if the number of instances of cough segments that indicate COPD and/or CHF goes down in a bout of cough over time, then that patient is likely progressing well, and doctor visits may not be necessary. On the other hand, if the instances of COPD and/or CHF cough increases over time, then, this may warrant a visit to the doctor. Currently, no systems exist that monitor acoustics in patient homes to monitor progression of COPD and CHF, and our research in this dissertation enables that.

Second is the notion of False Negatives and False Positives. It is always a challenge to interpret these in different contexts, and as such, we provide some perspectives here. We believe that considering the possibility of death due to worsening pulmonary and heart complications that are associated with COPD and CHF respectively, it is better to err on the side of caution. Hence, we recommend that False Negatives be paid utmost attention, since a False Negative means that a patient whose cough patterns are truly indicative of COPD has been predicted as healthy by an algorithm. In case, the algorithm repeatedly makes this mistake, the patient’s worsening progression may not be detected, and could result in death. Now, that does not mean that we need to ignore False Positives. Too many False Positives is counterproductive to the health care system, since that means too many
people are coming to the clinics even when symptoms don’t warrant a visit. This is also not desirable. Fortunately, the thresholds of predicting positive or healthy class in any AI algorithm can be adapted to fine tune False Negatives and False Positives. We do not make any specific recommendations in this dissertation, since that depends of a myriad of factors including cost of a clinical visit, cost of any procedure, number of facilities available in the area to treat patients, patient age, patient gender, stage of disease in the patient, how much care they have where they live, and much more. These are very interesting optimization problems that are complex to explore, but have significant impact when accomplished. We believe that our work in this dissertation - in terms of AI to monitor symptoms in home adds novel variables towards solving such important problems.

6.2 Limitations of Work

Chronic cough is a common symptom for many diseases. These diseases include, but are not limited to, asthma, pneumonia, the common cold, the flu and COVID-19. However, our systems are targeted specifically towards patients experiencing cough symptoms associated with COPD and CHF. More specifically, people who have already been clinically diagnosed with these diseases. Therefore, if someone uses our system and they do not have COPD or CHF, our system will likely provide them with inaccurate and misleading results. To prevent these issues, we recommend that apps like ours be installed by clinicians only during patient visits. There is literature that describes several relationships between COPD/CHF and other diseases, like COPD and Tuberculosis [85], COPD and Asthma [86],
and COPD and Pneumonia [87]. However we have not yet explored those relationships in depth and how they may fit within the scope of our research. These are issues we further discuss in our future works section.

Furthermore, in regards to practical use of our mobile application, we know that asking a user to accurately locate areas of wheezing on their bodies, on their own, can be a daunting task for them. During the developmental stages of our application design, we plan to spend a significant amount of time brainstorming and testing different methods to add realistic ease to this process. This includes surveying a range of health-care workers, specifically those who specialize in COPD/CHF treatment, and actual patients to gain insight on procedures they would find most useful for severity detection. Additionally, this includes several trial runs with the mobile application, where we would test, and allow health-care providers/users to test, the app and get consistent feedback on what changes and features are desired. Lastly, we are aware that there are pitch and frequency differences in regards to sounds (i.e. cough) produced by a male versus a female. If incorporated into our systems, those differences could lead to a difference in the results produced. However, we have not yet explored that in our work. At the moment, cough and wheezing sounds are accessed without regards to gender.

6.3 Future Works

At the moment, we are developing our mobile application *TussisWatch*. TussisWatch will target individuals who have been clinically diagnosed with Chronic Obstructive Pul-
monary Disease (COPD) and assist them with the daily monitoring of their symptoms. In order to accomplish this, we are planning to incorporate several essential features into the mobile application. First, the mobile application will assess the severity of cough and wheezing, using the machine learning algorithms (i.e. Support Vector Machine and Random Forests) that we developed in the previous chapters. This daily monitoring will enable users to keep track of their symptoms and help them to determine if their symptoms are improving or exacerbating enough to seek medical attention. Next, we plan to add educational components, where users can learn about COPD and how to live with it. This includes proper nutrition for diet, clinically approved breathing exercises, physical exercises, statistics regarding COPD and the different stages of the diseases, and education on proper use of medication(s) (i.e., inhaler or nebulizer), vaccinations and preventive care to stay healthy. This is especially important considering many COPD exacerbation cases are caused by lack of education. Additionally, we plan to add sections to application that will allow health-care providers access to their patients results, and reminders to the user about follow-up doctors appointments, appropriate times to take medication(s) and perform breathing and/or physical exercises.

As future work, we want to improve our classification accuracies further. To do so, we are carefully planning new data collection experiments. This time, instead of going to clinics, we will release our recording app to a larger sample of patients and control groups using social media platforms, and request them to use our app to record and store cough data for (say) a month. All cough data locally stored on the phone will be collected and
processed subsequently by us. In this manner, our data sets will be bigger. The data will be more realistic since it is obtained in natural settings of patients, and not in clinics where the cough is more voluntary for assessment. There will also be better diversity in terms of locations commonly visited by patients as well (e.g., clinics, homes, gyms, shopping centers etc.). With such kinds of data, our team plans to investigate (1) deep learning approaches for classification that do away with feature extraction; (2) design personalized models to enhance classification accuracies; (3) attempt more complex problems like evaluating the differences in chronic cough or wheezing symptoms experiences based on gender (i.e. male or female). Point (3) is especially important as there are studies that prove female COPD carriers experience harsher symptoms than male COPD carriers [84]. This will allow us to develop our system to not only be patient specific, but gender specific as well.

Moreover, we plan to explore how different sampling and bit rates of our cough and wheezing data can interfere with results. Currently, all our systems use 44100Hz sampling rate and 16 bit rate (per second) as these are the standard [60] and highly recommended to use unless there’s a valid reason to deviate from them [61]. Related studies [62][63] have deviated from them and we want to see if it will make a difference in our study and why. And, we plan to extend our system beyond just COPD and CHF severity detection, to COVID-19 via cough and wheezing. Currently, little research has been done to develop algorithms capable to detecting COVID-19, and differiating it’s cough patterns from other illnesses (i.e., COPD and CHF). Interviewing patients to understand their security and privacy expectations during design and deployment of a comprehensive self-care system are
additional directions of our future work. All these are exciting avenues for which results from this dissertation serve as a strong foundation.
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About the Author

Anthony Windmon received his Bachelor of Science degree in Computer Engineering, with a minor in Mathematics, from Bethune-Cookman University, located in Daytona Beach, FL, in Fall 2016. In Spring 2017, he joined the University of South Florida, located in Tampa, FL, to pursue his Ph.D. degree in Computer Science and Engineering under the supervision of Dr. Sriram Chellappan. Anthony received two graduate fellowships to assist with the funding of his Ph.D. education and research, namely the The Louis Stokes Alliances for Minority Participation (LSAMP) Bridge to the Doctorate (BD) (funded by the National Science Foundation) and the McKnight Doctoral Fellowship (funded by the Florida Education Fund). He earned his Ph.D. in Fall 2020. While continuing his research, Anthony is currently a Senior Model Analyst/Validator and Assistant Vice President, in Model Risk Management, at Citibank, N.A., located in the Tampa area. Moving forward, Anthony plans to make progress in his current industry, pursue entrepreneurship and eventually return to academia as a professor in Computer Science. His research interests lay at the intersection of Machine/Deep Learning and Healthcare.