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Ph.D. THESIS

A SOFTWARE LIBRARY FOR COMPUTERIZED CLINICAL HEALTH DECISION SUPPORT SYSTEM FOCUSING ON ACOUSTIC RESPIRATORY DATA ACQUISITION AND ANALYSIS

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FOREWORD

I would like to thank my family mom, dad for enduring help. Especially special thanks to my husband Dr. Abdurrahman HARMAN for motivating and supporting me throughout my years of study and through the process of researching and writing thesis. This accomplishment would not have been possible without them. Thank you.

November 2017 Güneş HARMAN

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbol	Explanation
a(k)	: AR method coefficient
Bs	: Baseline amplitude value
D	: New number of features
e(n)	: Error term (white noise)
e(p)	: Total least square error
Max(e)	: Local maximum
Min(e)	: Local minimum
N	: Number of features
p	: Order of AR model
P_{AR}	: AR method power spectrum density
P_{ARMA}	: ARMA method power spectrum density
P_{BURG}	: BURG method power spectrum density
U	: Power in the window function
y(m)	: Signal/Data
w(m)	: Window function
q	: Order of MA model

Abbreviation	Explanation
ALS	: Amyotrophic lateral sclerosis
ANN	: Artificial neural network
Bs	: Baseline amplitude value
AR	: Autoregressive model
ARMA	: Autoregressive moving average model
COPD	: Chronic obstructive pulmonary disease
DWT	: Discret wavelet transform
FD	: Fraction dimension
FFT	: Fast fourier transform
FT	: Fourier transform

GA	: Genetic algorithm
GMM	: Gaussian mixture model
HMM	: Hidden markov model
K_NN	: K nearest neighbour
LPC	: Linear prediction coefficients
MA	: Moving average model
MFCC	: Mel frequency cepstral coefficient
MLP	: Multi layer perceptron
NN	: Neural network
PCA	: Principle component analysis
PFC	: Peak factor coefficients
ROC	: Receiver operating characteristic
PFC	: Peak factor coefficients
SVM	: Support vector machine
STFT	: Short time fourier transform

ÖZET

DOKTORA TEZİ

SOLUNUM SES VERİLERİNİN ALIMI VE ANALİZİNE DAYALI BİLGİSAYARLI KLİNİK SAĞLIK KARAR DESTEK SİSTEMLERİ İÇİN BİR YAZILIM KÜTÜPHANESİ

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Bilgisayar ve elektronik alanında ki teknik gelişmeler ses sinyallerinin işlenmesini daha güvenli hale getirmiştir. Bilgisayar tabanlı akciğer seslerinin analizi, hastadan akciğer sesinin elektronik bir cihazla alınması daha sonra alınan bu seslerin sinyal işleme ve sınıflandırma teknikleri kullanılarak sınıflandırılmasından oluşmaktadır. Hekimler tarafından solunum seslerinin dinlemesinde kullanılan yöntemlerden biri olan stetoskobun hekimin duyma kapasitesi, deneyimi ve hastalıkları birbirinden ayıran farklı sesleri ayırmadaki kabiliyetine/deneyimine bağlı olarak dezavantajları vardır. Ayrıca insan kulağı başlangıç durumundaki hastalıkları fark etmekte zorlanmaktadır. Objektif değerlendirme için en güvenilir yol ölçülebilir ve kaydedilebilir olmasıdır. Akciğer ses sinyalleri analizinde esas olarak incelenen nefes alma ve nefes verme solunum döngüsü sağ ve sol akciğer lobu üzerinde bulunan belirli dinleme noktalarından sensor yardımıyla elde edilmiştir. Ayrıca, sağlıklı veya hasta olarak karar verme süreci nefes alma ve nefes verme solum aktivitesine göre yapılmıştır.

Öz nitelik çıkarma ve öz nitelik seçme teşhis ve tanı yöntemlerinden biri olan sınıflandırma için en belirleyici özelliklerdir. Çıkarılan öz nitelik işareti tanımlar ve sınıflandırma sonucunu etkiler. Bu çalışmanın amacı, akciğer ses sinyalleri üzerinde nefes alma ve nefes verme solunum döngüsüne bağlı olarak, parametrik (Otoregresif /Özbağlanım Yöntemi, Özbağlanım Hareketli Ortalamalar Yöntemi) ve parametrik olmayan (Hızlı Fourier Dönüşümü tabanlı Welch) öznitelik vektörleri ile farklı sınıflandırma algoritmaları (Yapay Sinir Ağları, Destek Vektör Makineleri ve K-En Yakın Komşuluk) uygulanarak hastalık veya sağlık durumu hakkında karar verilmesi üzerinedir.

Kasım 2017, 97 sayfa.

Anahtar kelimeler: Nefes alma-verme, Özellik seçme/çıkarma, Yapay Sinir Ağları, Destek Vektör Makineleri ve K-en Yakın Komşuluk

SUMMARY

Ph.D. THESIS

A SOFTWARE LIBRARY FOR COMPUTERIZED CLINICAL HEALTH DECISION SUPPORT SYSTEM FOCUSING ON ACOUSTIC RESPIRATORY DATA ACQUISITION AND ANALYSIS

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Advanced technological developments in computer and electronic environments have made it possible to reliable sound signal processing. The computer-based lung sound analysis involves recording the patient’s lung sounds via an electronic device, followed by lung sound signals analysis with signal processing techniques and classification of lung sounds based on specific signal characteristics. The stethoscope has commonly used the device to listen to respiration sounds. Although its widespread usage it has some disadvantages, depending on hearing sensitivity of doctor, and his/her experience about distinguishing sounds of different diseases. In addition to these, human ear may not recognize some sounds that belong to an early stage of illness. The most reliable method is measurability and recording ability for objective assessment. Analysis of the lung sound signals mainly investigated part of inhalation and exhalation respiratory phases are obtained from left and right side of the lung in special auscultation points by the help of the sensor. Additionally, decision-making process like healthy or pathological performed based on respiratory activities of inhalation and exhalation separately for each phase.

Feature extraction and feature selection is the most important parameter for classification in decision-making stage. Feature extraction is the very important step to improve correct classification. Signals, which are obtained from extraction phase define signal and affect classification results. The aim of this study is that, to test different feature extraction methods lung sound signals inhalation and exhalation phases separately and observe the performance of these methods and the phase by gathered results from classification. FFT-Welch AR, ARMA, feature extraction methods. Furthermore, Artificial Neural

Network (ANN), Support Vector Machine (SVM) and K- Nearest Neighbors (K-NN) are used for classification.

November 2017, 97 pages.

Keywords: Inhalation-exhalation, Feature Extraction/Selection, Artificial Neural Network (ANN), Support Vector Machine (SVM) K- Nearest Neighbors (K_NN)

1. INTRODUCTION

The sounds produced by the respiratory system refer to the specific sounds that are generated by the movement of air through the tracheobronchial tree. With regards to this definition, description and classification of the lung sounds' characteristics have vital importance for human life to resolve the lung physiology and the condition of the respiratory system.

Lung sounds are quite important to distinguish normal sounds from the pathological (abnormal) sounds. By the effect of the changes in the structure of the lung, characterization of the sounds has been changed. This change is to hear on the extra or additional sounds so unusual except the normal sounds. Pathological sounds generally an indicator of impending abnormality in the lungs such as an obstruction in the airway passages or pulmonary disease. This is a great importance in terms of diagnosis of the disease, various type of lung sounds may arise such as wheeze, rhonchi, crackles and many others to make a correct decision about the certain mechanism of the lung [1]. The sounds generated by lungs have also clinical importance to distinguish between diagnoses of lung disease and it is necessary to understand altered mechanism of the lung.

Auscultation is a process of listening body sounds for the purpose of health condition about respiratory system and distinguishing the sounds that indicate the assorted pathologies [2], or due to the physical arrangement or quality. A physician performs auscultation using a stethoscope, which is an instrument designed to amplify and attenuate the certain frequencies of interest. It is used to transform sounds from the body surface to human ear. In basic of chest physical examination with stethoscope is as follows ; listen the sounds from both left and right side of the lung in the same location side by side, same way and same arrangement in each time [3] in both inhalation and exhalation phases and lastly both anterior (front) chest and posterior (back) chest to compare the sounds. Because every pulmonary disease has a different signature and adapts the lung sounds wave from in a different way.

For example, crackle is pathological, discontinuous or explosive sound and generally occurs during the inspiration [4] and the best location to hear is the basis of lower lung lobes. The reason depends on the emerged crackle that suddenly open the airways. Wheeze is another pathological and continuous sound heard from the overall lung and generally occurs initially in the exhalation phase. Moreover, crackle has expanded frequency distribution in contrast to wheeze and appear in a common frequency band 400 Hz - 600 Hz [5]. Specific characteristic features of the pathological lung sounds are detailed in the following part of this section.

In auscultation process, the most important matter is to translate findings accurate symptoms into the sounds that pathological indicating a disease or normal behavior of the overall physiologic structure of lung. The characteristic of the lungs sounds heard (location) from all over the chest wall, one side of chest wall or one specific location of the chest wall, in phases of inspiration or expiration or both and the features depending on the situation play an important role in diagnosing the disease and it is great deal of physicians' own hearing and resourcefulness to distinguish the distinct rhythm of the sounds.

Auscultated have the collection of findings such as; timing, character, duration of continuous and discrete form of ventilation cycle, presence or absence of adventitious sound patterns. These are not simple, not to be clarified and not easy to be compared decision making or relationship between this huge information in a situation when physician evaluating the patient chart or clinical report or decision-making stage for inpatient or outpatient. Also, oftentimes make parallelism between that information are the most difficult part for most of the physicians. In addition, what mentioned above, qualitative nature subjectivity in acoustic knowledge among doctors, and changeability in decision-making stage about characteristics of the lung sounds become a considerable problem for conventional methods. Another problem is that, the inability of producing a permanent recording by conventional methods of auscultation to make interaction among other doctors.

So, a reasonable and measurable method for an objective assessment and reduction of the subjective factors of the lung sound for diagnosing the pulmonary disease is digital recording, by computerized and digitization methods. The mentioned drawbacks can be overcome via this method.

Advanced technological developments in computer and electronic environments have made it possible to reliable sound signal processing. The computer-based lung sounds analysis involve recording the patient's lung sounds via an electronic device, followed by lung sound signals analysis with signal processing techniques and classification of lung sounds based on specific signal characteristics.

Although several applications and studies have done up to now using these methods we will present a new perspective on the ability of sensor recording system for the classification of lung sounds signals, and that is going to be our major aim throughout this thesis. In this thesis, one channel of the sensor will accomplish auscultation and then the computer will be utilized to analyze the sounds gathered by the sensors. Analysis of the lung sound signals mainly investigated part of inhalation and exhalation respiratory phases are obtained from left and right side of the lung in special auscultation points by the help of the sensor. Additionally, decision-making procedure like healthy or pathological performed based on respiratory activities of inhalation and exhalation separately for each phase.

The vast majority of this study is that, analyzed breathing activities to detect presence or absence of respiratory disorder as healthy or pathological. Characterizations of inspiratory and expiratory phases of the respiration have essential information for the clinical case. For why, different breathing cycle (inhalation & exhalation) have their noticeable characteristics respectively because and related to different pathological information so this information is to comprise very important phenomena in the diagnosis of respiratory disease.

During the last two decade, many researchers captured respiratory sounds from both left and right lobe of the lung at the same time and recorded simultaneously. Additionally, analysis respiratory cycle of inspiration and expiration segments are taken only one cycle of inspiratory or expiratory or both for subsequent data analysis. Differently, in our study breath sounds are separately captured from both left and right lobe of the lung and also recorded separately. In the respiratory cycle process, whole inspiration and expiration phases are used for decision making stage.

In this study, parametric and nonparametric spectral estimation methods are used namely AR (Autoregressive), ARMA (Autoregressive Moving Average) and FFT-Welch. Power spectrum estimation using the FFT-Welch method is relatively simple, well-understood and easy to compute. This method is also fast [6]. The parametric (model-based) methods are also commonly used for spectral estimation. AR and ARMA are the best known of these for spectral analysis of breath sounds. They provide good frequency resolution.

In this thesis, parametric model based AR, ARMA, and nonparametric model based FFT-Welch spectral estimation methods are applied each of the respiratory phases. Power Spectrum of each part inspiration and expiration phases are obtained by using these methods. FFT-Welch, AR, and ARMA methods decide the size of feature vectors for each inspiration and expiration phases. The dimension of feature vectors is too large for an effective classification. Because of the large data size, significant information and dependency cannot efficient inferred. For the successful and short time classification process and performance, the dimension of features vectors should be reduced. In many studies, wavelet coefficients of frequency intervals produced by Discrete Wavelet Transform (DWT) have been used as features of respiratory sounds. But, in this study, decomposition rule of DWT was only used to determine the useful frequency intervals. In order to reduce the data size of the extracted feature vectors, we divided a 0-2000 Hz frequency band of Power Spectrum Density (PSD) into intervals. In decision-making stage like healthy or pathological performed in different machine learning algorithms Artificial Neural Network (ANN), Support Vector Machine (SVM) and K Nearest Neighbors (K_NN) are used.

The classification scheme by different classification algorithms, the best performance accrued by the K_NN classification methods by the combination of parametric and nonparametric based spectral estimation methods in all part of the decision making the stage especially in expiration phase. Also, in the whole process of the classification, to deciding on the healthy condition of the subject analysis according to inhalation and exhalation phases, the study suggest that, best diagnosis performance obtained as with an accuracy of approximately 97.2% the actually segmented lung sounds by the combination of AR based model with K_NN classification methods in expiration phase and the accuracy of approximately 88% automatically segmented lung sound by the combination of ARMA based model with KNN classification methods in expiration phase. Expiration phases have best classification result for right and left basal of the lung actual and automatically segmentation process.

1.1. THE RESPIRATORY SYSTEM

The detail of this section as follows, provides background information about the respiratory system, the anatomical structure of lung and basic clue relating to lung sounds. In the first part of the section, define respiratory system and anatomical structure of the lung and then discuss different types of lung sounds. When performing auscultation, normal lung sounds and abnormal lung sounds such as wheeze, crackles, rhonchi and others, explain these sounds basic characterization according to approved medical perspective and standard. Because these sounds comprise significant information for distinguishing between different types of lung disease. In the last part of section, explain basic respiratory disease properties such as Asthma Chronic Obstructive Pulmonary Disease (COPD), Bronchiectasis, Emphysema, Pneumonia and others.

1.1.1. Anatomy and Physiology

Every living cell within the human body requires a fresh supply of oxygen and the removal of carbon dioxide in order to survive. The vital function of “Respiratory System” is to supply oxygen (O_2) for body’s cells and get rid of carbon dioxide (CO_2) they produce. Respiration is the mechanism with living organisms drawing into oxygen and remove carbon dioxide. In a word, respiration is the act of breathing. The terms of respiration actually include to several important processes.

Breathing

- Moving the air into and out of the lungs also called “pulmonary ventilation”.
- Continuous replacement of gasses in alveoli

External Respiration

- Exchanging passes between the air in the lungs and blood.
- Oxygen (O2) in air diffuses into blood
- Carbon dioxide (CO2) in blood diffusion

Gas transport by Blood

- Transport of O2 to the body cells and return of CO2

Internal Respiration

- Exchanging gasses between the blood and body cells.
- O2 in blood diffuses into tissues

- CO_2 waste in tissues diffuses into blood

Cellular Respiration

- Using O_2 in the cell processes and production of CO_2[1].

The human respiratory system consists of “Respiratory Tract” (Upper and Lower) and the “Lung”.

The respiratory tract is a complex arrangement of organs and tissues. Its main functions are clean, warm, and moisten for taking in oxygen and getting rid of carbon dioxide. The tract can be divided into two parts, upper and lower: upper part comprises of the nasal cavity, pharynx (throat), and larynx and lower part comprise of the trachea, bronchi, and lung. The formal structure of *Upper Respiratory Tract* consists of all mechanism before lungs and *Lower Respiratory Tract* involves lungs and their all structure.

The lungs are a pair of breathing organs located with the chest which remove carbon dioxide from and bring oxygen to the blood. The lungs consist of the right and left lungs. The right lung is normally larger than the left. Each lung divided in lobes. The right lung has three, but the left lung has only two to accommodate the heart. The structure of both parts spongy and cone-shaped; extended from the trachea to below the heart and occupy most of the thorax. Figure 1.1 shows the basic structure of respiratory tract anatomy and anatomy of the lungs.

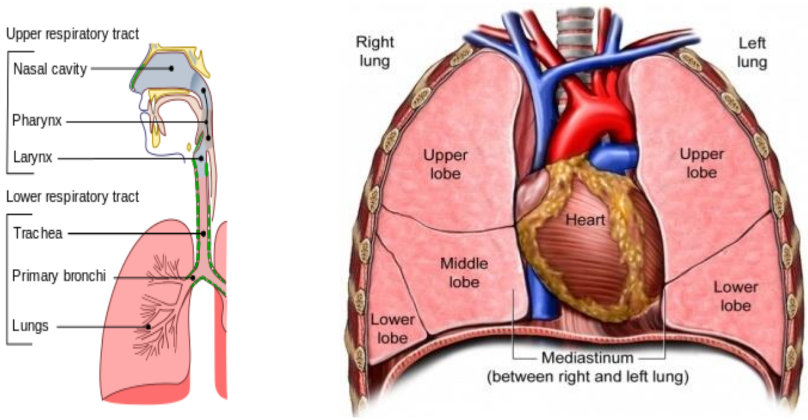


Figure 1.1. Respiratory tract and lung anatomy.

1.2. LUNG (BREATH) SOUND

Breath sounds also called lung sounds refer to specific sounds that are generated by the movement of air through the respiratory system. Breath sounds are probably generated by the turbulence of the air at the level of lobar or segmental bronchi and can be heard or detected all over the chest. The structure of lung sounds is so important because it gives exact information to detect abnormalities within the lung such as obstruction, inflammation or infection. Lung sounds characterized by following features:

- Duration of the sound is the length of the time. (How long the sound last inspiratory and expiratory phases, short or long),
- Intensity depends on the magnitude size or height. (How loud the sound is; soft, medium, loud or very loud),

  Intensity effected

  - Amplitude,
  - Energy source,
  - Distance the sounds travels and
  - The medium through which sound travels.

- The pitch of the sounds also called frequency is a determined number of a cycle per second. (How high or how low the sound is; low, medium or high), and
- Timing (When the sound occurs in inspiration – expiration phases).

Basically, lung sounds divided in two major categories: *“Normal Lung sounds* “and *“Adventitious Lung sounds”*. Normal lung sounds which are generated by healthy lungs and adventitious lung sounds by unhealthy lungs. The following part of this section gives a brief explanation about lung sounds, which used by the physician to make a decision about abnormalities and also for other researchers whose study are about lung sound analysis or which is parallel to this issue.

Figure 1.2 show basic structures of respiratory sounds which are described in the following section.

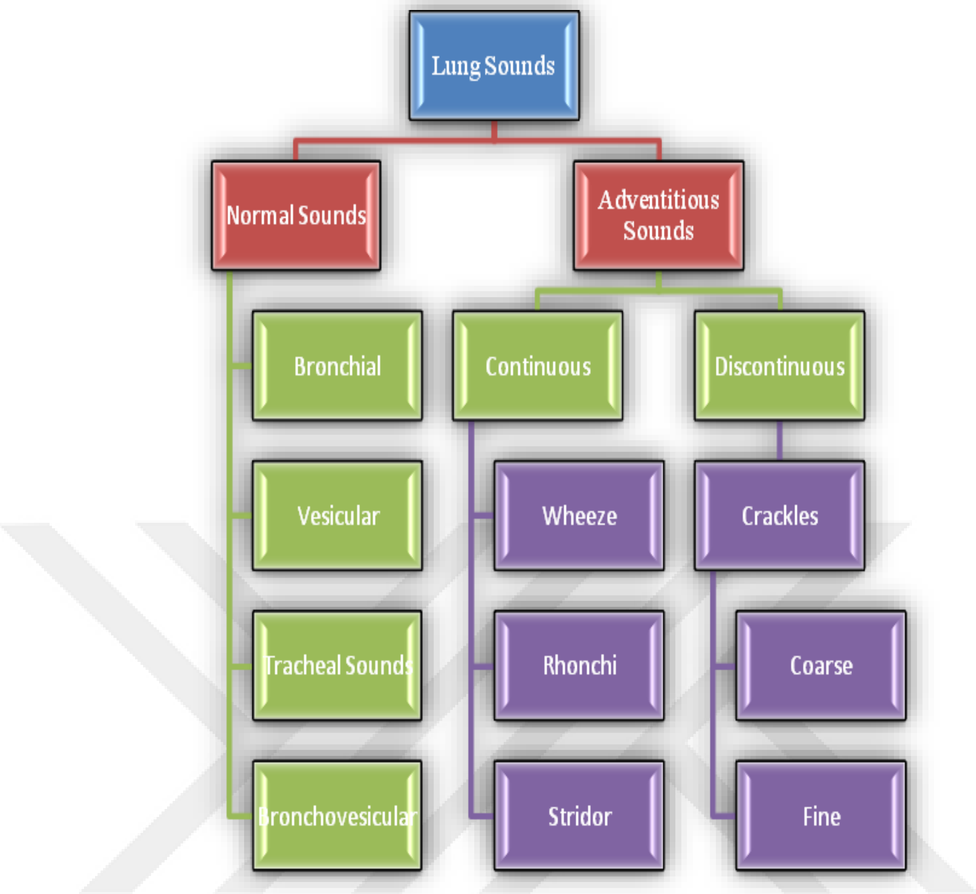


Figure 1.2: Basic structure of lung sounds.

1.2.1. Normal Lung Sounds

In general, normal lung sounds are made by turbulance of airflow in large airways. The respiratory sounds of the healthy subject over the chest and airways by normal spontaneous breathing are normal sounds. These sounds generally have soft character, nonmusical, low pitched, heard clearly long inspiratory phase and shorter expiratory phase. Normal sounds can be described as;

- Open airway,
- Normal respiratory rate,
- Normal respiratory rhythm and
- Chest expansion and relaxation that occurs normally.

Normal sounds can be subdivided as Tracheal, Vesicular, Bronchial, and Broncho-Vesicular Breath sounds depending on where they are recorded, location based.

Tracheal Breath Sounds are generally best heard in the neck over the trachea. These types of normal sounds are not filtered or little filtered so, loud and high pitch with harsh quality. Tracheal Breath Sounds are equipped with a high amount of sound energy and can be heard during both inspiration and expiration phases.

Vesicular Breath Sounds are normally heard throughout most of the lung fields and these sounds filtered by the lung and the chest wall like a low-pass filter. The sounds originate from air moving through small airways. Characteristically, vesicular breath sounds are soft, low-pitch and inspiratory phase lasts longer than the expiratory phase.

Bronchial Breath Sounds are arising in the bronchi and best reach from over trachea and larynx**.** Characteristically, bronchial breath sounds are loud, high-pitched but not quite as harsh. Generally, the duration is longer expiration phase and usually between the phases (inspiratory &expiratory), there is a pause.

Broncho-Vesicular Breath Sounds have normally heard the region of the chest that is close to large airway; anterior first and second intercostals spaces and between the scapula's. The sounds are moderate intensity and moderate pitched and like "blowing". The inspiration and expiration phases are about equal in duration and intensity and no duration between phases.

Normal Lung Sounds basic information are given briefly in Table 1.1

Table 1.1: Normal lung sounds basic information.

Name	Duration	Intensity	Pitch	Location
Tracheal Breath Sounds	Inspiratory and expiratory sounds are about equal	Very loud	High	Over the trachea in the neck.
Vesicular Breath Sounds	Inspiratory phase lasts longer than the expiratory phase.	Soft	Low	Over peripheral lung; best heard at base of lungs.
Bronchial Breath Sounds	Generally, longer Expiratory phase than the inspiratory phase.	Loud	High	The trachea and larynx.
Broncho-vesicular Breath Sounds	The inspiration and expiration phases are equal	Moderate	Moderate	Anterior first and second intercostals spaces and between the scapula's.

1.2.2. Adventitious Lung Sounds

Adventitious breath sounds refer to; "extra or additional sounds" that are superimposed on normal breath sounds and usually indicators of impending abnormality in the lungs such as an obstruction in the airway passages or pulmonary disease. These adventitious lung sounds are classified into subcategories based on acoustical quality, timing, and frequency waveform in order to describe the nature of the sound. The two main groups of adventitious sounds are called: continuous *(wheeze, rhonchi, and stridor)* and discontinuous (*crackles, fine crackles, and coarse crackles).* Generally, discontinuous sounds are short duration and sporadic, in contrast continuous sounds are long duration and may see full ventilation cycle in subjects.

Wheeze is continuous, high-pitched musical, whistling sounds that are most commonly heard initially on exhalation but also can be heard during inhalation, in addition, inspiration phase generally shorter than expiration phase. Wheeze sounds produced when air flows through a narrower than the normal or obstructed airway. Wheeze may be *fixed monophonic* or *polyphonic* according to timing in the respiratory cycle.

Fixed Monophonic wheeze is

- Single pitch,
- Obstruction of one airway.

Causes

- Bronchial Carcinoma and rarely Asthma and COPD

Polyphonic wheeze is

- Multiple pitches,
- Obstruction of airways.

Causes

- Asthma and COPD.

Rhonchi are continuous, low-pitched sounds and commonly resemble “snoring”. This adventitious breath sounds are presented both inspiration and expiration respiratory phases but primarily in expiration phase. They are caused by airway secretions and airway narrowing.

Causes

- Chronic Bronchitis**,** Pneumonia, and Asthma.

Stridor is continuous, high-pitched and a very loud musical sound typically occurs during inspiration but depending on its timing may present both respiratory cycle. This type of adventitious breath sounds are produced by turbulent of airflow in the upper airway.

Causes

- Laryngospasm, laryngitis, tumor, edema from anaphylaxis

Crackles are discontinuous, short and non-musical sounds that are most commonly heard in the bases of the lower lung lobes. Best heard in the early inspiratory phase, but can be heard sometimes on expiration phase. The reason depends on the emergence of crackles are suddenly opening the airways. Crackles may be fine or *coarse* according to their loudness, duration, timing, and pitch shortly, acoustic characteristics of the case

*Fine crackle*s are

- High- pitch,
- Loud intensity,
- Short duration less than 10 millisecond and
- Generally heard exclusively inspiratory phases.

Causes

- COPD, Pneumonia, Lung Abscess, TB Cavities and Bronchiectasis.

Coarse crackles are

- Low pitch,
- Less loud intensity,
- Longer duration longer than 10 milliseconds and
- Generally heard inspiratory phases but also expiratory phases.

Causes

- Pulmonary Fibrosis, Pulmonary Edema, Pneumonia, and Bronchiectasis.

Adventitious Lung Sounds basic information are given briefly in Table 2.1

Table 1.2: Adventitious Lung sounds basic information.

Name	Duration	Pitch	Location
Wheeze	Expiration phase is generally longer than inspiration	High	Overall lung fields
Rhonchi	Expiration phase is generally longer or equal inspiration	High	Predominate over trachea and bronchi
Stridor	The inspiration and expiration phases are equal	High	Over the trachea
Crackles	The inspiration and expiration phases are equal	High	Bases of the lower lung lobes

1.3. AUSCULTATION

Auscultation refers to listening for sounds within the body to provide information about to condition of the lungs and pleura. Auscultation is one of the oldest, most useful techniques in the diagnosis of various lung diseases. A physician performs auscultation with a stethoscope. It is an instrument designed to amplify and attenuate certain frequencies of interest.

Auscultation involves listening to body sounds produced by the airway such as lung, heart, stomach, blood vessels and etc. Pulmonary auscultation is one of the classical clinical usage to the assessment of respiratory disease. The sounds hearing during auscultation with a stethoscope can be classified according to quality, duration, frequency and intensity because the changes occurred in the respiratory system affected airflow, so the structure of sounds can be change. These types of sounds called abnormal sounds which can helpful diagnosis certain condition of the lung. Examiners listen to these sounds carefully to detect abnormalities and understand underlying pathology.

1.4. PATHOLOGY

Diseases affecting lung function activity and structure indicate two types of dysfunction: obstructive and restrictive.

Obstructive lung disease makes it difficult in exhaled because of narrowing or blockage of the airways. Three most common obstructive lung diseases are;

- Chronic obstructive pulmonary disease (COPD),
  - emphysema
  - chronic bronchitis
- Asthma,
- Bronchiectasis.

Restrictive lung disease refers to disorders that make it difficult to breathe air in because the lungs cannot fully expand due to in the elasticity of the lungs themselves or caused by a problem related to the expansion of the chest wall during inhalation. Inhale ability is affected by this type of disease. Most common Restrictive lung diseases are;

- Interstitial lung disease,
  - idiopathic pulmonary fibrosis,
  - autoimmune disease,
- Scoliosis,
- Neuromuscular disease,
  - muscular dystrophy or
  - amyotrophic lateral sclerosis (ALS).

1.5. PPORERTIES OF RESPIRATORY DISEASE

As we mentioned before lung sounds or breath sounds embody important clue about respiration system. It gives direct information about health and types of disease. In the following part is about basic information of respiratory disease.

Asthma is lifelong or chronic lung disease that makes harder to move air in and out of lungs due to narrower airflow passages. The most common complaint of asthma is severe shortness of breath so the breathing gets more difficult. There are generally two types of asthma “allergic” asthma usually result from a reaction to dust, pollen, smoke or another irritant in the air, most often occurs in children. “Intrinsic” or “nonallergic” asthma is most common in adults and usually result from infection, emotional stress or strenuous exercise.

Chronic obstructive pulmonary disease (COPD) a nonreversible lung disease that is a combination of chronic bronchitis and emphysema and a mixture of their signs and symptoms are common among patients.

Bronchiectasis is non-reversible permanent lung disease. In this disease [7] the airways become damaged for some reasons and it slowly loses their ability to clear out mucus. It means that it creates an environment to grow up bacteria. *Bronchiectasis people generally feel very tired and cannot concentrate easily.*

Emphysema is a permanent non-reversible lung disease. Patients who have this type of disease the sounds can be heard like; breathing sounds get reduces from left and right both lung sides and the time of exhaling get bigger than normal. Exhaling becomes more active than normal process so the patients use most of the energy to breathe. In this type of disease, the lung tissue loses its elasticity, the alveoli become distended with trapped air, and the walls of the alveoli destroyed so oxygen and carbon dioxide exchange become drastic.

Pneumonia is a common cause of death disease in many patients. In this type of disease, the lower respiratory tract is affected and caused lung inflammation.

[1]We borrowed most materials for this part of the thesis from [3], [7]–[11]

1.6. RELATED WORK

Advanced technological developments in computer and electronic environments have made it possible to reliable sound signal processing. The computer-based lung sound analysis involves recording the patient’s lung sounds via an electronic device, followed by lung sound signals analysis with signal processing techniques and classification of lung sounds based on specific signal characteristics.

Over the last few decades, with the advent of computer technology and data processing methods, researchers have tried to parameterize pulmonary sounds with an aim to make auscultation a more objective and valuable diagnostic tool. During the last two decades, much research has been carried out on computer-based respiratory sound analysis. A large part of these researchers include acquisition, filtering, feature extraction, spectral analysis and classification of respiratory sounds.

Abnormalities included crackles, wheeze, stridor, airway obstruction, and the others which cause to pathological changes of the lung consequently changes in produces characteristic of sounds. Recent researchers clarified that feature extraction, feature selection, and machine learning algorithms play main roles in recognition and classification of respiratory (pulmonary) sounds.

As we mentioned before many researchers proposed different techniques to analyze and categorize the lung sounds signals by using digital signal processing and pattern recognition techniques. Literature of computerized lung sounds analysis also supports that many researchers proposed different techniques. In the following part, presented work mainly focuses on lung sounds classification more precisely, by using different feature extraction, feature selection, classification algorithm and any combination of these methods.

Cohen and Landsberg [12] focus on breath sounds classification as normal and adventitious based on Linear Prediction Coefficients (LPC), and Energy Envelope features. Classification was based on according to two main categories as abnormal and breath sounds. These sounds are divided into subcategories among themselves. Type of the first group is Amphoric Breath Sounds (AM), Asthmatic Breath Sound (AS), and Cavernous Breath Sounds (CA), and the latter group includes Vesicular Breath Sounds (V), Broncho-Vesicular Breath Sounds (BV), Bronchial Breath Sounds (B), and Tracheal Breath Sounds (T). In Linear prediction and the Peak Factor Coefficients (PFC) were used as feature extraction algorithms. At the end of the study, seven different lung sounds are classified. The main goal of this work is to characterize a various type of respiratory sounds and then automatically classify them. As a result of their work done, only five out of 105 experiments gave wrong results.

Sankur et al., [13] proposed a classification of normal and abnormal (pathological) breath sounds by using K_NN and Quadric Classifier methods. The breath sounds were partitioned into segments and AR analysis was applied to these segments. Different number of AR parameters are applied each segment and the best classification result is obtain in order 6. The output was 87.5% for the Quadratic Classifier and 93.75% for K- NN.

Rietveld et al., [14] implemented classification of respiratory sounds in three categories. In feature extraction process Fourier Spectrum (FC) was used. The performance of Competitive Neural Network and Feed Forward Neural Network were relatively examined. Classification results were obtained with supervised networks up to 95% of the training vectors and, 43% of the test vectors could be classified correctly.

Dokur and Olmez., [15] classified respiratory sounds as: healthy and patients with asthma by using the classification methods as “Grow and Learn” Neural Network (GAL), Kohonen Network and Multilayer Perceptron (MLP). The sounds recorded from 20 subjects and, 10 subjects formed as healthy and rest of them pathological. Feature vectors were obtained by using wavelet coefficients. Wavelet coefficients are determined by using Daubechies-2. Dynamic programming selects the best samples. Grow and Learn Neural Network classification performance was reported 98% for the both cases in asthma and normal subjects.

The main goal of the study [16] is to filter out the discontinuous adventitious breath from vesicular breath sounds by finding a pattern which has non-stationary characteristics of the sounds such as squawks and fine/coarse crackles. These non-stationary waves in breath sound are extracted by Wavelet Transform based stationary–nonstationary filter (WTST–NST). In general, the result has excellent quality in the separated signal.

Kandaswamy et al., [17] categorized lung sounds as: normal, wheeze, crackle, squawk, stridor, or rhonchus. Discrete Wavelet Transform (DWT) level of seven was applied for the feature extraction method of lung sounds signal. ANN classification accuracy was reported 90% for categorization of lung sounds.

Yeginer et al., [18] proposed a classification of lung sounds according to the sub-phase features. The sounds were recorded from 45 subjects using electrets microphones. The characteristic of lung sounds like timing, pitch and occurrence change according to the disease. So, recorded sounds were divided into six sub-phases as follows: early (30%) inspiration and expiration, mid (40%) inspiration and expiration and late (30%) inspiration and expiration. AR parameters orders of 6, prediction error and expiration/inspiration duration are used as input vector of the neural classifier. The performance of classification is around 70 - 80% so the performance demonstrates sub-phase dependence for different diseases.

The main theme of the study [19] is multichannel acquisition of lung sounds classification as normal and abnormal. The sounds were recorded from 10 healthy and 19 unhealthy 29 patients in total. Microphone array of 5*5 sensors separated by 5 to 7 cm on the thoracic surface of the patient was attached vertically and horizontally the sounds frequencies range in between 75-2000 Hz. Features were extracted by using multivariate autoregressive model AR (MAR), feature vectors (FV) by SVD and Principal Component Analysis (PCA) used for dimensionality reduction and classification by supervised neural network under back propagation algorithm with Levenberg-Marquardt adaptation rule. Best performance was obtaining for SVD 20 nodes input and hidden layer, while for PCA 25 nodes for input and 10 nodes for hidden layer. Classification accuracy shows that MAR-PCA combination gives the best classification results of 87.68% for classification of lung sounds.

Guler et al., [20] presented artificial intelligence techniques by a combination of ANN and Genetic Algorithm (GA) based ANNs for classification of lung sounds in three categories: normal ,wheeze and crackles. The sounds were captured by electronic microphone from the chest wall. Complete breath cycle (inspiration & expiration) were selected. PDS of each cycle was calculated by using Welch's method. Classification performance in the rage of 81-91% for ANN and 83-93 % GA based ANN respectively.

In another research, Guler et al., [21] implemented two-stage classifier: time waveforms pattern in the segment and six phases: early, mid, late expiration and early, mid, late inspiration phase decision pattern ejected from the first part. The sounds recorded from 57 subjects, classified as, 18 chronic obstructive patients, 19 restrictive patients, and 20 healthy subjects. AR parameters are used for the feature vector. Correct classification accuracy of the segments is 70–80% and 80–90% for the subjects.

The main objective of the study [22] is to compare ANN and K_NN by using different feature sets. Sound signal phases are divided as: inspiratory and expiratory. Three different feature extraction methods were applied. Crackle parameters in addition to AR model coefficients parameters gave the best classification results for both classifiers K-NN and ANN with the requirement to Wavelet Transform based parameters and AR model coefficients.

Bahoura [23] presented in pattern recognition methods used classification of respiratory sounds as: normal and wheeze. The feature extraction methods based on Fourier Transform (FT), Linear Predictive Coding, Wavelet Transform and Mel-Frequency Cepstral Coefficients (MFCC) in combination with the classification methods based on Vector Quantization, Gaussian Mixture Models (GMM) and ANN were used. Receiver Operating Characteristic (ROC) curves were used for the evaluation of feature extraction and classification methods. The combination of B-MFCC and GMM gives best the result for the classification of normal and wheeze respiratory sounds.

Parkhi and Pawar [24] implemented the Short Time Fourier Transform (STFT) spectrum analysis to automatically detect the wheeze and crackles from the lung sounds. The experimental result shows that the characteristics of timing, shape and repeatability of normal and abnormal lung sounds are so different from each other.

Hashemi et al.,[25] analyzed the wheeze sounds and classified them as monophonic and polyphonic types. Respiratory sounds were recorded from 140 different subjects using an electronic stethoscope. This study is divided into two main parts; feature extraction and classification, In the first part, seven different wavelets which are consisting Haar, Symmlet of order 8, Daubechies of orders 2, 8 and 10 and Bi-orthogonal of orders 1,5 and 2,8 are used by this way. 46 features are extracted from every signal. The first 5, 10 and 15 features are selected based on the area under ROC curve. In the second part, different Neural Networks (NN) Multilayer Perceptron (MLP) structure was implemented by using features obtained in the first part. Experimental results show that 15-45-2 system namely input layer, hidden layer, and output layer gave best the accuracy rate of 89.28%.

Mayorga et al., [26] presented normal lung and adventitious lung sounds classification based on Quantile Vectors obtained by using Fast Fourier Transform (FFT) analysis from signal frames of 400ms and overlapping by 100ms. Lung sounds are taken from different sources; 8 normal, 4 crackles, 7 wheezes, 4 stridor, 5 asthmas from R.A.L.E and 28 normal subjects from ITM. The system achieved 100% accuracy and it supported that Quantile Vectors were successful for normal and adventitious lung sound classification.

Abbasi et al., [27] classified normal and abnormal lung sounds by using NN and Support Vector Machine (SVM) based on Wavelet coefficients. The extracted features of signals are: (1) the mean of the coefficients in any sub-band, (2) the mean of the power of the wavelet coefficients in any sub-band, (3) the standard deviation of the coefficients in any sub-band, (4) the ratio of the mean values beside sub-bands. The features one and two demonstrate the frequency distribution of the signal and the features three and four indicate the extent of changes in a frequency distribution. The lung sounds were classified into six classes as normal, wheeze, stridor, crackles, rhonchi, squawks. Classification result indicates that SMV is successful classified with an accuracy of 93.51 -100% for the classification of lung sounds.

In a study [28] the lung sounds were recorded from multiple (four) auscultation points: three of them are from the chest, one is from back in patients with pulmonary emphysema and healthy subjects. Firstly, respiratory segmentation is made according to each auscultation point. Then the number of adventitious sounds was decided based on these points and lastly where the adventitious sounds observed. Classification result shows that; multiple auscultation points increase classification accuracy.

Palaniappan et al., [29] presented a recent literature review about the computer based respiratory sound analysis and the various methods used in the analysis of respiratory sounds. 55 articles published in various electronic resource libraries such as IEEE, Springer, Elsevier, Pub Med and ACM on various computers based respiratory sound analysis. The study suggests that ANN, GMM, Hidden Markov Model (HMM), k –NN and fuzzy analysis were extensively used in machine learning, FFT, AR, Fractal-Dimension (FD) analysis, MFCC and Wavelet Analysis was extensively used in signal processing techniques.

Additionally in the other literature study [30] gives an overview of Artificial Intelligent (AI) techniques about computer based respiratory sounds analysis and the types and characteristics of normal and abnormal respiratory sounds as well as. A brief overview of the types of sound/pathology analysis, feature extraction methods such as AR, MFCC, energy, entropy, spectral features, and wavelets. Classifier ANN, SVM, k-NN. "Hybrid machine learning" lung sounds classification proposed in this research increase the performance of classification.

Another literature review made by Rizal et al., [31] contributes important information about methods and application of respiratory sound analysis. Respiratory sounds characteristics, data source: recorded or from the database, signal processing: time, frequency and time-frequency domain, feature extraction methods and lastly classification methods.

The aim of study [32] was to detect and classify the crackle to find deformities in the lung. The frequency spectrum of the lung sounds signal was analyzed by using STFT, the frequency peaks were detected for analysis. The duration of crackle signal acquisition was 250 msec. The results of the study show that characteristics of crackle sounds are repetitive, high pitch and obstructive airway diseases like pulmonary edema.

In another research, Mankar and Malvia [33] predicted the crackles sound as repetitive, high pitch with respect to normal lung sounds depending on the spectrogram analysis of normal and abnormal (crackles) sounds by using STFT analysis.

Gadge et al., [34] presented a combinatorial method of frequency and adaptive domain filtering used for removal of the artifacts from the heart sound signal. After filtering the sound, power distribution over a frequency range was used for respiratory sounds analysis. The peak power of normal subject is above 130 Hz, for the fine crackles sound signal maxima the range of 60-138 Hz and pleural sound maxima is observed below 60 Hz. The result of the study shows that normal and abnormal lung sounds can be classified by using the maxima is a range.

Sello et al., [35] deal in breath sounds analysis application by using a wavelet-based method based on mean wavelet energy power distribution work. The method was applied in healthy subjects and patients with different respiratory diseases. Results show that different power spectra patterns characterize from the disease. Frequency range is 148-2000 Hz.

Uysal et al., [36] presented a classification of normal and abnormal lung sounds by using Wavelet coefficient intended. 34 recording lung sounds were taken from R.A.L.E database 14 normal, and rest of them abnormal. Feature vectors were obtained by using wavelet coefficients and were determined by using Daubechies-7. In the classification process, ANN and SMV were respectively used. The results of the study show that both classifiers give 100% performance for the classification of lung sounds.

Rady et al., [37] analyzed different lung sounds for wheeze detection and classified as monophonic or polyphonic. The approaches consist of two systems in first for detecting respiration, respiratory rate and respiratory onset time and the second system for wheeze quantifier and qualifier. Quantifier detects a total number of wheezes and onset time whereas, qualifier calculates duration, mean frequency, frequency trend and wheeze classification. AR model orders of 100 were used for power spectral density. Overall performances of the classification for wheeze episode detection are 90% sensitive and 91% accurate.

Ulukaya et al., [38] proposed a Multiple Signal Classification (MUSIC) algorithms to differentiate wheeze types, without a need for a pre-training algorithm. 20 recordings were considered in this research, 11 of they were related to monophonic and the rest of them polyphonic wheeze. The sounds were taken from 14 channels; the length of data for each channel is 15sn at a sampling rate of 9600 Hz. The success of method for 80ms segment sounds 100% and 78% for monophonic and polyphonic respectively. Cut-off frequency ranges in between 112,5-1087,5 intervals and it is conformed to standard in the literature.

Zhang et al., [39] implemented Mathematical Morphology technique in spectrogram analysis to detect crackles. 16 kinds of different 1-D wavelet based adopted methods were used (db2, db3, bior 2.2, and bior 3.1) to analyze crackle signal. The spectrogram of the signal was saved as pseudo-color bitmap. After that, following method was applied; first pseudo-color Bitmap was converted into gray Bitmap then converted black and white 2 bitmaps by setting the threshold value. After all ellipse areas become the main object in spectrogram Max area, Euler number, Centroid, Major axis length, Eccentricity, Minor axis length which are morphology parameter were used for crackles recognition. The result of the study shows that 86% crackles detected accurately, while 8% inaccurately.

Lu and Bahoura [40] introduced an integrated system for crackles extraction and classification. Wavelet–packet transform (WPST-NST) was used for crackles separation, fractal detection used for crackles detection. This detector can find the crackle boundaries even if the indication of crackles is weak. In crackle detection; crackle-peak-detector (CPD) is based on the fractal detection. In the classification process is to classify as fine or coarse, 91,5% classification performance was obtained by using spectral and waveform analysis (maximal deflection width and, peak frequency, Gaussian bandwidth) and GMM.

In another research Heider Et al., [41] implemented the GMM contingent on Bayes rule to differentiate and resolve the normal breath sounds from crackles and bronchial breath sounds. In the first part of the feature set pitch, energy and spectrogram are delivered a full spectrum of sounds; latter nine features are from wavelet decomposition by Daubechies wavelet of order 2, 5th level decomposition tree. As a rank test, a different number of features are selected to classify the crackles-normal sounds and bronchial - normal sounds. The outcome of the system as follows; 100% specificity, 92.85% sensitivity, 100% positive predictivity value and 97.56 % accuracy.

Güçlü et al., [42] presented a classification of respiratory sounds as healthy or asthmatic. 33 sound signals; 11 of them normal and the rest asthmatic are used for the analysis. Respiratory Sound signals were acquired using a Sony ECM T150 microphone with an air capsule**.** The sampling rate is 8kHz and 16 bits. The sounds analysis can be divided into three stages; preprocessing: frequency spectrums of sound signal obtain by using FFT, feature extraction: features vector obtained using Fuzzy c-Means Clustering (FCM) and apply PCA classification: ANN is performed for classification. Classification results indicate that FCM_PCA achieves more accurate result than FCM.

In another study Güçlü et al., [43] presented the classification of respiratory sounds based on inhalation and exhalation by using ANN. The spectrum of the signal obtained by using FFT and FCM was used to reduce the signal data. 50 sound signals; 25 of them normal and the rest asthmatic we are used in the analysis. The sound signals acquired system with [42]. In the study, sound signals were divided as inhalation and exhalation because the structure of lung show that narrowed airway (exhalation) gives acceptable information about the disease. Overall classification result shows that exhalation gives the best accuracy around 88%.

The study [44] mentioned MFCC techniques the detection and classification of breath cycles as inhale and exhale. Cycles of breathing groups are an inspiratory/expiratory phase and duration. In the frequency domain, MFCC features indicate the inhale and exhale differences. For now, there is any no practical application of this method.

The main goal of the study [45] is to clarify and classify the breath sounds. Average power spectrum density is used for representing these sounds. The sounds recorded from the bronchial region of the chest and the sounds classified as inspiratory and expiratory and also normal and abnormal. In the classification procedure, ANN Back propagation algorithm was used. According to true positive results, the research is acceptable; however, it is not suitable for long term breath sounds.

Shyamalee et al., [46] mainly focused on to a comparison of different feature set and classification method to analyze the breath sounds as healthy or unhealthy. Classification performance has evaluated the results of true positive rate (sensitivity), true negative rate (specificity), negative predictive value and precision. The sounds data was obtained from R.A.L.E and Littman repository. LS, K-NN, Parzen Window, Batch and Single Sample Margin (BM and SMM) and SVM are used as a classifier. The features of both normal and abnormal respiratory samples are obtained by using WPDC level 3, Gray Level Co-occurrence Matrix (GLCM) and MFCC method, in additional to the statistical features. Experimental results show that the best features are WPDC and MFCC, the best classifier is LS, SVM, SSM or BM.

1.7. GOAL

The main goal of this thesis is that, development of exceptional, non-invasive, respectable, easy to use apply and a reliable method to capturing lung sounds and identify health condition of the subject. Briefly, by using computerized approach gives a new point of view to analyze and clarify lung sound signals.

The first step is to capture lung sounds from the subject in specific auscultation points by using electrets type of sensor recording system. Digitized lung sounds data were sending to the computer. The sound signals were then filtering for remove of external and internal noise and also in this part respiratory sound signal divided in different respiratory activities as inspiration and expiration using the method of ‘enveloped’. Different feature extraction methods are applied in order to convert raw inspiratory and expiratory sound data some type of parametric features. In the last step, classify the sound signal data as healthy or pathological (unhealthy).

The overall goal of the thesis is to transform respiratory sounds data into a clinically useful tool in such way to detect the presence or absence of respiratory disease. The basic system flow diagram of lung sounds acquisition; processing and analyzing are shown in Figure 1.3.

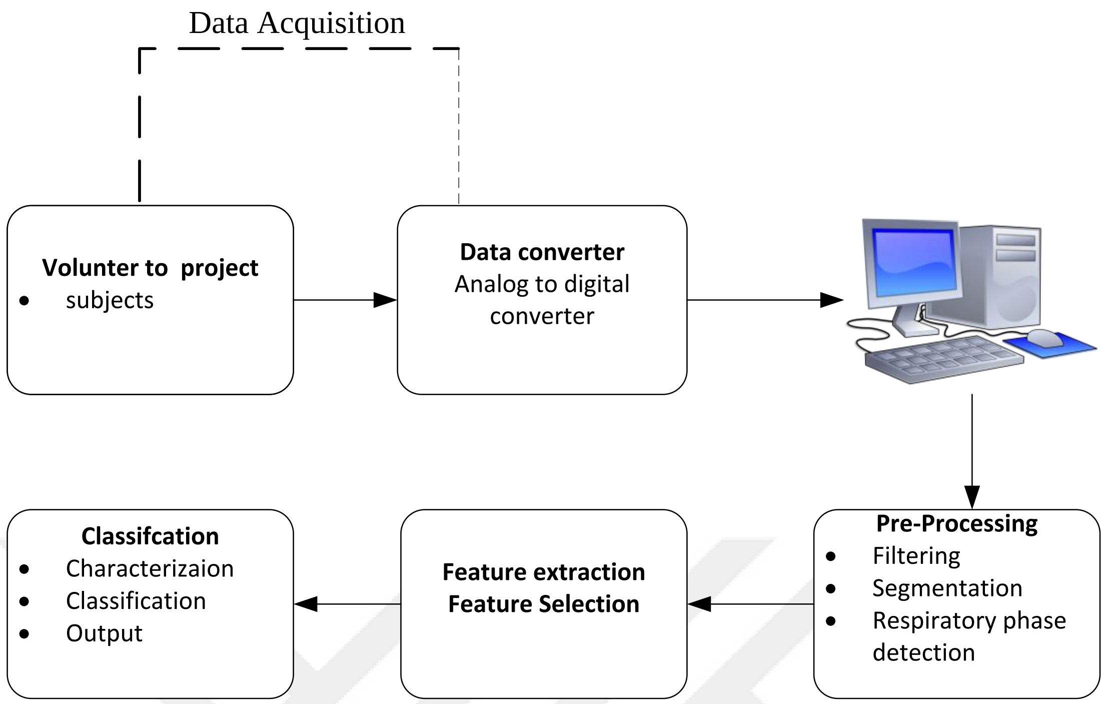


Figure 1.3: Basic system block diagram.

Data Acquisition-In order to record lung (respiratory) sounds from subjects (volunteers) by using standard one channel handmade microphones.

Pre-Processing- is performed for two main goals. Primarily, for the purpose of noise or artifacts reduction (heart and other artifacts' sounds). Because, original lung sounds data, raw lung sounds signals contains countless external or internal noise and remove these from the signal and the second priority is enhance the quality of the sound for other parts.

Feature Extraction & Selection-In order to convert raw data some type of parametric representation (features) by using a different form of feature extraction methods.

Classification- In order to use, for categories and analysis of data for diagnostic decision making. In brief, classify the lung sounds signal data as healthy or unhealthy (pathological).

Each of flow diagram phases is detailed in the later section of the thesis.

1.8. OBJECTIVE AND CONTRIBUTION OF THIS WORK

In this thesis, the following are the major contributions demonstrated in this thesis:

1) In this project, the sounds captured from each of the subjects by electronic condensed type of microphone over the different auscultation point of the chest surface. These sounds save in the computer and its hard drive. These sounds can be used between physicians to understand and analyze the structure of the lung sound signal and have the opportunity to make a comparison between various type of lung sound characteristics because pathological changes of the lung consequently change in produces characteristic of sounds.
2) This project provides a possible choice for the idea of the medical diagnosis system. In some situations, it might help to physicians to diagnose complicated event which is difficult for a decision. Physicians can associate this opportunity and their experience to identify the initial stage of diseases.
3) This project provides the identification of the respiratory phases because inspiratory and expiratory phases of the respiration have essential information for the clinical case. Different breathing cycle (inhalation & exhalation) have their noticeable characteristics respectively because and related to different pathological information so, this information is to comprise very important phenomena in the diagnosis of respiratory disease and decision-making about the health condition of the subject.

1.9. ORGANIZATION OF THE THESIS

The presented document is divided over three main parts. The first part is the main purpose of thesis and general information about the anatomical structure of the respiratory system and some basic information about lung sounds and lung disease additionally, gives background information about recent research. The second part includes implementation detail of hardware system setup and recording information from the clinical subject by using a simple microphone, breathing pattern information namely respiratory phase detection inhalation and exhalation, feature extraction, feature selection and classification theory information. In the last part is the main part of this work classification-decision making stage of lung sounds signals, based on healthy condition as healthy or unhealthy

In this thesis, we developed an algorithm for detection, analysis and classification of respiratory condition as healthy or pathological. A summary chapter overview will be provided in the following part.

Introduction

This chapter present, most importantly the main purpose, objective, and contribution of the thesis. Additionally, provides a background information about the respiratory system, the anatomical structure of lungs and the lung sounds, and gives essential information about recent research.

Materials and Methods

This chapter related to an implementation detail of experimental hardware setup, sound recording points (test location) and the recording information of data is described. This section also includes the detail information of lung sound segmentation. According to each respiratory cycle the lung sound signal labeled as inspiration and expiration phases based on starting and ending time. Additionally, the analysis procedure of the recorded lung sounds, filtering of the recorded data, respiratory phase detection of recorded lung sound signal, preprocessing, feature extraction and lastly the feature selection of lung sounds data is presented.

Result

In this part of the project decision-making is occurs. Lung, sound signal can categorize/classify as healthy or pathological (patient) by using different machine learning methods namely: ANN (Artificial Neural Network), SVM (Support Vector Machine) and lastly k-NN (K- Nearest Neighbor).

Discussion

In this part of the project summarization of concisely the principal implications of the findings, explanation of how the results and conclusions of this study are important.

Conclusion and Recommendation

This is the last part, concludes of the thesis and look for feature research to improve the performance of electronic stethoscope, pre-processing and classification methods.

2. MATERIALS AND METHODS

This part comprises of three subheadings. First, Hardware and Data Acquisition; related to an implementation detail of hardware setup and sound recording information of the data is described. Second, Methodology; is the analysis procedure of the recording lung sounds and lastly, Classification; theory and implementation detail information about the algorithms which are used to classified lung sound signals as healthy or un-healthy.

2.1. HARDWARE AND DATA ACQUISITION

This chapter related to an implementation detail of experimental hardware setup, sound recording points (test location) in the subject and the recording information of the data is described. Also, this part includes the detail information of lung sound segmentation. According to each respiratory cycle the lung sound signal labeled as inspiration and expiration phases based on starting and ending time of the signal.

2.1.1. Microphones

The basic idea of auscultation by stethoscope is that convert “the sounds waves into pressure waves" that can be heard by human ear. The basic definition of “microphone" is converted sounds into electrical signals. In real time application, respiratory sounds captured and recorded by microphones or contact sensor. According to literature studies because of the high-quality recording "condenser microphone" [17], [20], [47]–[56], the type is used most commonly.

The microphone which used in this project, ECM T-150 Sony electrets condenser type microphone with a sampling frequency of 8kHz and 16-bit resolution used to get a signal over the basic location of the chest wall. The microphone impedance is 2.2 k and response bandwidth in between 50-15000 Hz.

2.1.2. Hardware System

The microphone can be used one or all direction, we used one direction for sounds recording by stethoscope head. These ranges of bandwidth include not only lung sounds but also heart muscle and other sounds which come from other intra-corporeal sounds. Therefore, the sounds have to be filtered before analyzing the signal. We can divide the filtering stage into two parts. In the first stage, Bessel type 5 Hz high pass filter with analog filter order of six was used and we utilized OP275 operational amplifier to build the circuitry of the first stage. In the second stage, however, Butterworth type low pass filter implemented as a switch capacitor filter order eight was used and the MAX295 integrated circuit was employed to build the circuitry of the second stage. The sounds signal converted to the computer. Basic sound recording system implementation architecture designed and the applied system block diagram are showing the order. Figure 2.1 and Figure 2.2.

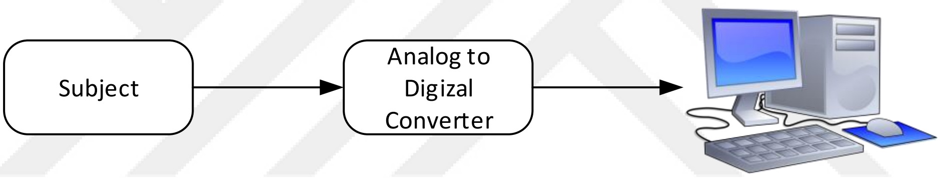


Figure 2.1: Basic sound recording system implementation architecture design.

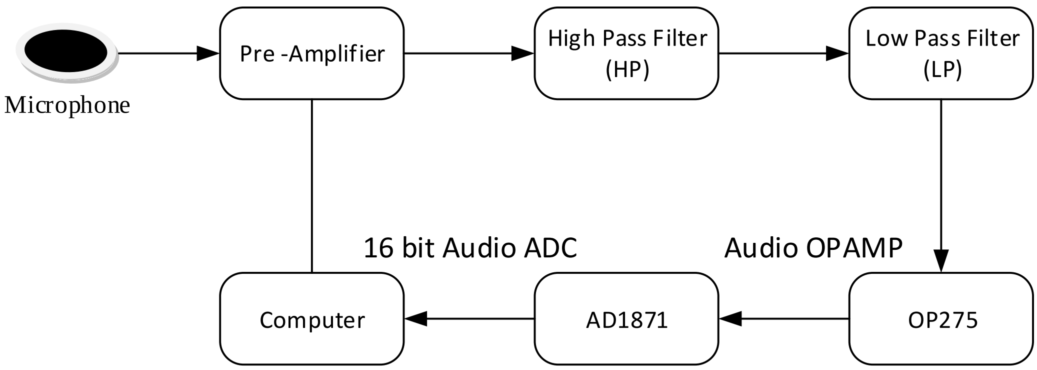


Figure 2.2: Applied system block diagram.

With the help of the microphone, lung sounds are recorded. While designing the analog card, different IC's and component are used, the best configuration is chosen according to noise and power consumption performance. Analog system output is connected to the microphone input on the single board computer. Samsung S3C2440A microprocessor working at 400 MHz was used and it is a part of the subsystem. 64MB 100MHz SDRAM was utilized as a random-access memory and 64MB NAND Flash memory was used as a nonvolatile memory, hard drive, of the computer system. In addition to those an SD card was employed as a removable memory for convenience. Final IC's component "Sound system designed and implementation" are shown in Figure 2.3 and detail component of Amplifier-Band Pass filter are shown in Figure 2.4.

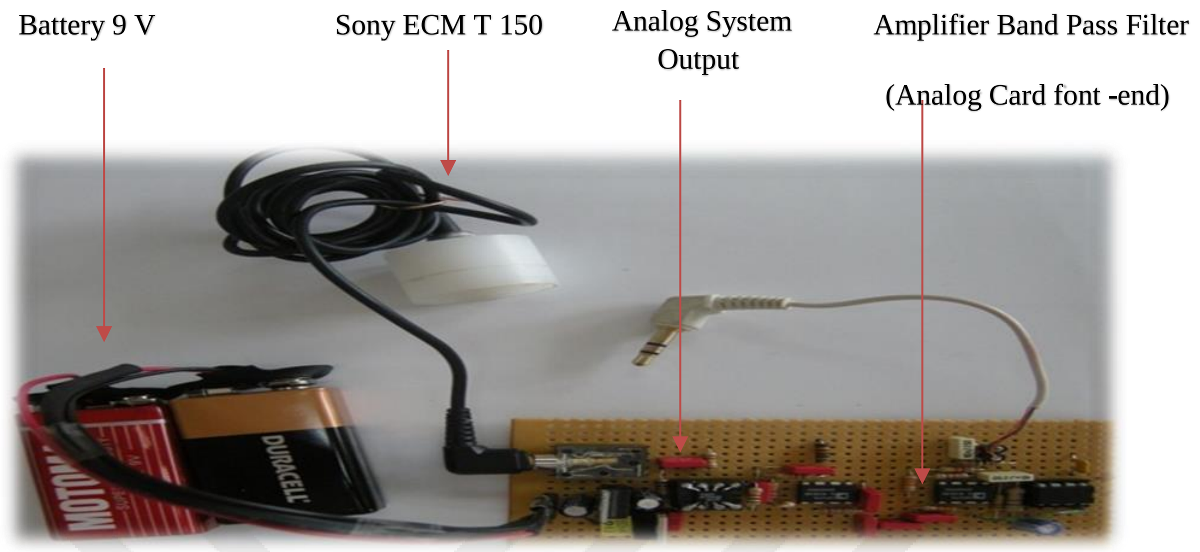


Figure 2.3: Sound system designed and implementation.

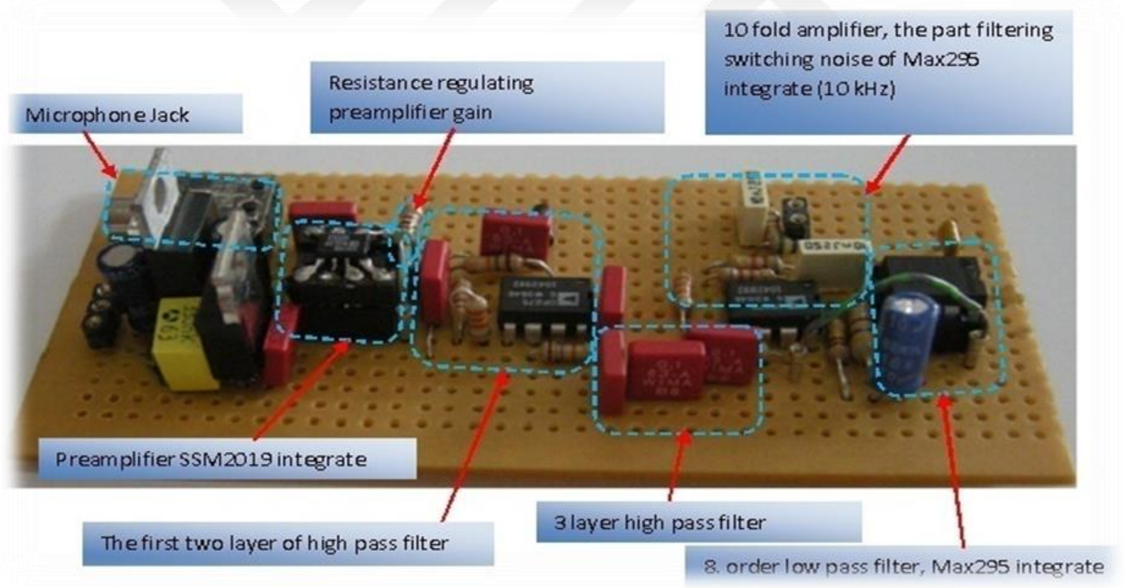


Figure 2.4: Analog Card front-end system design.

2.2. DATA ACQUISITION

This section gives information about recording procedure to obtain a respiratory sound signal from subject both healthy and pathological condition.

2.2.1. Sensor Placement

In recent studies by using electrets condenser type microphone/sensor, researchers used different location of auscultation points for example;

- over the lung surface [47]–[49], [57]–[59],
- chest wall [20], [60], [61],
- posterior chest wall [50], [62], [63].

In this study, lung sounds captured by using ECM T 150 Sony electrets condenser type microphone. Signal acquisition positions are identified in order to get acceptable and applicable analysis, also research about is there any differences between the sounds in a different location.

Respiratory lung sound signal acquisition position/location specified in below:

- Midclavicular line,
    - right midclavicular line
    - left the midclavicular line
- Manubrium Sterni,
- Under scapula,
    - Right lobe of lung
    - Left lobe of the lung
- Interval of, 3rd, 4th5th, and 6th.

Illustration of signal acquisition positions by using microphone and signal outputs are shown in Figure 4.5. The subject is in sitting position and breathing activities normally, in regular breathing cycle as inhalation and exhalation. The microphone is holding the interval of, 3rd, 4th, 5th, and 6th. Duration of each sound in between 10 and 14 seconds.

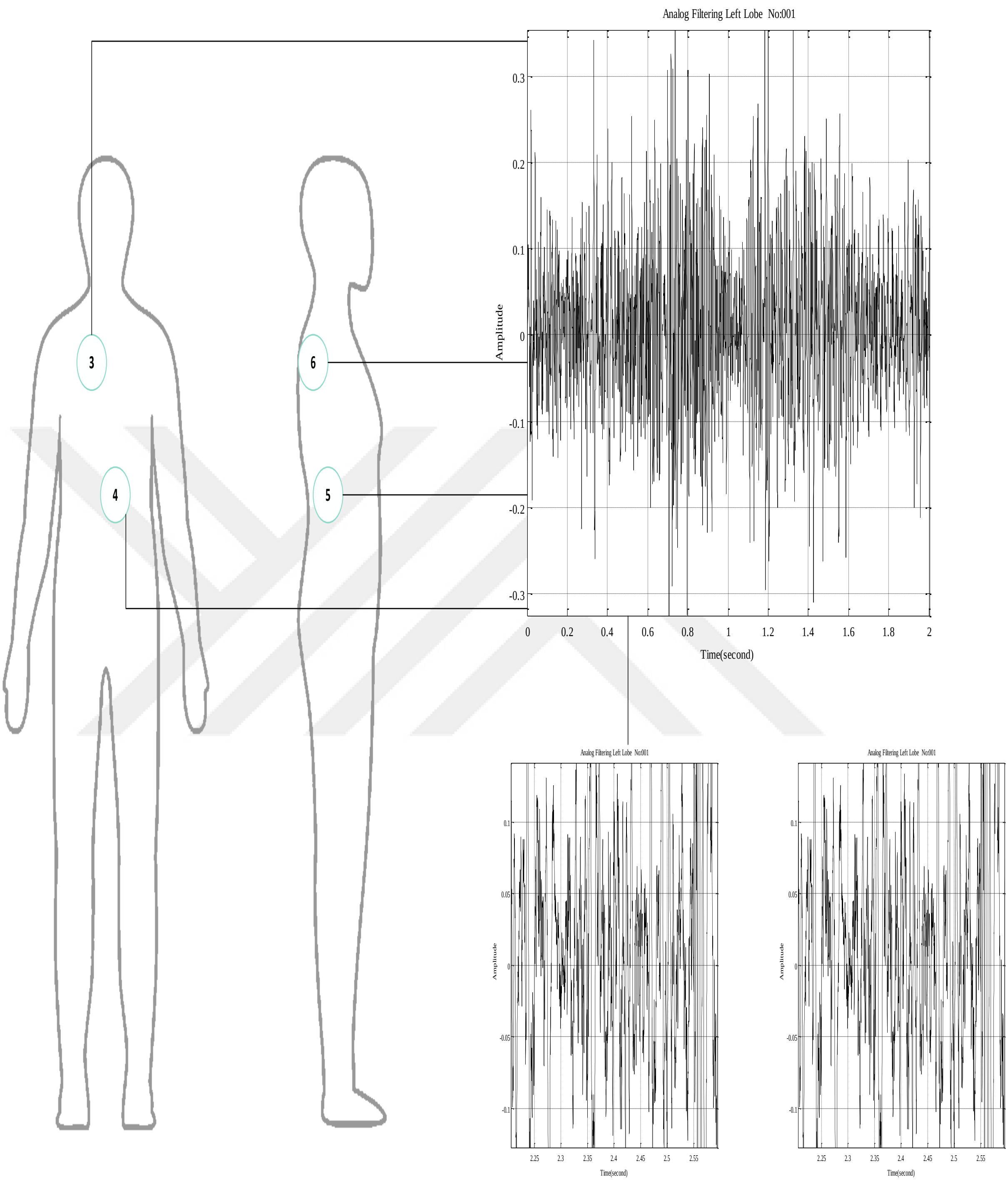


Figure 2.5: Signal acquisition position and outputs.

2.2.2. Recording Procedure

These lung sounds data was recorded in custom made recording system. All the lung sounds were recorded in College of Medicine at University of Gaziantep Hospital from volunteers who visit lung disease clinic. The sounds recorded in a noiseless clinical ambient room at the hospital under physician care. Volunteers classified age, gender, and smoker/non-smoker. According to Ethical approval was obtained from local “Ethical Committee”.

Including criteria for volunteers;

- Volunteers or participants gave written informed consent before the recording and examination procedure.
- Volunteer’s age is above 18 years old.
- The participants determined by the physician. Who are suitable for this study?
- Volunteers with normal are not found any lung sound disease.
- Volunteers with abnormal, patient have lung disease (Asthma or COPD).

The sounds recorded from subjects;

- Volunteers during normal breathing.
- Volunteers in regular breathing cycle as inhalation and exhalation.
- Both left and right side of the lung and same location.
- Duration of sounds in between 10 and 14 seconds.

In this project, some of the restriction can affect the research while recording or measurement of lung sounds signals.

- Measuring time period of each participant is different from each other.
- How many respiration cycles measured during treatment.
- Recording process some participant holds the breath, not consistent breathing.
- Environmental noise not completely eliminate.
- Recorded data restriction, computer restriction, equipment restriction.

This work is supported by "Analysis of the Respiratory Disease Diagnosis and Electronic Auscultation Sound Device Design” project TUBITAK under MAG104M38.

2.3. RECORDING/MEASURING INFORMATION

In this project total, 60 sound signals recorded from participate; 25 of them normal, 25 of them asthmatic and 10 subjects are COPD. These sounds recorded during normal breathing, in regular respiration cycle, both left and right posterior bases of the lungs in the same location and the duration of sounds in between 10 and 14 seconds respectively.

Distribution of age, gender and smoker information according to subject' condition Healthy, Asthma and COPD are detailed in Table 2.1.

Table 2.1: Distribution of subjects'.

Subject	male	female	smoker	non-smoker	Age between
Healthy	16	9	7	18	24-55
Asthma	7	18	9	16	19-63
COPD	6	4	4	6	25-80
Total	**39**	**21**	**20**	**40**	

In the recording process, recorded lung sounds signals were divided as breath cycle and then each breath cycle was segmented into inspiration and expiration phases based on starting and ending of each phase.

All of the above information followed under the control of by physicians. For each subject the files created by doctors. The created files comprising from, files name of each breath sounds, recording level of each breath cycle, the time beginning/ending of inspiration and expiration phases and lastly the time elapsed between the beginning and end of the exhalation/inhalation phases as shown in Table 2.2, 2.3 2.4 and 2.5. In the starting point for identification of each breath was at the beginning of the inspiration time.

In the following figures, in Figure 2.6 comprises of the healthy person and the sound signal is captured from right basal of the lung. The information given in Table 2.2, which includes the breath cycle and timing information, is referring to in Figure 2.6. Although the preparing files starting from inhaling activity time would have made grouping/labeling, some subjects began the breathing activities as exhale like in Figure 2.6. The starting point of the inspiration time; the period of 0.7 sec after the microphone is touching the patient's body.

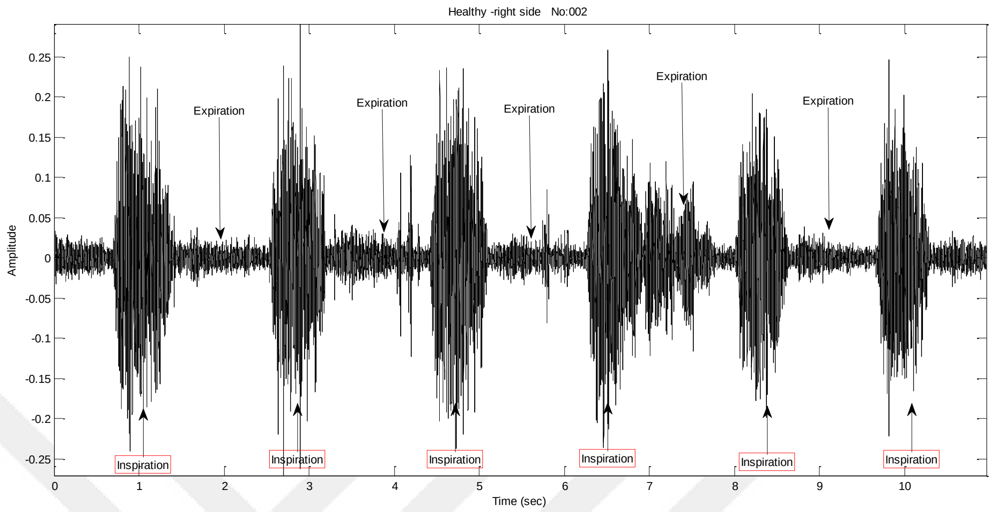


Figure 2.6: Health subject respiratory sound, right basal of the lung.

Table 2.2: Lung sound segmentation data sheet for Figure 2.6 subjects'.

Breath Cycle	Inhale starting	Inhale ending	Inhale total duration	Exhale starting	Exhale ending	Exhale total duration
1	0.096	0.835	2.849	0.0882	2.187	2,0988
2	2.197	2.945	0.748	2.955	4.192	1.237
3	4.230	4.921	0.691	4.931	6.101	1.17
4	6.201	6.868	0.667	6.900	8.077	1.177
5	8.087	8.192	0,105	9.001	10.130	1.129
6	10.140	10.897	0,757	10.900	12.087	1.187

Figure 2.7 comprises of the healthy person and the sound signal is captured from left basal of the lung. The information given in Table 2.3, which includes the breath cycle and timing information, is referring to in Figure 2.7. The starting point of the inspiration time; the period of 0.1 sec after the microphone is touching the patient's body.

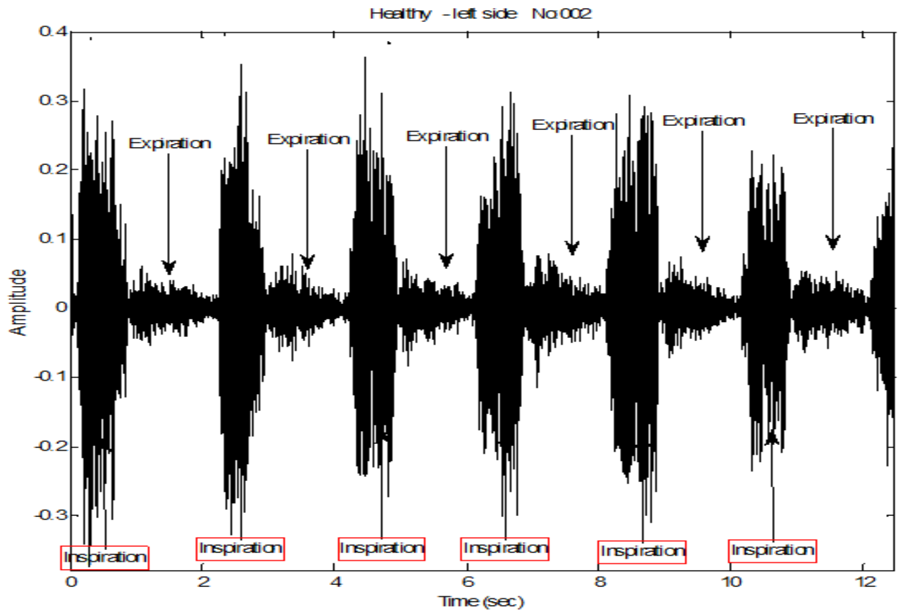


Figure 2.7: Health subject respiratory sound, left basal of the lung.

Table 2.3: Lung sound segmentation data sheet for Figure 2.7 subjects'.

Breath Cycle	Inhale starting	Inhale ending	Inhale total duration	Exhale	Exhale ending	Exhale total duration
1	0.119	0.858	0.739	0.95	2.245	1.295
2	2.3	2.945	0.645	3.001	4.186	1.185
3	4.29	4.926	0.636	5.001	6.154	1.153
4	6.2	6.897	0.697	6.909	8.146	1.237
5	8.17	8.955	0.785	9.101	10.209	1.108
6	10.291	10.895	0.604	11	12.48	1.48

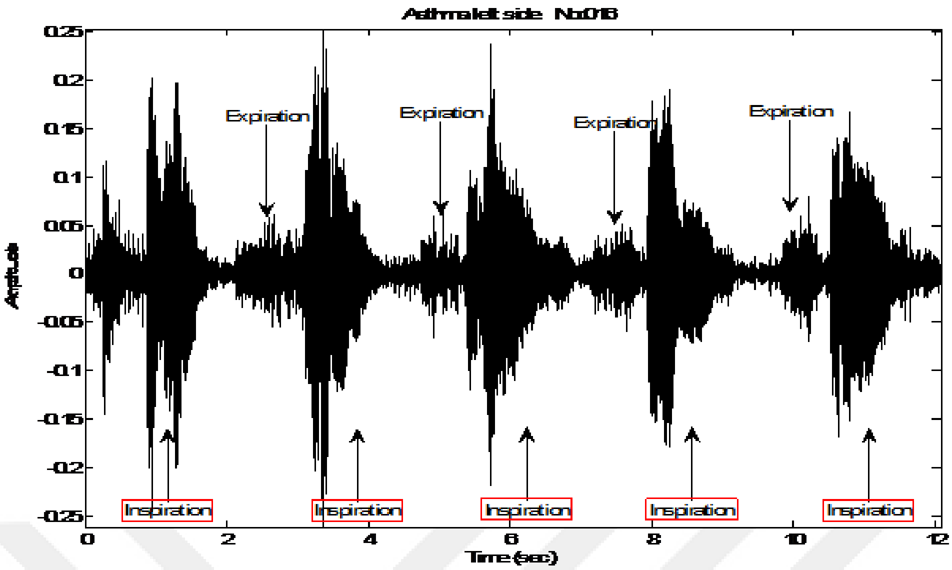


Figure 2.8: Unhealthy (Asthma) subject respiratory sound, left basal of the lung.

Table 2.4: Lung sound segmentation data sheet for Figure 2.8 subjects'.

Breath Cycle	Inhale starting	Inhale ending	Inhale total duration	Exhale Starting	Exhale ending	Exhale total duration
1	0.845	1.625	0.78	1.7	3.027	1.327
2	3.08	3.993	0.913	4.113	5.311	1.198
3	5.367	6.407	1.04	6.502	7.911	1.409
4	8.001	8.867	0.866	9.001	10.438	1.437
5	10.501	11.588	1.087			

Figure 2.8 comprises of the unhealthy person (asthma patient) and the sound signal is captured from left basal of the lung. The information given in Table 2.4, which includes the breath cycle and timing information, is referring to in Figure 2.8. The starting point of the inspiration time; the period of 0.9 sec after the microphone is touching the patient's body.

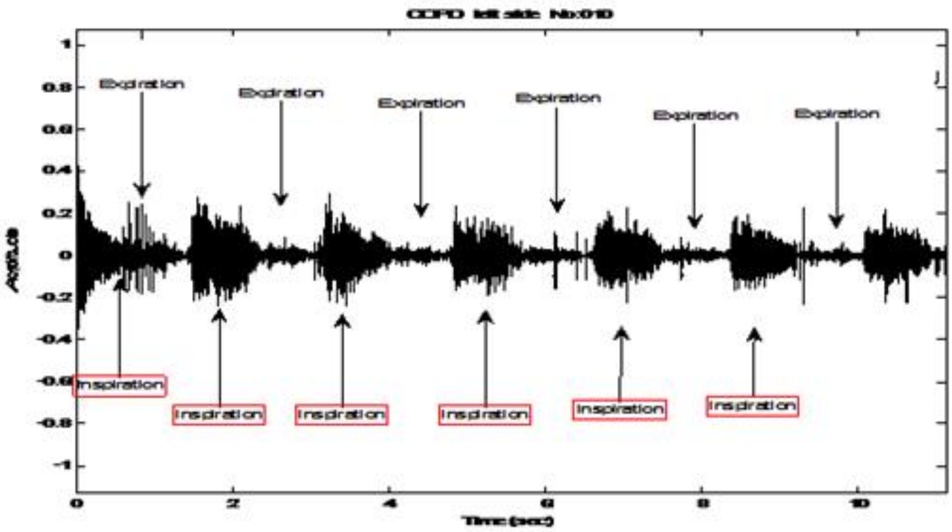


Figure 2.9: Unhealthy (COPD) subject respiratory sound, left basal of the lung.

Table 2.5: Lung sound segmentation data sheet for Figure 2.9 subjects'.

Breath Cycle	Inhale starting	Inhale ending	Inhale total duration	Exhale starting	Exhale ending	Exhale total duration
1	0.001	0.607	0.606	0.671	1.41	0.739
2	1.501	2.268	0.767	2.391	3.111	0.72
3	3.121	4.06	0.939	4.161	4.752	0.591
4	4.781	5.701	0.92	5.801	6.547	0.746
5	6.581	7.59	1.009	7.61	8.351	0.741
6	8.401	9.257	0.856	9.271	10.06	0.789
7	10.92	10.941	0.021	-	-	-

Figure 2.9 comprises of the unhealthy person (COPD patient) and the sound signal is captured from left basal of the lung. The information given in Table 2.5, which includes the breath cycle and timing information, is referring to in Figure 2.9. The starting point of the inspiration time; the period of 0.1 sec after the microphone is touching the patient's body.

Each respiratory cycle includes inspiration and expiration phases. Respiratory phases which used in this study consist of more than one and a different number of breath cycles because the duration of the sound capturing from subject varies in between 10-12 sec.

In the segmentation or labeling process of the lung sound signal, each respiratory phase encloses at least one and a different number of inspiratory or expiratory phases. As a result of the segmentation of the sound signal is;

- ✓ 60 right basal inhalation segments.
- ✓ 60 left basal inhalation segments.
- ✓ 60 right basal exhalation segments.
- ✓ 60 left basal exhalation segments.

Distribution of the lung sound segments according to 3 pulmonary conditions are shown in Table 2.6.

Table 2.6: Distribution of the lung sound segments compatible to three pulmonary condition.

Right Basal	**Left Basal**
60 inhalation sound segments	60 inhalation sound segments
25 normal /healthy	25 normal /healthy
25 asthma	25 asthma
10 COPD	10 COPD
60 exhalation sound segments	60 exhalation sound segments
25 normal /healthy	25 normal /healthy
25 asthma	25 asthma
10 COPD	10 COPD

2.4. METHODOLOGY

The analysis procedure of the recorded lung sounds will be discussed in this part. This includes filtering of the recorded data, respiratory phase detection of recorded lung sound signal, preprocessing, feature extraction and lastly the feature selection of lung sound data. The whole process is outlined in Figure 2.10 and each of the parts will be discussed separately.

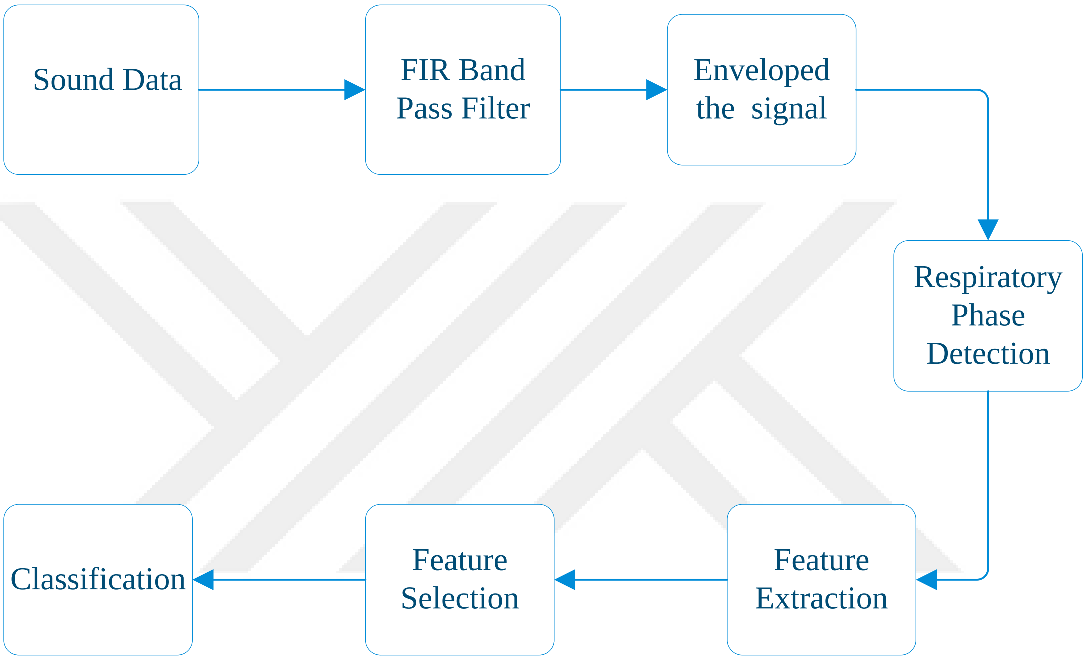


Figure 2.10:Implemented methodology.

2.4.1. De-nosing

The aim of this stage is totally referred to "de-noising" of the signal from artifacts. More clearly, remove or reduce unwanted component from the signal. The area of Digital Signal Processing especially in biomedical signals, the probability distribution of noise are different from each other especially recorded biomedical signals a wide range of noise can become out, by the reason of external and the internal noise source , there is no specific or perfect methods for noise reduction. External noise sources are because of technical and environmental, the internal noise source is the sound that appeared to the function of other organs in the human body such as heart, muscle, and other sounds.

Audio data have been recorded in clinical area. While recording lung sounds signal from volunteers the environment situation tries to keep as possible as quite but still some noise was recorded; the voice of people in the hospital hall, announce and in physical examination treatment, the sounds arising from the microphone (sensor) sliding which is placed on the chest wall.

The field of signal process, removing and identifying noise and artifacts' sounds from data has crucial importance before any other processing techniques. The reason is that to enhance the quality of the raw data for some type of parametric representation.

2.4.2. Filtering Recorded Data

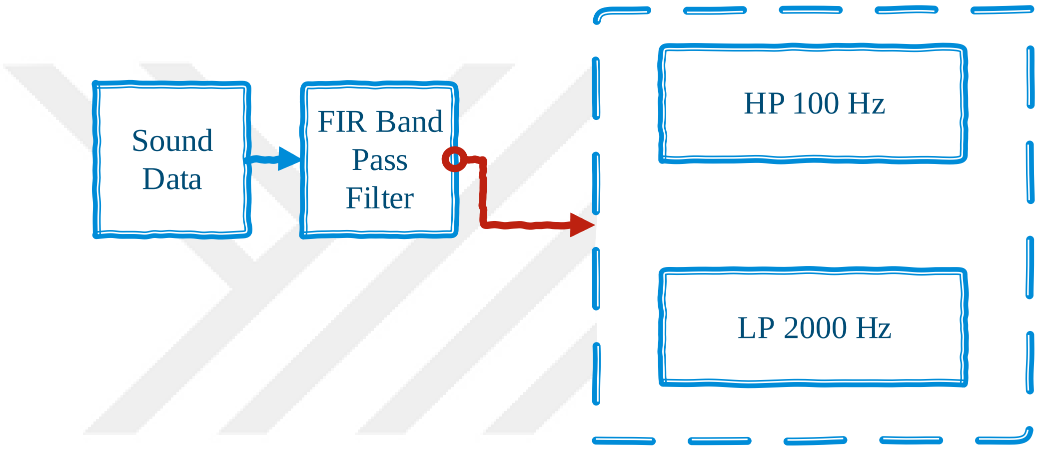


Figure 2.11: Filter design implementation.

The current problem of lung sound recording process is noise from contact between the recording device and the skin and environmental noise that corrupt the lung sound signals. In a healthy lung, the frequency range of normal breathing sounds extends to 1000 Hz such as vesicular breath sounds, on the other hand, pathological sounds such as wheeze, crackles, and other abnormal sounds frequency can appear up to 2000 Hz [64]. This means that frequency component above 2000 Hz is not involved relevant information around respiratory sounds. During the lung sound signal recording process to minimize the effect of noise sources such as heart beat, muscle movement, and other sounds respiratory sound signal filtered at 100 Hz. In the previous studies different frequency range and different range of high and low cut-off frequencies are used. Various band pass filters have been proposed in the literature such 70-2000 Hz [65], [66], 80-4000 Hz [67], 20-1200 Hz [68], 150-2000 Hz [69], 148-2000 Hz [35], 75-2000 Hz [19].

In this thesis, the frequency range of interest in recorded lung sound signal dominant frequency range in between 100 to 2000 Hz, At the beginning of the filtering stage, the bandpass finite impulse response filter (FIR) the range of 100 Hz to 2000 Hz applied recorded lung sounds signals after removing DC components. Respiratory sound signals filtered with a high-pass filter at 100 Hz and a low-pass filter at 2000 Hz (see Figure 2.11). In this project, band pass filter is designed 6th order Bessel high-pass filter and 8th order Butterworth low pass filter.

The first, begin with original input: time-amplitude signal representation. Figure 2.12 shows original recorded lung sounds waveform of time-amplitude and Figure 2.13 shows the waveform of respiratory sound signals after band-pass filtered.

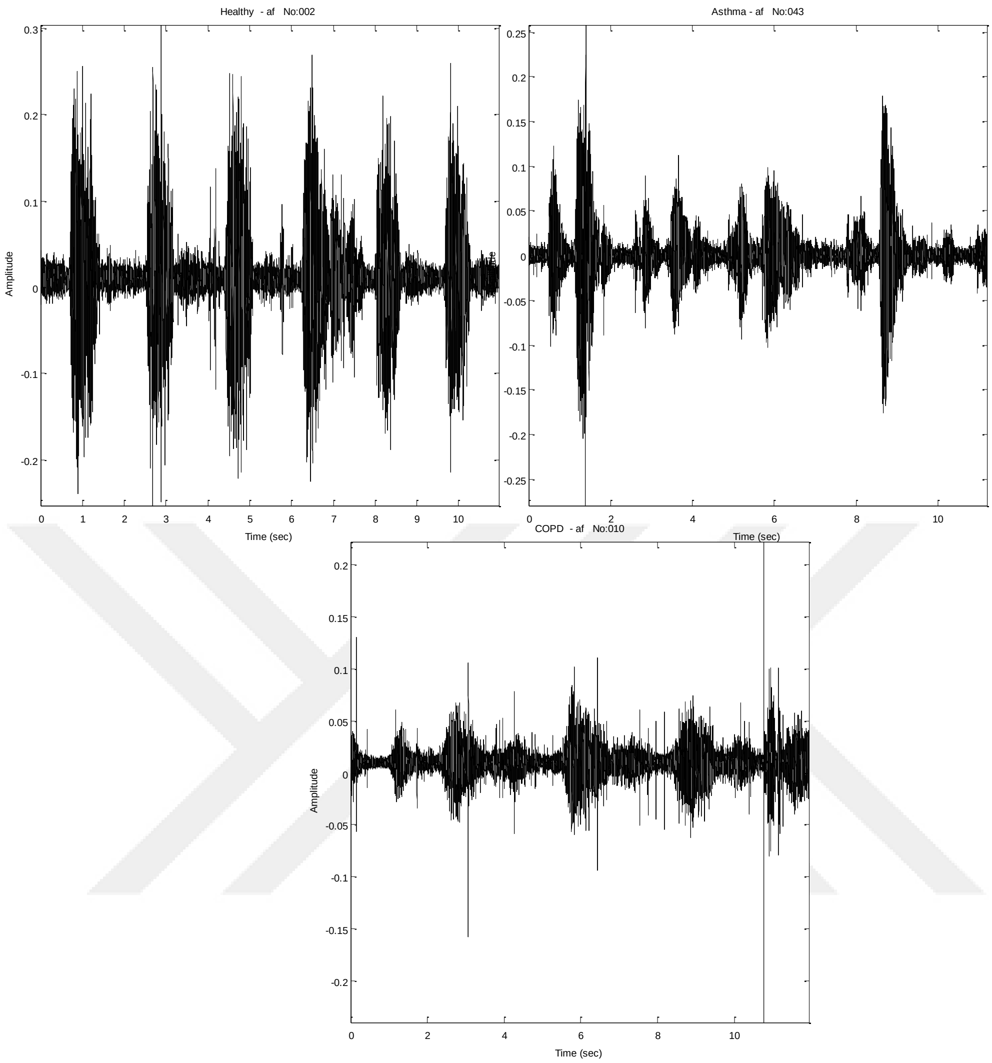


Figure 2.12: Time in Second (x-axis), Amplitude (y-axis) a) Original waveform of the input signal healthy subject, b) Original waveform of the input signal asthma patient c) Original waveform of the input signal COPD patient.

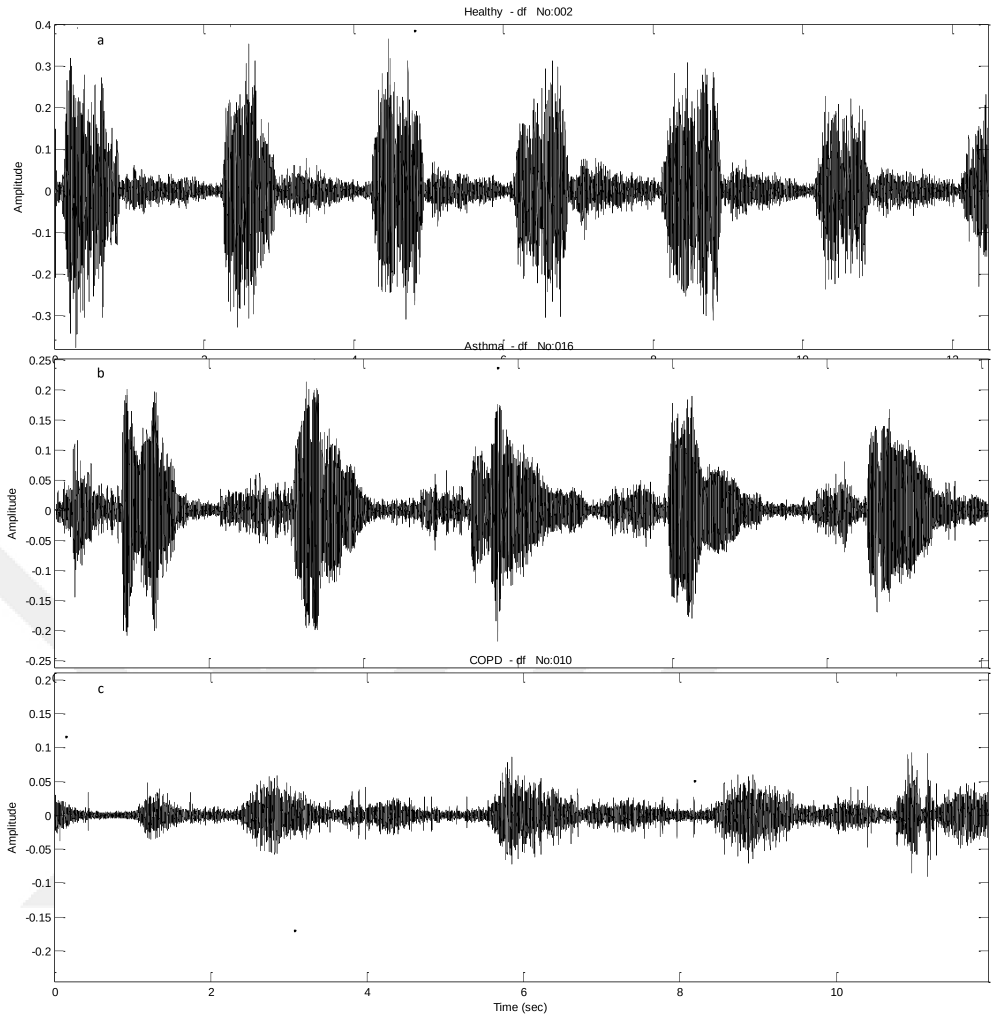


Figure 2.13: Time in Second (x-axis), Amplitude (y- axis) a) healthy subject respiratory sound signal after filtering stage, b) asthma patient respiratory sound signal after filtering stage and c) COPD patient respiratory sound signal after filtering stage.

2.5. RESPIRATORY PHASE DETECTION

The mechanism of breath sound is probably generated by the turbulence of the air at the level of lobar or segmental bronchi. During breathing activity, the process takes a place as a result of changes air flow in the lungs. Breathing activity. in other word respiration process consists of two phases' inhalation and exhalation. Inhalation process the airway is expanding, in contrast, exhalation process airway, is narrower, so intensity level is different from each other. In the comparable flows, intensity level of each respiration cycle has a different property from each other inspiratory phase has greater intensity than expiration phase as shown in Figure 2.14.

Identification of inspiratory and expiratory phases of the respiration has essential information for the clinical case. Different breathing cycle (inhalation & exhalation) have their noticeable characteristics respectively because and related to different pathological information so this information is to comprise very important phenomena in the diagnosis of respiratory disease and decision-making about the health condition of the subject.

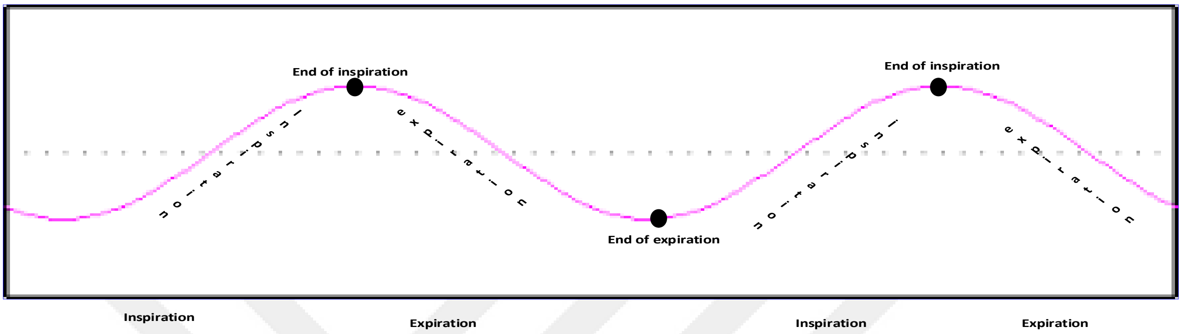


Figure 2.14: Lung sounds waveform: inspiration - expiration cycle.

2.5.1. Enveloped of Recorded Data

The main purpose of the Envelope detection of the signal is to find overall shape of the recorded lung sounds signal. It means that, the outline of the signal. It helps to compute automatically each breathing phase. Basic step implementation of overall envelope detection scheme is shown in Figure 2.15.

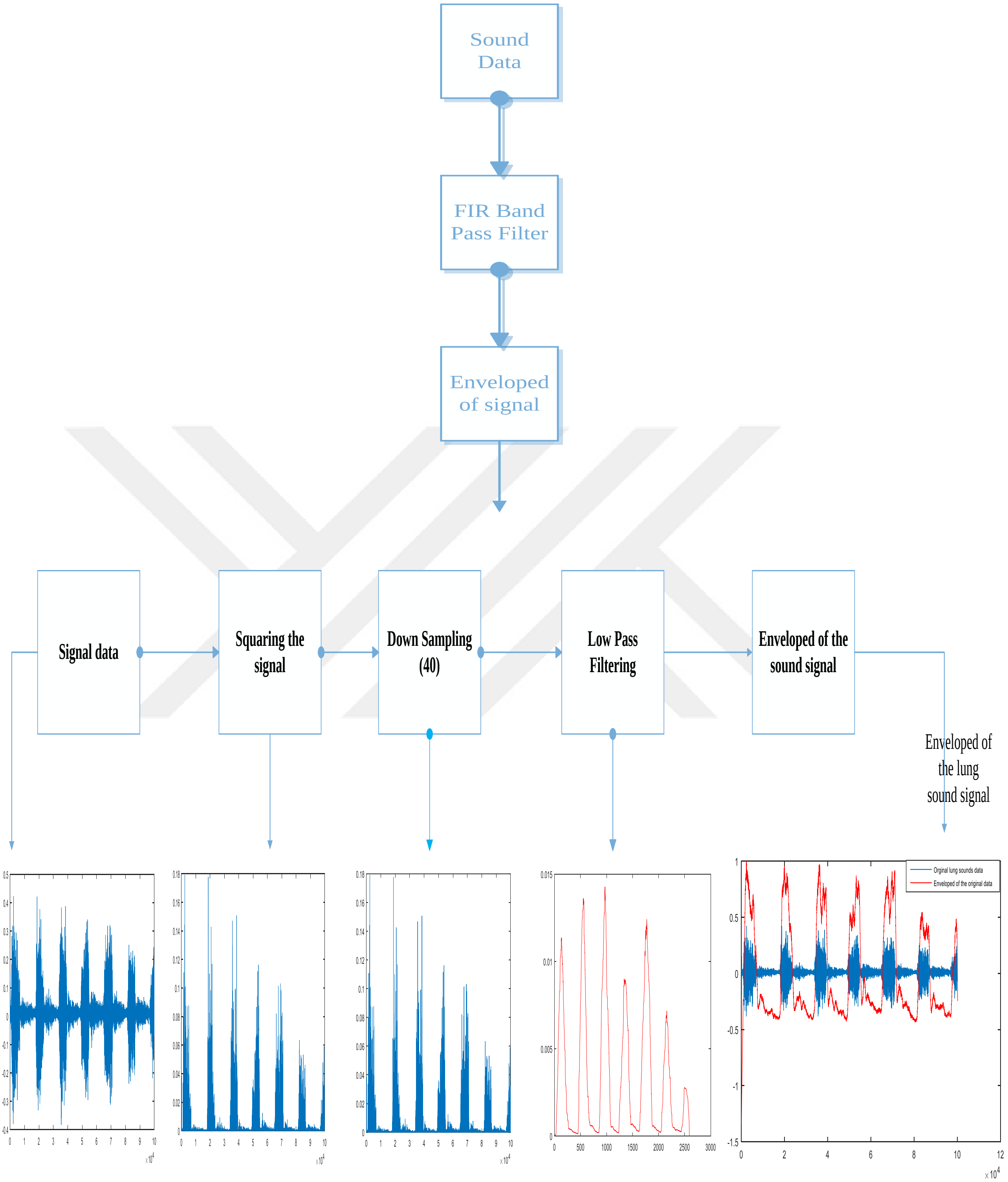


Figure 2.15: Implementation of envelope detection process.

Enveloped detection technique is used in this project the basic steps follow as;

- ✓ The first stage is squaring: to eliminate energy loss of the signal.
- ✓ The second stage is down-sampling the output of the first stage. The respiratory cycle involves two phases as inhale and exhale. If we accept that, the respiratory phase period duration approximately 1.5 sec, the new sampling frequency must be at least 3Hz. In this project sampling frequency (fs) of recorded signals is 8000 Hz and the down-sampling factor is taken 40, the new sampling frequency is now 200 Hz. (= sampling frequency/down sampling factor = 8000/40=200). The new sampling frequency is much greater than 3 Hz.
- ✓ In the third stage, low-pass filtering has applied the signal, reduce computational burden.

Finally, after all of the stages are a process, overall shape (envelope) of the signal is shown in Figure 2.16. The sound signal actually contains 6 respiratory cycles, it means that input signal involves 6 inhalations and 6 exhalation phases. The duration of the recorded lung sound signal approximately 12 sec.

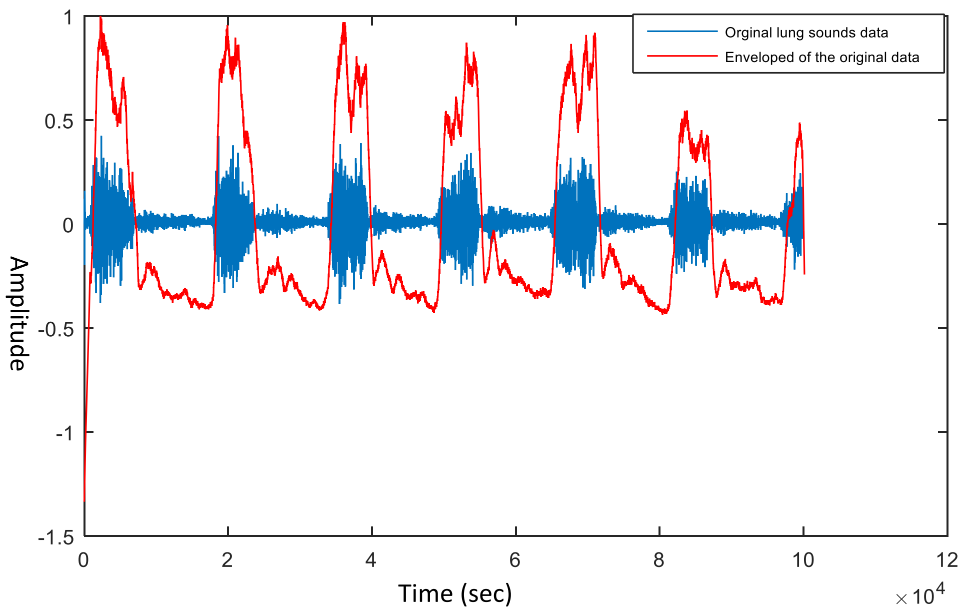


Figure 2.16: Original lung sound signal and outlines.

In this part of the project, the first stage is that we have to find the respiratory cycle of each subject and compare them with the actual cycle. Table 2.7 and Table 2.8 compares the result of actual and acquired respiratory cycle of each healthy and unhealthy subject.

Table 2.7: Respiratory cycle measurement result for a healthy subject.

Subject	Acquired Respiratory Cycle	Actual Respiratory Cycle
N001	6	5
N002	5	5
N003	7	7
N004	4	4
N005	5	4
N006	6	6
N007	4	4
N008	7	7
N009	8	7
N010	5	4

HEALTHY SUBJECT

Table 2.8: Respiratory cycle measurement result for unhealthy subject.

Subject	Acquired Respiratory Cycle	Actual Respiratory Cycle
N001	5	4
N002	5	5
N003	4	3
N004	4	4
N005	7	7
N006	6	6
N007	5	4
N008	8	7
N009	6	6
N010	6	6

UNHEALTHY SUBJECT

When we compare the actual respiratory cycle and the acquired respiratory cycle in all data set, %80 of the success rate have been achieved.

2.5.2. Phase Detection

After enveloped process, we find overall shape of the respiratory signal (Figure 2.16). The second part, we will automatically find each phase. We defined a Baseline amplitude value (Bs), threshold value to identifying the peak value of local-maximum Max(i) and local-minimum Min(e). Each of the peaks value is equivalent to the respiratory phase of middle-points and end-point respectively. Max(i) responsible the point of time at which is the half of the inspiration and Min(e) responsible the point of the time end of expiration. The automatically phase decision process first rule is that the starting point for identification of each breath was at the beginning of the inspiration time.

In Figure 2.17 show respiratory phase detection example signals. The process code is written in MATLAB R2015a. Written program basic outline as follows;

1. We defined a Bs = 0.0045 value for automatically to decide each of the Max(i) and Min(e) peak value. This threshold value resolves by experimentally.
   - If the first peak of the value < Bs look for the closest max point
     - Starting point for identification of each breath was at the beginning of the inspiration time
   - If the first peak of the value >Bs means that it is acceptable for processing and start point for respiration cycle.
2. After each Max(i) points, we check if there is Min(e)
   - If exist, continue the process
   - If not exist, means that end of respiration. End of the time does not exceed the duration of time.
3. Max(i) peak value time =half of the inpiration phase time
4. Min(e) peak value time = end of expiration phase time

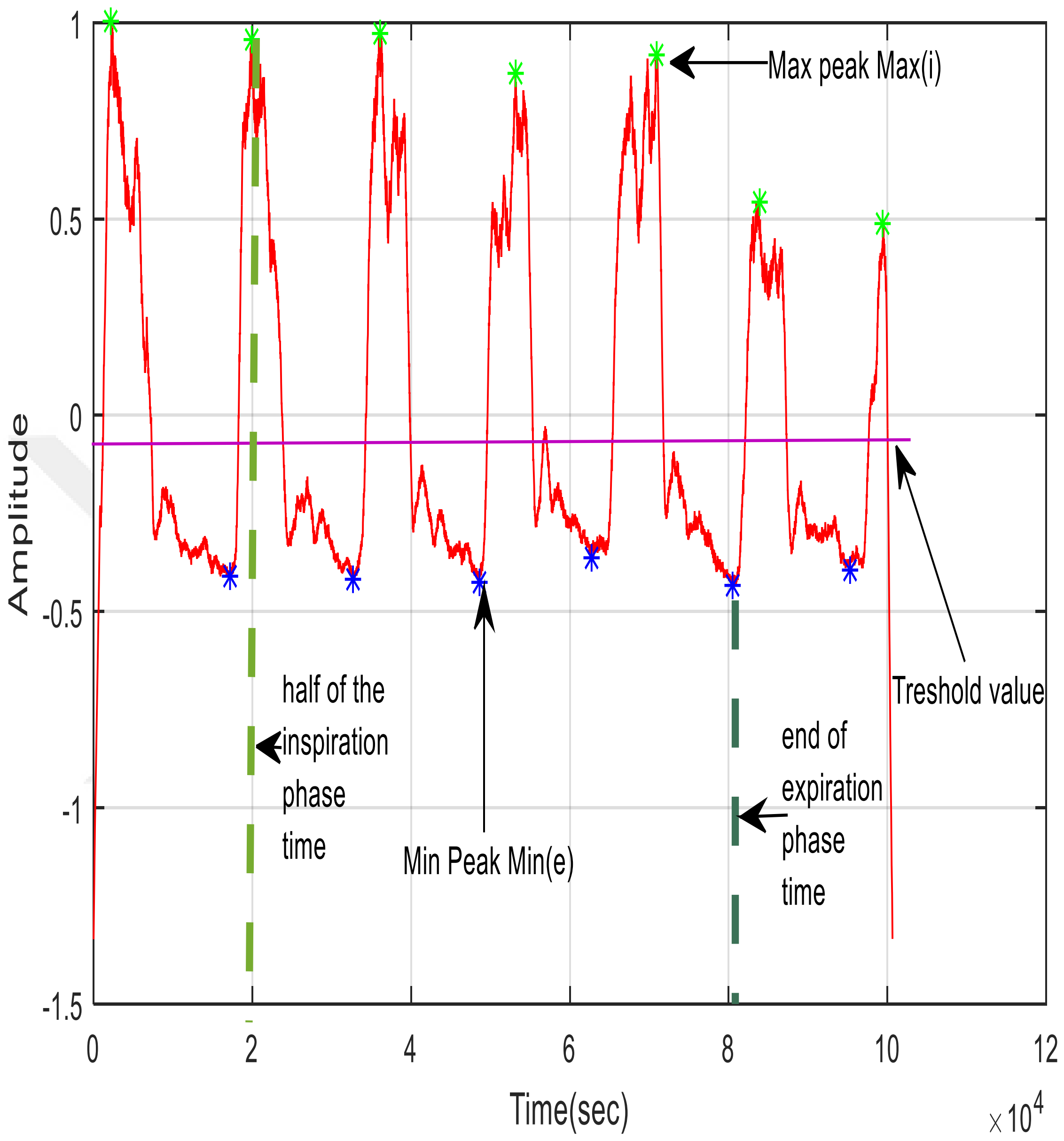


Figure 2.17: Respiratory phase detection signal.

2.6. FEATURE EXTRACTION

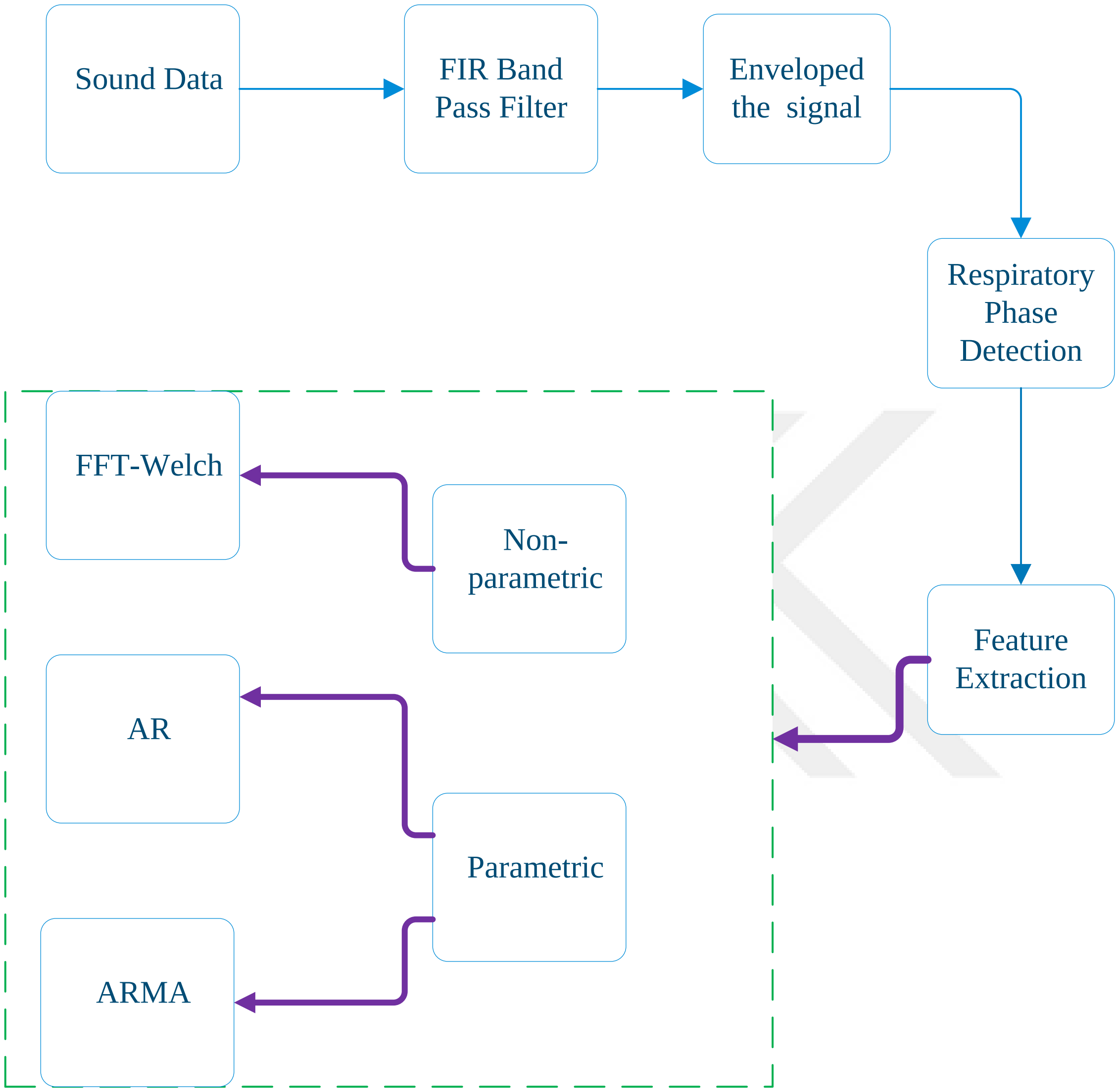


Figure 2.18: Feature Extraction process.

Feature extraction is an essential pre-processing step for pattern recognition and machine learning problems. It is often decomposed into feature construction and feature selection. Feature extraction is the process that transforms from a larger problem space into a smaller feature space. It is a special form of dimensionality reduction and mapping as shown in Equation (2.1)

$$F: R^N < R^D \qquad D \ll N \tag{2.1}$$

Where N is a number of features, D define the new number of features which is smaller than N.

In this project, we used different spectrum analysis methods namely FFT-Welch (nonparametric), AR and ARMA (parametric) (see Figure 2.19). Detailed information about spectrum analysis methods is given in the following part of the study.

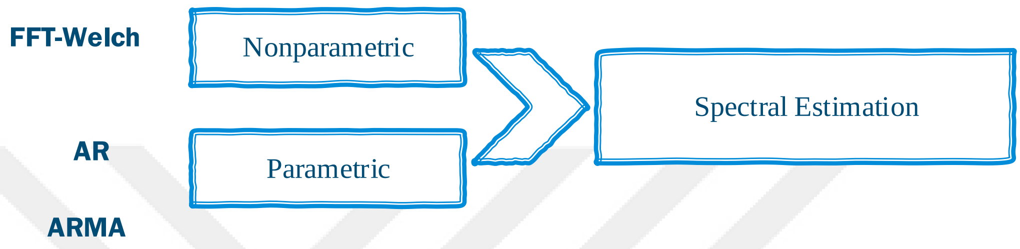


Figure 2.19: Spectral estimation methods.

2.6.1. FFT- Welch

The method is one of the FFT-based techniques and defined as nonparametric (classical) methods. Welch methods based on the definition of periodogram spectrum estimation, which are the result of converting the signal in the time domain a series of $\cos x$ or $\sin x$ waves with different intensity, power, amplitude, frequency and phases, [70] the purpose of the Welch methods is that assessment the power of the signal at different frequencies.

In this method signal/data y(m) is divided by the length of N samples, and is divided into K segments length of M and overlapping by D points.

$$yi(m) = y(m + iD) \qquad m = 1, \dots \dots \dots \dots, N \;\; i = 1, \dots \dots \dots, K \tag{2.2}$$

Intervals before the computing periodogram of the data segments overlapped and window. The purpose of computing a PSD is to see how the frequency content of given signals varies with frequency. Periodogram of the ith window segment and modified periodogram is defined as Equation (2.3)

$$Pxx(f) = \ {}^{1}/_{NU} \left[\!\left[\sum_{n=1}^{N} w(m)yi(m)e^{-j\pi fm}\right]\!\right]2 \tag{2.3}$$

w(m) is the window function and U is the power in the window function and defined

$$U = {}^{1}/_{U} \sum_{m=1}^{N} w^{2}\,(m) \tag{2.4}$$

and lastly power spectrum of the Welch is an average of the K periodograms obtained from the signal which is overlapped and windowed segments of the data

$$Pxx\,(f) = {}^{1}/_{K} \sum_{i=1}^{K} Pxx(f) \tag{2.5}$$

Respiratory sounds power spectral density for a full cycle of inspiration and expiration phases are calculated by using Welch methods for each subject. In this method, overlapping intervals are taken as %50 and windowed using" Hamming" window. Figure 2.20 show the original waveform of lung sounds signals and after Welch method applied these signals.

<u>FFT-Welch Parameters</u>

- Hamming Window.
- 1024 Window length.
- 1024 Nfft.
- 8000 Hz sampling frequency.

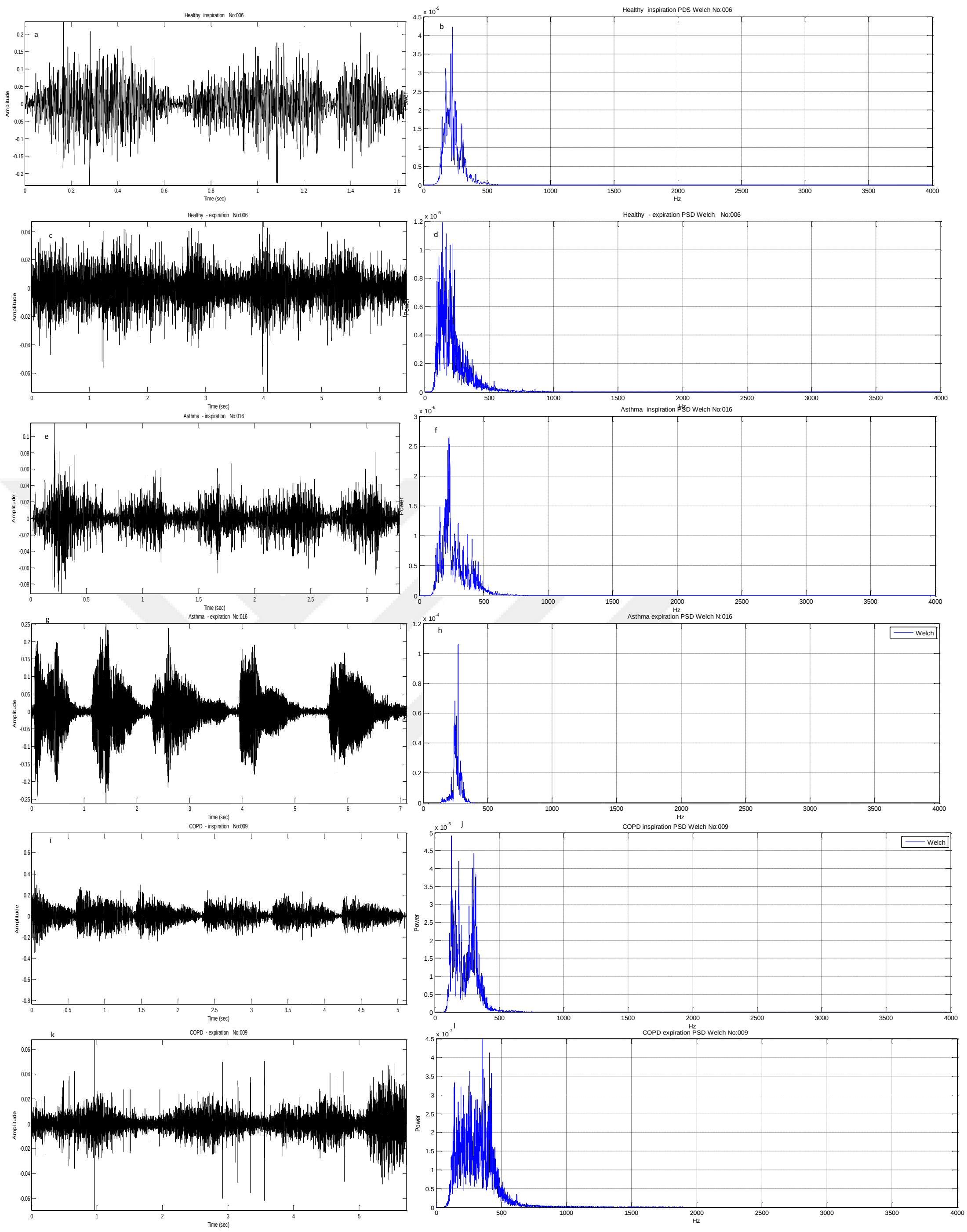


Figure 2.20: a) time-amplitude of inspiration signal for healthy subject, b) Welch PSD of a c) time-amplitude of expiration signal for healthy subject d) Welch PSD of c, e) time-amplitude of inspiration signal for asthmatic patient, f) Welch PSD of e, g) time-amplitude of expiration signal for asthmatic

patient, h) Welch PSD of g, i) time-amplitude of inspiration signal for COPD patient, j) Welch PSD of i, k) time-amplitude of expiration signal for COPD patient, l) Welch PSD of k.

2.6.2. AR Model

AR method is commonly used for PSD estimation between in parametric or model-based methods. The AR model is an infinite impulse response filter or an all-pole filter [6] and is named according to the number of observations in past periods. AR model based on the previous output of the model.

In the AR modeling to get the amplitude of the signal in a certain period, by adding the different amplitudes of the previous samples and adding estimation error [71] This process is in Equation (2.6)

$$\boldsymbol{x}(\mathbf{n}) = -\sum_{k=1}^{p} \mathbf{a}(\mathbf{k})\mathbf{x} - \mathbf{k}) + \mathbf{e}(\mathbf{n}) \quad \textbf{(2.6)}$$

(k) AR methods coefficient, e(n) error term, shortly white noise

AR (p) model can be defined by AR parameters {a (1), a (2) … a (k)} and e(n) white noise (error term). There are several algorithms to estimate parameters of AR such as Burg, Yule-Walker. PSD of AR methods is obtained basically from following Equation (2.7) and (2.8)

$$\boldsymbol{P}_{AR(f)} = \frac{\sigma^2}{|A(f)^2|} \quad \textbf{(2.7)}$$

$$\boldsymbol{A(f) = 1 + a_1 e^{-j2\pi f} + \cdots + a_p e^{-j2\pi f_p}}$$

$$\boldsymbol{P_{AR}}(\mathbf{f}) = \boldsymbol{x} = \frac{\boldsymbol{\sigma^2}}{|\mathbf{1} + \sum_{\mathbf{k=1}}^{\mathbf{p}} \mathbf{a(k)e^{-j2\pi fk}}|} \quad \textbf{(2.8)}$$

AR-burg is one of the commonly used methods and effective results that R methodically. This method is based on the principle of minimizing the substantially forward and backward prediction errors. By using AR-burg PSD estimation obtained basically from following Equation (2.9).

$$P_{BURG}(f) = \frac{e_p}{\left|1+\sum_{k=1}^{p} a(k)e^{-j2\pi fk}\right|^2} \tag{2.9}$$

e_p is total least square error and it being the sum of the forward and backward prediction errors.

Parametric or model based methods, selection of order is very important, if a model with the low order is chosen, the highly smoothed spectrum is obtained. If the order of model is selected too high, we faced the risk of spurious low-level peaks in the spectrum [6].

One of the most important aspects of the use of AR methods is the selection of the model orders. Since inhalation and exhalation phases show different characteristics, separate AR-Burg models were applied to each phase in this study.

While the order of the AR-Burg model was set as 7 for inhalation phases of right basal and 12 exhalations of the same basal. Orders of AR-Burg which are applied to left basal inhalation and exhalation phases were determined respectively as 20 and 14. Figure 2.21 show PSD estimation of the lung sounds signals by AR-burg method.

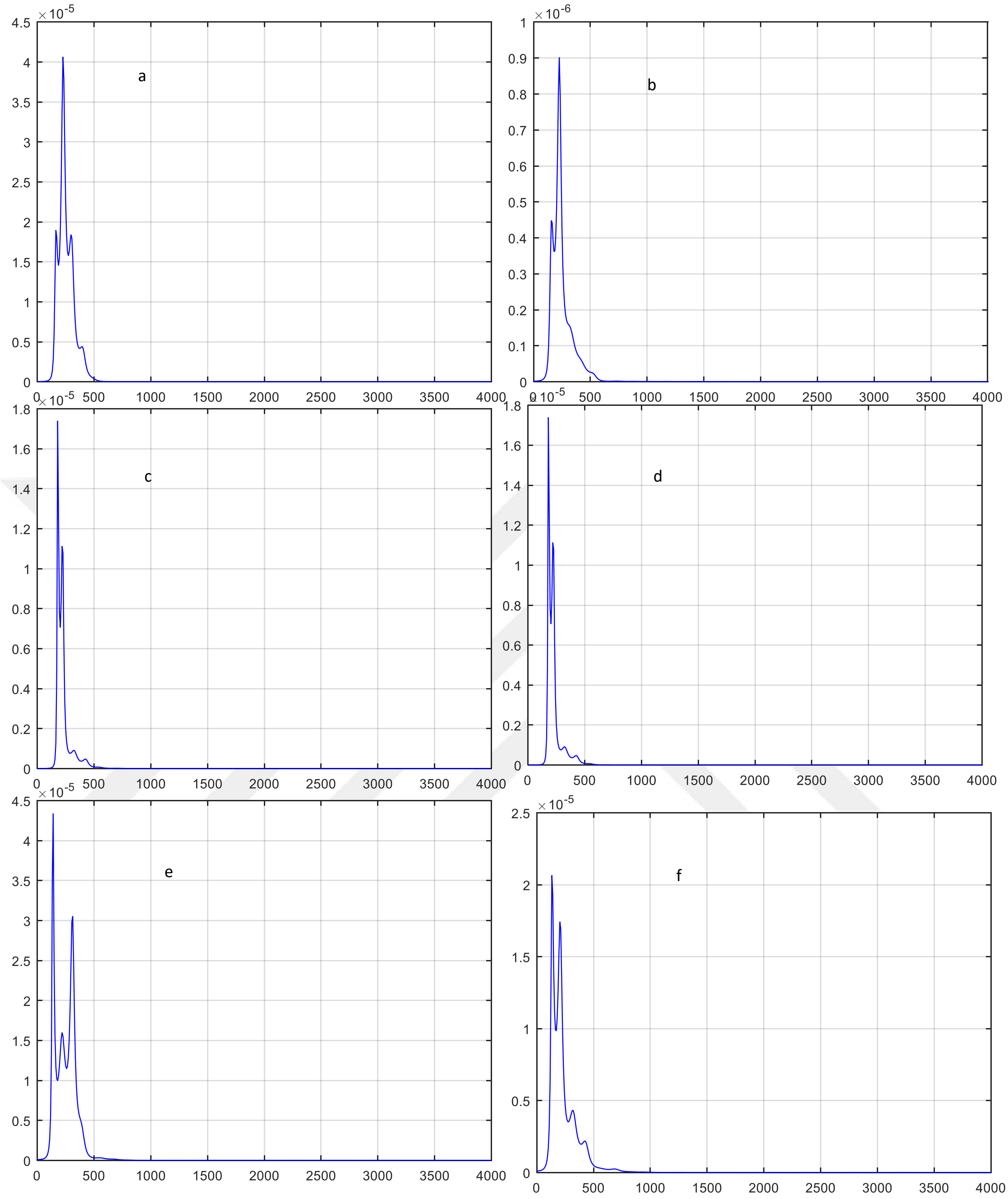


Figure 2.21: a) Figure 2.17 (a) an AR-burg PSD b) Figure 2.17 (c) AR-burg PSD c) Figure 2.17 (e) AR-burg PSD d) Figure 2.17 (g) AR-burg PSD e) Figure 2.17 (f) AR-burg PSD f) Figure 2.17 (j) AR-burg PSD.

2.6.3. ARMA Model

Auto-Regressive Moving Average (ARMA) model is a combination of both the method of AR and Moving Average (MA) model. In this method, any period of observation values of a time series is expressed as a linear combination of values of the predecessor certain number of observations and the error term.

ARMA models the order of p,q can be expressed as *p* is the order of AR model and q is the order of MA model and this combination refers to ARMA (p,q) and express as in Equation (2.10)

$$x(n) = -\sum_{k=1}^{p} a(k)x(n-k) + \sum_{k=0}^{q} \emptyset(k)e(n-k) \tag{2.10}$$

By using ARMA PSD estimation obtained basically from following Equation (2.11) and (2.12)

$$P_{ARMA} = \frac{P_{MA}(f)}{P_{AR}(f)} \tag{2.11}$$

$$P_{ARMA} = \frac{\sum_{k=-q}^{p} \emptyset(k)e^{-2jfk}}{\left|1+\sum_{k=1}^{p} a(k)e^{-2jpk}\right|} \tag{2.12}$$

As we mention in the AR model, one of the most important aspects of the use of ARMA methods is the selection of the model orders. Since inhalation and exhalation phases show different characteristics, separate ARMA models were applied to each phase in this study.

p,q orders rate for ARMA models as follows;

- Right basal inhalation sound: 24,22.
- Right basal exhalation sound:16,15.
- Left basal inhalation sound: 27,26.
- Left basal exhalation sound: 28,27.

Figure 2.22 show PSD estimation of the lung sounds signals by ARMA method.

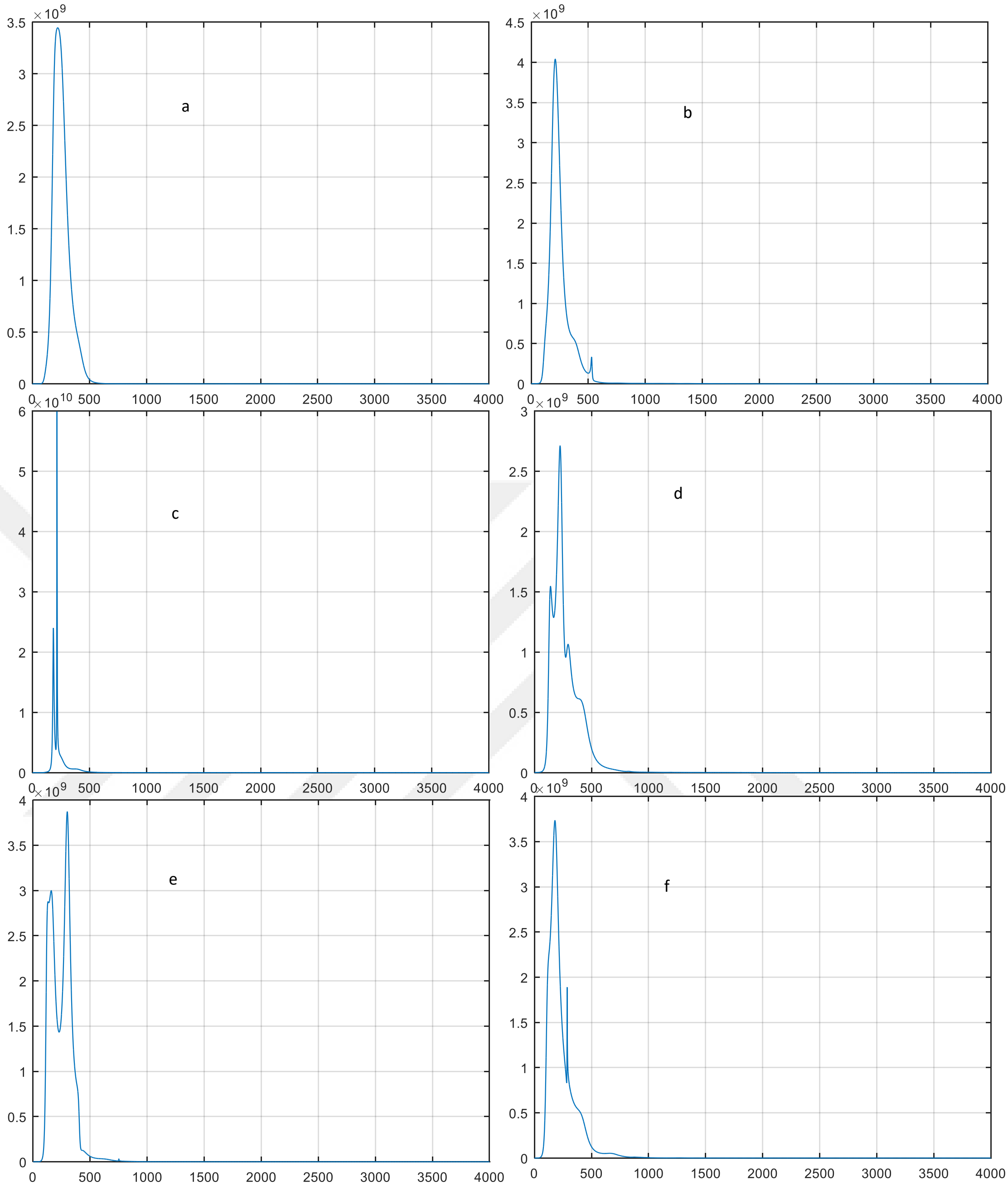


Figure 2.22: a) Figure 2.17 (a) ARMA PSD b) Figure 2.17 (c) ARMA PSD c) Figure 2.17 (e) ARMA PSD d) Figure 2.17 (g) ARMA PSD e) Figure 2.17 (f) ARMA PSD f) Figure 2.17 (j) ARMA PSD.

2.7. FEATURE SELECTION

In this thesis, parametric AR, ARMA, and non-parametric FFT-Welch spectral estimation methods are applied each of the respiratory phases. Power Spectrum of each part inspiration and expiration phases are obtained by using these methods. FFT-Welch, AR, and ARMA methods decide the size of feature vectors for each inspiration and expiration phases. These features refer to a number of FFT points parameter use for calculation Power spectrum density (PSD) estimation. This parameter namely **nfft** and it is decided the size of PSD. If we assume that nfft is L, in the PSD there are (L/2)+1 (points) points. For all the methods the ntff values were chosen 1024, PSDs with 1024/2+1 (513) points were obtained as feature vectors for each respiratory phase. The dimension of feature vectors is too large for an effective classification. Because of the large data size, significant information and dependency cannot efficient inferred. For the successful and short time classification process and performance, the dimension of features vectors should be reduced. In order to reduce the data size of the extracted feature vectors, we divided a 0-2000 Hz frequency band of PSDs into intervals as presented in Table 2.9.

Table 2.9: Frequency intervals of PSD.

Interval	Frequency Interval
F1	1000-2000
F2	500-1000
F3	250-500
F4	125-250
F5	62.5-125
F6	31.25-62.5
F7	0-31.25

Division of the frequency bands into intervals was carried out using decomposition rule of discrete wavelet transform (DWT). In discrete wavelet transform, the signal is passed through both the high and low pass filters simultaneously. Cut-off frequencies of these filters are designed as one-fourth of the sampling frequency. For the 8000 Hz sampling frequency, DWT produces frequency intervals like Figure 2.23. H represent high pass filter and L represents low pass filter.

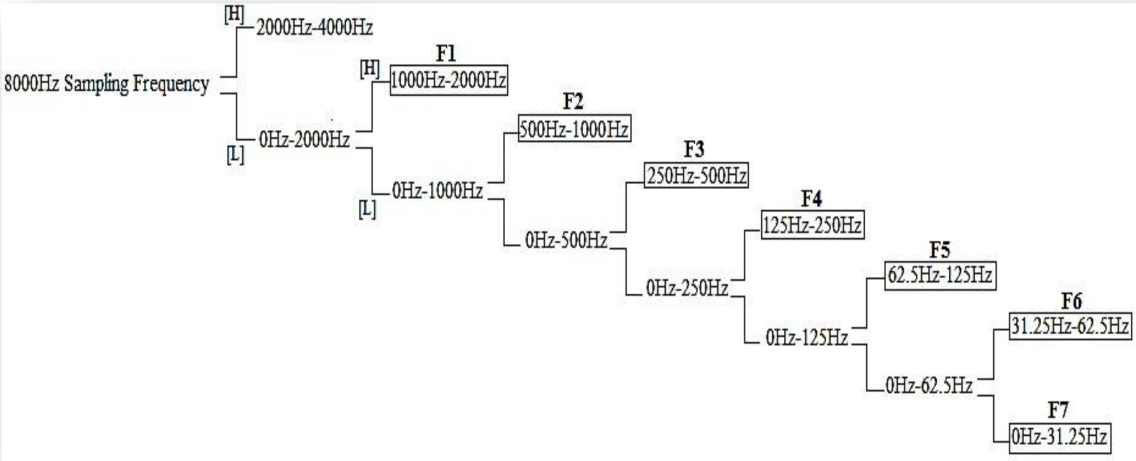


Figure 2.23: Frequency band range.

In many studies, wavelet coefficients of frequency intervals produced by DWT have been used as features of respiratory sounds. But, in this study, decomposition rule of DWT was only used to determine the useful frequency intervals. For our respiratory sounds with 8000 Hz sampling frequency, computed PSDs are scattered 0-2000 Hz frequency bands. Therefore, for each PSD, our frequency intervals are F1, F2, F3, F4, F5, F6 and F7. These intervals were generated using decomposition rule of DWT. Since the respiratory sounds do not have any useful frequency and power components in low frequencies, we discarded F6 and F7 frequency intervals. First, five frequency intervals were selected to be used to create feature vectors. Statistical features were extracted from the PSD values belonging to first five frequency intervals.

These statistical features;

1. Mean of the absolute values of the PSD values in each selected frequency interval.

2. Maximum of the PSD values in each selected frequency interval.

3. The standard deviation of the PSD values in each selected frequency interval.

4. The ratio of the absolute mean values of adjacent frequency intervals.

- Feature1 (mean) and Feature 2 (maximum) features represent the frequency distribution of the sound signal.
- Feature 3 (standard deviation).

Feature 4 (ratio of the absolute mean values) describe the amount of changes in a frequency distribution.

Table 2.10: Feature Vectors.

Feature Numbers	Features
1,2,3	mean(abs(PSD Values in F1)) max(PSD Values in F1) std(PSD Values in F1)
4,5,6	mean(abs(PSD Values in F2)) max(PSD Values in F2) std(PSD Values in F2)
7,8,9	mean(abs(PSD Values in F3)) max(PSD Values in F3) std(PSD Values in F3)
10,11,12	mean(abs(PSD Values in F4)) max(PSD Values in F4) std(PSD Values in F4)
13,14,15	mean(abs(PSD Values in F5)) max(PSD Values in F5) std(PSD Values in F5)
16	mean(abs(PSD Values in F1)) mean(abs(PSD Values in F2))
17	mean(abs(PSD Values in F2)) mean(abs(PSD Values in F3))
18	mean(abs(PSD Values in F3)) mean(abs(PSD Values in F4))
19	mean(abs(PSD Values in F4)) mean(abs(PSD Values in F5))

Feature vectors of the respiratory sound segments were created using these statistical features as seen in Table 2.10, 5 mean values, 5 max values, 5 standard deviation values and 4 ratios of the absolute mean values are the features of our sound segments.

After the feature extraction phase, feature vectors consist of these 19 values applied as input parameters into machine learning algorithms.

2.8. CLASSIFICATION THEORY

In this part of the project, classification theory part occurs. Lung sound signals can be classified as healthy or patient by using different machine learning algorithms namely ANN (Artificial Neural Network), SVM (Support Vector Machine) and K-NN (K-Nearest Neighbor). Figure 2.24 shows the overall scheme of the classification process.

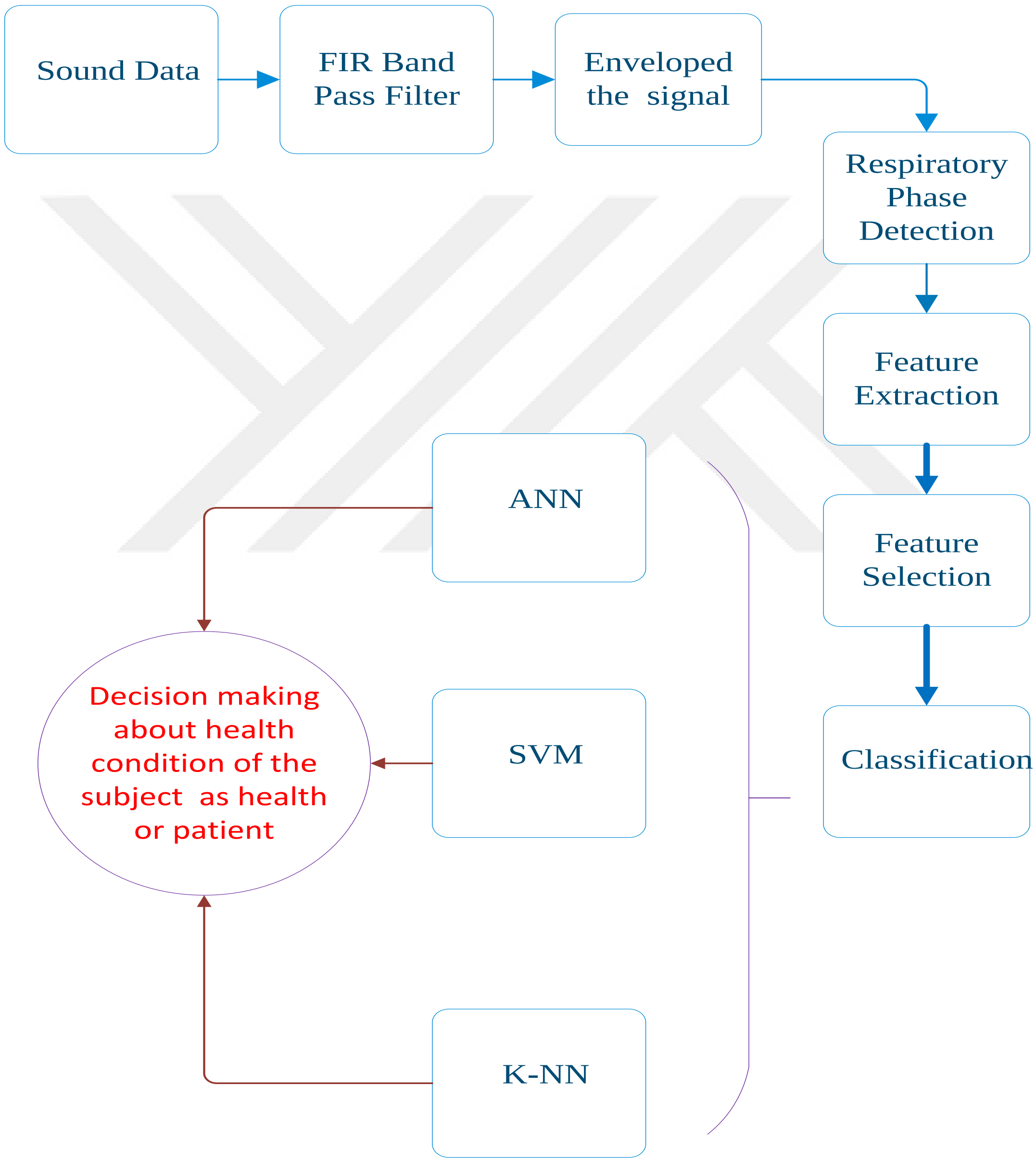


Figure 2.24: Overall scheme of the classification process.

2.8.1. ANN (Artificial Neural Network)

ANN, inspired by the human brain developed, through main links connecting to each other and each of them has its own memory that is information processing elements [16][27]. ANN are modeled by inspired of biological neural networks but has a simpler structure than them. ANN system modeling is used in classification and interpretation works such as recognition and interpretation of speech recognition, handwriting recognition, fingerprint recognition, physiological signs (heart function, brain function, respiratory function, etc.)

In addition to this, ANN is also used to solve complex problems such as business, industry, finance, industry, education and science fields. In this study, one of the most important and widely used models of ANN, that is, Multi-Layered Perceptron (MLP) architecture, supervised error Back-Propagation learning algorithm has been used. In all layers, sigmoid activation function is used.

In the basic scheme of the one hidden layer neural network, totally there are three layers. The first layer is the input layer which is the inputs of all feature vectors. The second layer is the 'hidden' layer. The hidden layer receives the weighted sum of the incoming signal sent by the input units. The hidden units send output signals towards to the neurons in the next layer. Information is propagated forward until the network produces an output. The third layer is the output layer which consists of the result of the classification process. Neural network architecture can be seen in Figure 2.25.

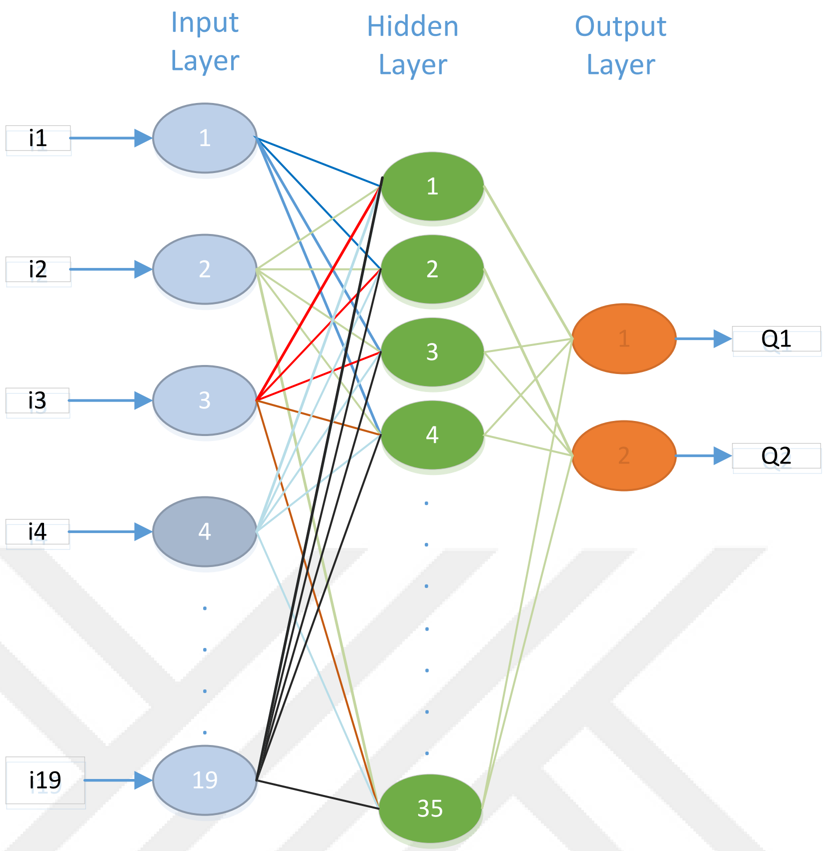


Figure 2.25: Neural Network Architecture.

2.8.2. SVM (Support Vector Machine)

SVM is the supervised machine learning algorithm and used for classification or regression. SVM is specifically used to solve both linear and non-linear classification problem in a supervised manner which presents one of the kernel-based methods. SVM is used for classification of both linearly separable and inseparable data.

SVM is to form an optimal separating hyperplane in such a way that the margin of separation between two classes is maximized [27].This approach can be extended to patterns which are linearly separable by transformations of original data to map into new space due to using kernel trick. SVM assigns support vectors that are formed a margin between two classes, thus providing that the data is more separable than in the case of the other classifiers. Support vector machines are naturally resistant to overfitting because any interior points aren't going to affect the boundary.

2.8.3. K_NN

K-NN is used in statistical prediction and pattern recognition as a non-parametric algorithm that is a technique to classify cases according to as their similarity to other cases. The similarity metrics do not consider the relation of attributes that result in the incorrect distance and then impact on classification precision.

K-NN is measured by a distance function such as Euclidean Distance, Minkowski Distance, or Mahalanob is Distance. If K = 1, then the case is simply assigned to the class of its nearest neighbor. Training the nearest neighbor technique requires calculating the distances between cases based on their values in the feature set. The nearest neighbors to a given case have the smallest distances which are calculated by using one of distance method [28]. The k-nn algorithm can be summarized as:

- ✓ A positive integer k is specified, along with a new sample,
- ✓ We select the k entries in our database which are closest to the new sample,
- ✓ We find the most common classification of these entries,
- ✓ This is the classification we give to the new sample.

The model is simple, easy and has to ability to perform very well in the certain data set, however, it requires the large memory storage,and chosen the value of ***k*** to have an important effect the performance of the algorithm.

3. RESULTS

3.1. CLASSIFICATION PERFORMANCE EVALUATION

Before we produce the decision of the machine learning algorithm, we have to point out that some terminology uses to analyze the overall performance of these algorithms. These terms are namely: **Sensitivity, Specificity, and Accuracy.**

Before the explanation these terms we have to explain some metric by brief example:

True Positive Rate (TP) is that the percentage of the unhealthy lung sounds correctly classified as unhealthy.

True Negative Rate (TN) is that the percentage of the healthy lung sounds correctly classified as healthy

False Positive Rate (FP) is that the percentage of the healthy lung sounds classified as unhealthy.

False Negative Rate (FN) is that the percentage of the unhealthy lung sounds classified as healthy.

Classification Sensitivity (%) (Equation 3.1)

$$\boldsymbol{sensitivity = \frac{TP}{TP+FN}} \tag{3.1}$$

Classification Specificity (%) (Equation 6.2)

$$\boldsymbol{specificity = \frac{TN}{TN+FP}} \tag{3.2}$$

If we suppose that number of sample as M accuracy performance is Equation (6.3)

Total Classification Accuracy (%)

$$\boldsymbol{accuracy} = \frac{\boldsymbol{TN+TP}}{\boldsymbol{M}} \times \mathbf{100} \qquad \textbf{(3.3)}$$

In the classification process ANN, SVM, and K_NN are used to decision-making stage health condition of the subject as healthy or pathological. Features are extracted by using parametric and non-parametric power spectral estimation methods. The feature set divided into two set Training (including training) and testing (testing) stages. 50% of the data which is given for classification was used for test and the other half is for learning.

3.1.1. FFT – Welch Method Based Classification Performance Result

In the following section, classification performance of ANN, SVM, and K-NN (as healthy or pathological (patient)) were evaluated based on FFT-Welch spectral method. Table 3.1 and 3.2 are containing confusion matrixes analysis, specificities, and sensitivities based on the ANN and SVM classification algorithms.

Table 3.3 classification accuracies of different machine learning algorithms performance were evaluated based on FFT-Welch spectral estimation methods. It gives decision making information about the health condition of the subject based actual and automatically segmented Lung Sound Signal.

Table 3.1: Confusion matrixes, sensitivity, and specificity values using FFT-Welch based method and ANN for right and left basal inhalation-exhalation sounds.

	Phases	**Class1**		**Class2**	
		Sensitivity (%)	**Specificity (%)**	**Sensitivity (%)**	**Specificity (%)**
Right basal	**Inspiration**	**92**	74	71	92
	Expiration	72	73	68	72
Left basal	**Inspiration**	**96**	73	70	71.8
	Expiration	70	74	71.4	82.6

Table 3.2: Confusion matrixes, sensitivity, and specificity values using FFT-Welch based method and SVM for right and left basal inhalation-exhalation sounds**.**

	Phases	**Class1**		**Class2**	
		Sensitivity (%)	**Specificity (%)**	**Sensitivity (%)**	**Specificity (%)**
Right basal	**Inspiration**	70	82.1	**97**	71.4
	Expiration	72.1	81.7	85	85.7
Left basal	**Inspiration**	88	89.2	91.4	90
	Expiration	71.2	82.2	**94**	73

ANN classification process based on FFT-Welch power spectral estimation method have agood result in inspiration phases both left and right basal of the lung for distinguishing healthy condition of the subject.

SVM classification process based on FFT-Welch power spectral estimation method have agood result in expiration phases both left and right basal of the lung.

Table 3.3: Classification accuracies of FFT-Welch spectral estimation, Actual and automatically segmented Lung Sound Signal of healthy and unhealthy class using ANN, SVM, and K-NN.

	Classification Algorithm	***Classification Accuracy (%) Actual Lung Sound Signal***		***Classification Accuracy (%) Automatically segmented Lung Sound Signal***	
		Inhalation	***Exhalation***	***Inhalation***	***Exhalation***
Right basal	**NN**	81.6	70	71.2	68
	SVM	81.7	73.3	75.4	70.4
	K-NN	**90.4**	**92.4**	**80.2**	**78.2**
Left basal	**NN**	80	70.1	75.3	69
	SVM	90.1	**82.7**	70	71.4
	K-NN	**93.7**	82	81.7	**72.7**

In table 3.3 show overall classification results based on FFT-Welch estimation result and also it gives classification information about automatically segmented lung sound signal. As we can see that classification FFT-Welch based methods segmentation part are not well as well as actually segmented lung sound signals. Especially in exhalation phases of the lung sounds signal, it seems that the result to be close to worse.

Also, we have to mention that, Neural Network-based classification algorithm has worst result according to SVM and K-NN in both actual inhalation- exhalation and automatically segmented inspiration-expiration lung sound signals. In whole classification scheme based on FFT- Welch spectral method, K_NN classification algorithm has remarkable result in both inhalation and exhalation breathing process and also in actual and automatically segmented lung sound signals.

3.1.2. AR Method Based Classification Performance Result

In the following section, classification performance of ANN, SVM, and K-NN (as healthy or pathological (patient)) were evaluated based on AR spectral method. Table 3.4 and 3.5 are containing confusion matrix analysis, specificities, and sensitivities based on the ANN and SVM classification algorithms. Table 3.6Classification accuracies of different machine learning algorithms performance was evaluated based on AR spectral estimation methods. It gives decision making information about the health condition of the subject based actual and automatically segmented Lung Sound Signal.

Table 3.4: Confusion matrixes, sensitivity and specificity values using AR based method and ANN for right and left basal inhalation-exhalation sounds.

	Phases	Class1		Class2	
		Sensitivity (%)	Specificity (%)	Sensitivity (%)	Specificity (%)
Right basal	Inspiration	70	87.5	71	73
	Expiration	88	74.3	74	89.2
Left basal	Inspiration	91.1	83.3	70	75.9
	Expiration	73.8	76.5	86.1	75.6

ANN classification process based on AR power spectral estimation method have agood result in right basal expiration phases and left basal inspiration phase of the lung for distinguishing healthy condition of the subject.

Table 3.5: Confusion matrix, sensitivity and specificity values using AR based method and SVM for right and left basal inhalation-exhalation sounds.

	Phases	Class1		Class2	
		Sensitivity (%)	**Specificity (%)**	**Sensitivity (%)**	Specificity (%)
Right basal	**Inspiration**	83	82.7	**97**	88.9
	Expiration	84.1	74.3	85	87.4
Left basal	**Inspiration**	**95.8**	96.5	**91.4**	93.5
	Expiration	70	84.3	94	75.6

In the whole process of the SVM classification based on AR power spectral estimation method has a good result in left basal inspiration phases both left and right basal of the lung for distinguishing healthy condition of the subject.

In Table 3.6 show overall classification results based on AR spectral estimation result and also it gives classification information about automatically segmented lung sound signal as we can see that classification AR based methods segmentation part are not well as well as actually segmented lung sound signals. Especially in exhalation phases of the lung sounds signal, it seems that the result to be close to worse.

Table 3.6: Classification accuracies of AR based Actual and automatically segmented Lung Sound Signal of healthy and unhealthy class using ANN, SVM, and K-NN.

	Classification Algorithm	*Classification Accuracy (%) Actual Lung Sound Signal*		*Classification Accuracy (%) Automatically segmented Lung Sound Signal*	
		Inhalation	***Exhalation***	***Inhalation***	***Exhalation***
Right basal	**NN**	70	80	69.2	71.1
	SVM	**91.6**	88.3	70.2	**78.6**
	K-NN	90	**92.6**	**78.1**	70.2
Left basal	**NN**	76.6	70	77.1	69
	SVM	**96.6**	78.3	75,7	69.6
	K-NN	96.2	**97.2**	**79.8**	**70.2**

Also, we have to mention that, Neural Network-based classification algorithm has worst result according to SVM and K-NN in both actual inhalation- exhalation and automatically segmented inspiration-expiration lung sound signals. In whole classification scheme based on AR spectral method, K_NN classification algorithm has remarkable result in both inhalation and exhalation breathing process and also in actual and automatically segmented lung sound signals.

3.1.3. ARMA Method Based Classification Performance Result

In the following section, classification performance of ANN, SVM, and K-NN (as healthy or pathological (patient)) were evaluated based on ARMA spectral estimation method. Table 3.7 and Table 3.8 are containing confusion matrix analysis, specificities, and sensitivities based on the ANN and SVM classification algorithms. Table 3.9classification accuracies of different machine learning algorithms performance was evaluated based on ARMA spectral estimation methods. It gives decision making information about the health condition of the subject based actual and automatically segmented Lung Sound Signal.

Table 3.7: Confusion matrixes, sensitivity, and specificity values using ARMA based method and ANN for right and left basal inhalation-exhalation sounds.

	Phases	Class1		Class2	
		Sensitivity (%)	**Specificity (%)**	**Sensitivity (%)**	**Specificity (%)**
Right basal	**Inspiration**	**87.5**	84	**88.9**	91.4
	Expiration	80	70.6	82.4	77.8
Left basal	**Inspiration**	80	70.4	70	73.7
	Expiration	**90**	72	**83.5**	84.4

ANN classification process for healthy and based on ARMA power spectral estimation method have agood result in right basal inspiration phases and left basal expiration phases of the lung for distinguishing healthy condition of the subject.

Table 3.8: Confusion matrixes, sensitivity, and specificity values using ARMA based method and SVM for right and left basal inhalation-exhalation sounds.

	Phases	Class1		Class2	
		Sensitivity (%)	**Specificity (%)**	**Sensitivity (%)**	**Specificity (%)**
Right basal	**Inspiration**	81.4	78	97.2	70
	Expiration	91.7	78.6	71.3	70
Left basal	**Inspiration**	75	72.7	91.7	78.6
	Expiration	70	81.3	76.9	70.1

In the whole process of the SVM classification based on ARMA power spectral estimation method has a good result in left and right basal inspiration phases for distinguishing healthy condition of the subject.

Table 3.9: Classification accuracies of ARMA based Actual and automatically segmented Lung Sound Signal of healthy and unhealthy class using ANN, SVM, and K-NN**.**

	Classification Algorithm	***Classification Accuracy (%) Actual Lung Sound Signal***		***Classification Accuracy (%) Automatically segmented Lung Sound Signal***	
		Inhalation	***Exhalation***	***Inhalation***	***Exhalation***
Right basal	**NN**	88.3	72.2	69.1	68
	SVM	73.3	70.3	72.9	71.9
	K-NN	71	97	65	80.1
Left basal	**NN**	72.2	75	70	74.3
	SVM	70	70	70	73.5
	K-NN	97	90	82.8	88

In table 3.9 show overall classification results based on ARMA power spectral estimation result and also it gives classification information about automatically segmented lung sound signal. As we can see that classification ARMA based methods segmentation part are not well as well as actual segmented lung sound signals. Especially in inhalation phases of the lung sounds signal, it seems that the result to be close to worse.

Also, we have to mention that, SVM-based classification algorithm has worst result according to ANN and K-NN in both actual inhalation- exhalation and automatically segmented inspiration-expiration lung sound signals. In whole classification scheme based on AR spectral method, K_NN classification algorithm has remarkable result in both inhalation and exhalation breathing process and also in actual and automatically segmented lung sound signals

3.1.4. Overall Classification Performance Result

Table 3.10 show the overall classification accuracy result according to different spectral analysis method. It is indicated using ANN, SVM and K_NN show overall classification results by using different machine learning algorithms and spectral estimation based FFT-Welch, AR, and ARMA method and also it gives classification information about automatically segmented lung sound signal.

Classification accuracy according to different spectral analysis is indicated using ANN, SVM, and K_NN

To explain the results in detail;

for right lobe of the lung,

- ✓ K-NN classification algorithm remarkable result by the combination of FFT-Welch spectral estimation method in actual Lung Sound Signal exhalation phase and automatically segmented Lung Sound Signal in inhalation phase.
- ✓ K-NN classification algorithm remarkable result by the combination of AR spectral estimation method in actual Lung Sound Signal exhalation phase and in automatically segmented Lung Sound Signal in inhalation phase by the combination of SVM classification algorithm with AR spectral estimation methods.
- ✓ K-NN classification algorithm remarkable result by the combination of ARMA spectral estimation method in Actual and automatically segmented Lung Sound Signal exhalation phase.

for left lobe of the lung,

- ✓ K-NN classification algorithm remarkable result by the combination of FFT-Welch spectral estimation method in actual and automatically segmented lung sound signal inhalation phase
- ✓ K-NN classification algorithm remarkable result by the combination of AR spectral estimation method in actual Lung Sound Signal exhalation phase and automatically segmented Lung Sound Signal in inhalation phase.
- ✓ K-NN classification algorithm remarkable result by the combination of ARMA spectral estimation method in actual Lung Sound Signal inhalation phase and automatically segmented Lung Sound Signal in exhalation phase.

As we can see that whole process of the classification scheme K_NN remarkable result by the combination parametric and nonparametric based spectral estimation methods in all part of the decision making the stage.

Expiration phases have best classification result for right and left basal of the lung actual and automatically segmentation process.

Table 3.10: Overall Classification accuracies.

Phases	*PSD*	*Classification Algorithm*	*Classification Accuracy (%) Actual Lung Sound Signal*		*Classification Accuracy (%) Automatically segmented Lung Sound Signal*	
			inhalation	*exhalation*	*inhalation*	*exhalation*
Right basal	**FFT-Welch**	**ANN**	**81.6**	**70**	**71.2**	**68**
		SVM	**81.7**	**73.3**	**75.4**	**70.4**
		K-NN	**90.4**	**92.4**	**80.2**	**78.2**
	AR	**ANN**	**70**	**80**	**69.2**	**71.1**
		SVM	**91.6**	**88.3**	**70.2**	**78.6**
		K-NN	**90**	**92.6**	**78.1**	**70.2**
	ARMA	**ANN**	**88.3**	**72.2**	**69.1**	**68**
		SVM	**73.3**	**70.3**	**72.9**	**71.9**
		K-NN	**71**	**97**	**65**	**80.1**
Left basal	**FFT-Welch**	**ANN**	**80**	**70.1**	**75.3**	**69**
		SVM	**90.1**	**82.7**	**70**	**71.4**
		K-NN	**93.7**	**82**	**81.7**	**72,7**
	AR	**ANN**	**76.6**	**70**	**77.1**	**69**
		SVM	**96.6**	**78.3**	**75,7**	**69.6**
		K-NN	**96.2**	**97.2**	**79.8**	**70.2**
	ARMA	**ANN**	**72.2**	**75**	**70**	**74.3**
		SVM	**70**	**70**	**70**	**73.5**
		K-NN	**97**	**90**	**82.8**	**88**

4. DISCUSSION

The main goal of this thesis is that development of exceptional, non-invasive, respectable, easy to use apply and a reliable method to capturing lung sounds and identify health condition of the subject according to Lung sounds. Because these sounds quite important to distinguish normal sounds from the pathological (abnormal) sounds. By the effect of the changes in the structure of the lung, characterization of the sounds has been changed. This change is to hear on the extra or additional sounds so unusual except the normal sounds. Pathological sounds generally an indicator of impending abnormality in the lungs such as an obstruction in the airway passages or pulmonary disease.

In the clinical case, identification of respiration as inspiratory and expiratory phases has essential information. Different breathing cycle (inhalation & exhalation) have their noticeable characteristics respectively because and related to different pathological information so this information is to comprise very important phenomena in the diagnosis of respiratory disease and decision-making about the health condition of the subject.

In this thesis, the first step is to capture lung sounds from the subject in specific auscultation points by using electrets type of sensor recording system. Digitized lung sound data were sending to the computer. The sound signals were then filtering for remove of external and internal noise and also in this part respiratory sound signal divided in different respiratory activities as inspiration and expiration using the method of 'enveloped'. Different feature extraction methods are applied in order to convert raw inspiratory and expiratory sound data some type of parametric features. In the last step, classify the sound signal data as healthy or pathological (unhealthy).

Considering the information has been given in the above; in this thesis, parametric model based AR, ARMA, and non-parametric model based FFT-Welch spectral estimation methods are applied each of the respiratory phases. Power Spectrum of each party inspiration and expiration phases are obtained by using these methods. FFT-Welch, AR, and ARMA methods decide the size of feature vectors for each inspiration and expiration phases. The dimension of feature vectors is too large for an effective classification. Because of the large data size, significant information and dependency cannot efficient inferred. For the successful and short time classification process and performance, the dimension of features vectors should be reduced. In many studies, wavelet coefficients of frequency intervals produced by DWT have been used as features of respiratory sounds. But, in this study, decomposition rule of DWT was only used to determine the useful frequency intervals. In order to reduce the data size of the extracted feature vectors, we divided a 0-2000 Hz frequency band of PSDs into intervals.

The classification scheme by different machine learning algorithms, the best performance accrued by the K_NN classification methods by the combination parametric and nonparametric based spectral estimation methods in all part of the decision making the stage especially in expiration phase. Also, in the whole process of classification, to deciding on the healthy condition of the subject analysis according to inhalation and exhalation phases, the study suggest that, best diagnosis performance obtained as with an accuracy of approximately 97.2% the actually segmented lung sounds by the combination of AR based model with K_NN classification methods in expiration phase and the accuracy of approximately 88 % automatically segmented lung sound by the combination of ARMA based model with K-NN classification methods in expiration phase.

5. CONCLUSION AND RECOMMENDATIONS

The detection and analysis of lung sounds or respiratory sounds is helpful in distinguish abnormalities in breathing patterns. In this application we have examined lung sound signals analysis; part of inhalation and exhalation respiratory phases are obtained from left and right side of the lung in special auscultation points by the help of the sensor. Additionally, decision-making process like healthy or pathological performed based on respiratory activities of inhalation and exhalation separately for each phase.

The mechanism of breath sounds is probably generated by the turbulence of the air at the level of lobar or segmental bronchi. During breathing activity, the process takes a place as a result of changes air flow in the lungs. Breathing activity in other word respiration process consists of two phases' inhalation and exhalation. Inhalation process the airway is expanding, in contrast, exhalation process airway, is narrower, so intensity level is different from each other.

Respiratory sounds ventilation cycle (inhale & exhale) characteristic information is to provide essential information about respiratory disorders and pathological condition of patient. Because, inhalation and exhalation phases have their noticeable characteristics as mentioned related to different pathological information so this information is to comprise very important phenomena in the diagnosis of respiratory disease and decision-making about the health condition of the subject.

Using the various types of classification algorithms (ANN, SVM and K_NN) the lung sound signals classified as normal or pathological according to ventilation cycle. The best performance accrued by the K_NN classification methods by the combination parametric and nonparametric based spectral estimation methods in all part of the decision making the stage especially in expiration phase. Also, in the whole process of classification, to deciding on the healthy condition of the subject analysis according to inhalation and exhalation phases, the study suggest that, best diagnosis performance obtained as with an accuracy of approximately 97.2% the actually segmented lung sounds by the combination of AR based model with K_NN classification methods in expiration phase and the accuracy of approximately 88 % automatically segmented lung sound by the combination of ARMA based model with K-NN classification methods in expiration phase.

In this work lung sound signals recorded from participate; normal, asthmatic and chronic obstructive lung disease (COPD) subjects. These sounds recorded during normal breathing, in regular respiration cycle, both left and right posterior bases of the lungs in the same location. This group of lung sounds is related to obstructive lung disease and this pattern of dysfunction makes difficulty in exhaled because of narrowing or blockage of airways. In the whole decision-making process, exhaling phase seems to give better results in diagnosing of the lung disease. This has been proven clinically as the correctness of the study.

In some cases, the automatic respiratory cycle determination and segmentation of respiratory phases provide alternative way of medical diagnosis and way to decrees diagnosis time using intelligent model. It is essential importance to the diagnosis of the respiratory disorders. It might help to diagnose complex cases which are difficult to perceive. Physicians can combine this possibility and their knowledge to detect early stage of respiratory disease.

REFERENCES

[1]. E. Andrès, A. Hajjam, and C. Brandt, “Advances and innovations in the field of auscultation, with a special focus on the development of new intelligent communicating stethoscope systems,” *Health Technol. (Berl).*, vol. 2, no. 1, pp. 5–16, 2012.

[2]. N. Boucher, A. Prystupa, A. Witczak, E. Walczak, and G. Dzida, “Lung auscultation – Identification of common lung sound abnormalities and associated pathologies,” vol. 7, no. 1, pp. 32–35, 2013.

[3]. “Pulmonary Concepts In Critical Care Breath Sounds.” [Online]. Available: http://micunursing.com/breath.htm.

[4]. a R. a Sovijärvi, F. Dalmasso, J. Vanderschoot, L. P. Malmberg, and G. Righini, “Definition of terms for applications of respiratory sounds,” *Eur Respir. Rev*, vol. 10, no. 77, pp. 597–610, 2000.

[5]. L. J. Hadjileontiadis, *Lung Sounds: An Advanced Signal Processing Perspective*, vol. 3, no. 1. 2008.

[6]. J. G. Proakis, D. G. Monolakis, G. Proakis John, and G. Manolakis Dimitris, *Digital signal processing: principles, algorithms, and applications*. 1996.

[7]. “www.differerencesbetween.net.” [Online]. Available: www.differerencesbetween.net.

[8]. R. Care, “Lung Disorders Introduction to Respiratory Care,” pp. 1–31.

[9]. Limmer et al, “No Title,” in *emergency Care*, 11th ed., .

[10]. Lippincott Williams & Wilkins, “auscultation skills,” in *Auscultation Skills: Breath & Heart Sounds*, 2009, pp. 171-173–173.

[11]. “USA lungs.” [Online]. Available: http://www.lung.org/.

[12]. A. Cohen and D. Landsberg, “Analysis and automatic classification of breath sounds.,” *IEEE Trans. Biomed. Eng.*, vol. 31, pp. 585–590, 1984.

[13]. B. Sankur, Y. P. Kahya, E. C. Gulert, and T. Engin, “Comparison of AR-based algorithms for respiratory sounds classification,” *Comput. Biol. Med.*, vol. 24, pp. 67–76, 1994.

[14]. S. Rietveld, M. Oud, and E. H. Dooijes, “Classification of asthmatic breath sounds: preliminary results of the classifying capacity of human examiners versus artificial neural networks.,” *Comput. Biomed. Res.*, vol. 32, pp. 440–448, 1999.

[15]. D. Z. and O. T., “Classification of respiratory sounds by using an artificial neural network,” *Int. J. Pattern Recognit. Artif. Intell.*, vol. 17, pp. 567–580, 2003.

[16]. L. J. Hadjileontiadis and S. M. Panas, “Separation of discontinuous adventitious sounds

from vesicular sounds using a wavelet-based filter," *IEEE Trans. Biomed. Eng.*, vol. 44, pp. 1269–1281, 1997.

[17]. A. Kandaswamy, C. S. Kumar, R. P. Ramanathan, S. Jayaraman, and N. Malmurugan, "Neural classification of lung sounds using wavelet coefficients," *Comput. Biol. Med.*, vol. 34, pp. 523–537, 2004.

[18]. M. Yeginer, K. Ciftci, U. Cini, I. Sen, G. Kilinc, and Y. P. Kahya, "Using lung sounds in classification of pulmonary diseases according to respiratory subphases.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 1, pp. 482–485, 2004.

[19].. H. G. Martinez-Hernandez, C. T. Aljama-Corrales, R. Gonzalez-Camarena, V. S. Charleston-Villalobos, and G. Chi-Lem, "Computerized classification of normal and abnormal lung sounds by multivariate linear autoregressive model.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 6, pp. 5999–6002, 2005.

[20]. I. Güler, H. Polat, and U. Ergün, "Combining neural network and genetic algorithm for prediction of lung sounds," *J. Med. Syst.*, vol. 29, pp. 217–231, 2005.

[21].. E. C. Güler, B. Sankur, Y. P. Kahya, and S. Raudys, "Two-stage classification of respiratory sound patterns," *Comput. Biol. Med.*, vol. 35, pp. 67–83, 2005.

[22]. Y. P. Kahya, M. Yeginer, and B. Bilgic, "Classifying respiratory sounds with different feature sets," in *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, 2006, pp. 2856–2859.

[23]. M. Bahoura, "Pattern recognition methods applied to respiratory sounds classification into normal and wheeze classes," *Comput. Biol. Med.*, vol. 39, pp. 824–843, 2009.

[24]. A. Parkhi and M. Pawar, "Analysis of deformities in lung using short time Fourier transform spectrogram analysis on lung sound," in *Proceedings - 2011 International Conference on Computational Intelligence and Communication Systems, CICN 2011*, 2011, pp. 177–181.

[25]. A. Hashemi, H. Arabalibiek, and K. Agin, "Classification of wheeze sounds using wavelets and neural networks," *Int. Conf. Biomed. Eng. Technol.*, vol. 11, pp. 127–131, 2011.

[26]. P. Mayorga, C. Druzgalski, O. H. Gonzalez, and H. S. Lopez, "Modified classification of normal lung sounds applying Quantile vectors," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2012, pp. 4262–4265.

[27]. S. Abbasi, R. Derakhshanfar, A. Abbasi, and Y. Sarbaz, "Classification of normal and abnormal lung sounds using neural network and support vector machines," *2013 21st Iran. Conf. Electr. Eng.*, pp. 1–4, May 2013.

[28]. S. Matsutake, M. Yamashita, and S. Matsunaga, "DISCRIMINATION BETWEEN HEALTHY SUBJECTS AND PATIENTS USING LUNG," pp. 1296–1300, 2013.

[29]. R. Palaniappan, K. Sundaraj, N. Ahamed, A. Arjunan, and S. Sundaraj, “Computer-based Respiratory Sound Analysis: A Systematic Review,” *IETE Tech. Rev.*, vol. 30, p. 248, 2013.

[30]. R. Palaniappan, K. Sundaraj, and S. Sundaraj, “Artificial intelligence techniques used in respiratory sound analysis--a systematic review.,” *Biomed. Tech. (Berl).*, vol. 59, pp. 7–18, 2014.

[31]. A. Rizal, R. Hidayat, and H. A. Nugroho, “Signal Domain in Respiratory Sound Analysis : Methods , Application and Future Development,” vol. 11, no. 1005–1016, 2015.

[32]. G. Serbes, C. Ş. Okan, Y. Kahya, and N. Ayd, “ZAMAN-FREKANS ANAL İ Z İ KULLANARAK PULMONER ÇITIRTI TESP İ T İ PULMONARY CRACKLE DETECTION USING TIME-FREQUENCY ANALYSIS,” pp. 12–15, 2012.

[33]. J. V. Mankar and P. K. Malviya, “Analysis of lung diseases and detecting deformities in human lung by classifying lung sounds,” *2014 Int. Conf. Commun. Signal Process.*, pp. 1059–1063, Apr. 2014.

[34]. P. Gadge, B. Mokal, and U. Bagal, “Respiratory Sound Analysis using MATLAB,” *Int. J. Sci. Eng. Res.*, vol. 3, pp. 1–4, 2012.

[35]. S. Sello, S. kyung Strambi, G. De Michele, and N. Ambrosino, “Respiratory sound analysis in healthy and pathological subjects: A wavelet approach,” *Biomed. Signal Process. Control*, vol. 3, pp. 181–191, 2008.

[36]. S. Uysal, H. Uysal, B. Bolat, and T. Yıldırım, “Classification of Normal and Abnormal Lung Sounds Using Wavelet Coefficients,” *2014 IEEE 22nd Signal Process. Commun. Appl. Conf. (SIU 2014)*, no. Siu, pp. 2138–2141, 2014.

[37]. R. M. Rady, I. Mohamed, E. Akkary, A. N. Haroun, and N. A. Elmoneum, “Respiratory Wheeze Sound Analysis Using Digital Signal Processing Techniques,” pp. 5–8.

[38]. S. Ulukaya and T. Üniversitesi, “Üfürüm Tipinin Belirlenmesi için Yeni Bir Yöntem A Novel Method for Determination of Wheeze Type,” 2015.

[39]. K. Zhang, X. Wang, F. Han, and H. Zhao, “The detection of crackles based on mathematical morphology in spectrogram analysis,” *Technol. Heal. Care*, vol. 23, no. s2, pp. S489–S494, 2015.

[40]. X. Lu and M. Bahoura, “An integrated automated system for crackles extraction and classification,” *Biomed. Signal Process. Control*, vol. 3, pp. 244–254, 2008.

[41]. A. Haider, M. D. Ashraf, M. U. Azhar, S. O. Maruf, M. Naqvi, S. G. Khawaja, and M. U. Akram, “Separation and Classification of Crackles and Bronchial Breath Sounds from Normal Breath Sounds Using Gaussian Mixture Model,” vol. 8835, pp. 495–502, 2014.

[42]. “Classification_Respiratory_Sounds.” .

[43]. G. Güçlü, B. Karlik, and H. R. Öz, "Akciğer Ses Sinyallerinin Nefes Alma ve Nefes Vermeye Bağlı Olarak Sınıflandırılması Classification of Pulmonary Sound Signals Based on Inhalation and Exhalation," pp. 4–7, 2000.

[44]. A. Abushakra, M. Faezipour, and A. Abumunshar, "Efficient frequency-based classification of respiratory movements," *2012 IEEE Int. Conf. Electro/Information Technol.*, pp. 1–5, 2012.

[45]. L. R. Waitman, K. P. Clarkson, J. a. Barwise, and P. H. King, "Representation and classification of breath sounds recorded in an intensive care setting using neural networks," *J. Clin. Monit. Comput.*, vol. 16, pp. 95–105, 2000.

[46]. S. S. V R, V. Gupta, V. Parthasarathy, P. K. S, and V. Mahesh, "Comparison of Classifier Performance in their Ability to Classify Respiratory Sounds," pp. 1–5, 2014.

[47]. L. J. Hadjileontiadis, "Discrimination analysis of discontinuous breath sounds using higher-order crossings," *Med. Biol. Eng. Comput.*, vol. 41, no. 4, pp. 445–455, 2003.

[48]. X. Lu and M. Bahoura, "An automatic system for crackles detection and classification," in *Canadian Conference on Electrical and Computer Engineering*, 2007, pp. 725–729.

[49]. G. Dorantes-Méndez, S. Charleston-Villalobos, R. González-Camarena, G. Chi-Lem, J. G. Carrillo, and T. Aljama-Corrales, "Crackles detection using a time-variant autoregressive model.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2008, pp. 1894–7, 2008.

[50]. S. Aydore, I. Sen, Y. P. Kahya, and M. Kivanc Mihcak, "Classification of respiratory signals by linear analysis," in *Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009*, 2009, pp. 2617–2620.

[51]. I. Sen, M. Saraclar, and Y. P. Kahya, "Acoustic mapping of the lung based on source localization of adventitious respiratory sound components," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2010, pp. 3670–3673.

[52]. M. Bahoura and C. Pelletier, "New parameters for respiratory sound classification," in *Canadian Conference on Electrical and Computer Engineering, 2003. IEEE CCECE 2003.*, 2003, vol. 3, pp. 1457–1460 vol.3.

[53]. K. S. Baydar, a. Ertuzun, and Y. P. Kahya, "Analysis and classification of respiratory sounds by signal coherence method," *Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (IEEE Cat. No.03CH37439)*, vol. 3, no. 2, pp. 2–5, 2003.

[54]. M. Bahoura and C. Pelletier, "Respiratory sounds classification using cepstral analysis and Gaussian mixture models.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 1, no. 2, pp. 9–12, 2004.

[55]. S. Matsunaga, K. Yamauchi, M. Yamashita, and S. Miyahara, "Classification between normal and abnormal respiratory sounds based on maximum likelihood approach," *2009*

IEEE Int. Conf. Acoust. Speech Signal Process., 2009.

[56]. F. Jin, S. Krishnan, and F. Sattar, “Adventitious sounds identification and extraction using temporal-spectral dominance-based features,” *IEEE Trans. Biomed. Eng.*, vol. 58, no. 11, pp. 3078–3087, 2011.

[57]. A. Kandaswamy, C. S. Kumar, R. P. Ramanathan, S. Jayaraman, and N. Malmurugan, “Neural classification of lung sounds using wavelet coefficients,” *Comput. Biol. Med.*, vol. 34, no. 6, pp. 523–537, 2004.

[58]. M. Bahoura and C. Pelletier, “Respiratory sounds classification using Gaussian mixture models,” in *Electrical and Computer Engineering, 2004. Canadian Conference on*, 2004, vol. 3, pp. 1309–1312.

[59]. F. Jin, F. Sattar, and D. Y. T. Goh, “Automatic wheeze detection using histograms of sample entropy.,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society*, 2008, vol. 2008, pp. 1890–3.

[60]. Y. P. Kahya, U. Cini, and O. Cerid, “Real-time regional respiratory sound diagnosis instrument,” *Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (IEEE Cat. No.03CH37439)*, vol. 4, pp. 3098–3101, 2003.

[61]. H. Polat and I. Güler, “A simple computer-based measurement and analysis system of pulmonary auscultation sounds,” *J. Med. Syst.*, vol. 28, no. 6, pp. 665–672, 2004.

[62]. S. Matsunaga, K. Yamauchi, M. Yamashita, and S. Miyahara, “Classification between normal and abnormal respiratory sounds based on maximum likelihood approach,” in *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2009, pp. 517–520.

[63] I. Sen and Y. P. Kahya, “A multi-channel device for respiratory sound data acquisition and transient detection.,” *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 6, pp. 6658–6661, 2005.

[64]. H. Pasterkamp, S. S. Kraman, and G. R. Wodicka, “Respiratory sounds: Advances beyond the stethoscope,” *American Journal of Respiratory and Critical Care Medicine*, vol. 156, no. 3 I. pp. 974–987, 1997.

[65]. J. A. Fiz, R. Jan??, M. Lozano, R. G??mez, and J. Ruiz, “Detecting unilateral phrenic paralysis by acoustic respiratory analysis,” *PLoS One*, vol. 9, no. 4, 2014.

[66]. F. Nogata, Y. Yokota, Y. Kawamura, H. Morita, and Y. Uno, “2015 , AJCIS , Audio-visual recognition of auscultatory breathing sounds using FFT & wavelet , 2925-11144-1-PB Audio-visual Recognition of Auscultatory Breathing Sounds using Fourier and Wavelet Analyses,” no. November 2015, 2016.

[67]. I. Sen, M. Saraclar, and Y. P. Kahya, “A Comparison of SVM and GMM-Based Classifier Configurations for Diagnostic Classification of Pulmonary Sounds.,” *IEEE Trans. Biomed. Eng.*, vol. 62, no. 7, pp. 1768–76, 2015.

[68]. N. Q. Al-Naggar, “A new method of lung sounds filtering using modulated least mean square — Adaptive noise cancellation,” *J. Biomed. Sci. Eng.*, vol. 2013, no. September, pp. 869–876, 2013.

[69]. P. D. Welsby, G. Parry, and D. Smith, “The stethoscope: some preliminary investigations.,” *Postgrad. Med. J.*, vol. 79, no. 938, pp. 695–8, 2003.

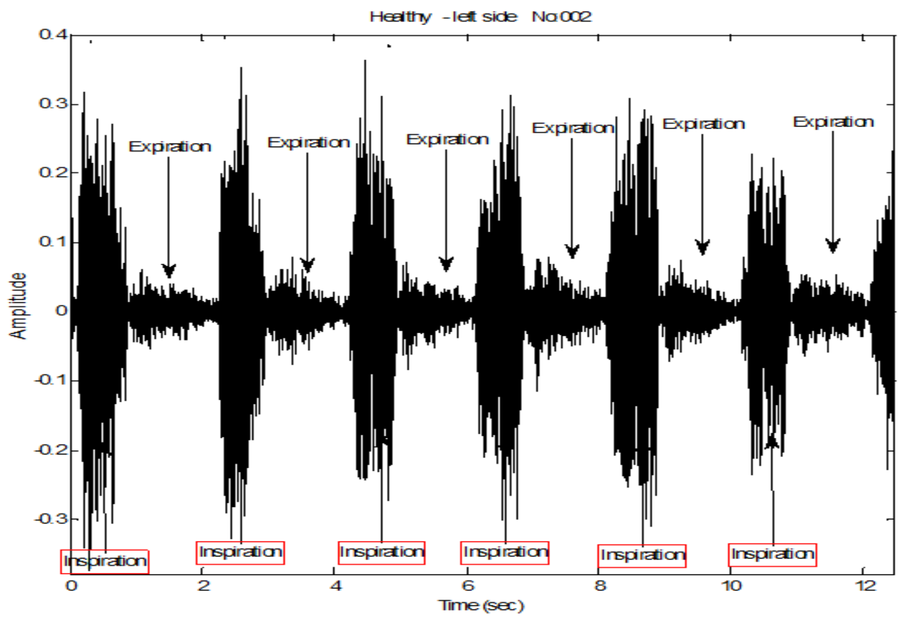
[70]. I. Güler, H. Polat, and U. Ergün, “Combining neural network and genetic algorithm for prediction of lung sounds,” *J. Med. Syst.*, vol. 29, no. 3, pp. 217–231, 2005.

[71]. A. Alkan and A. S. Yilmaz, “Frequency domain analysis of power system transients using Welch and Yule-Walker AR methods,” *Energy Convers. Manag.*, vol. 48, no. 7, pp. 2129–2135, 2007.

APPENDICES

Diagnosis values information for all subject and segmentation.

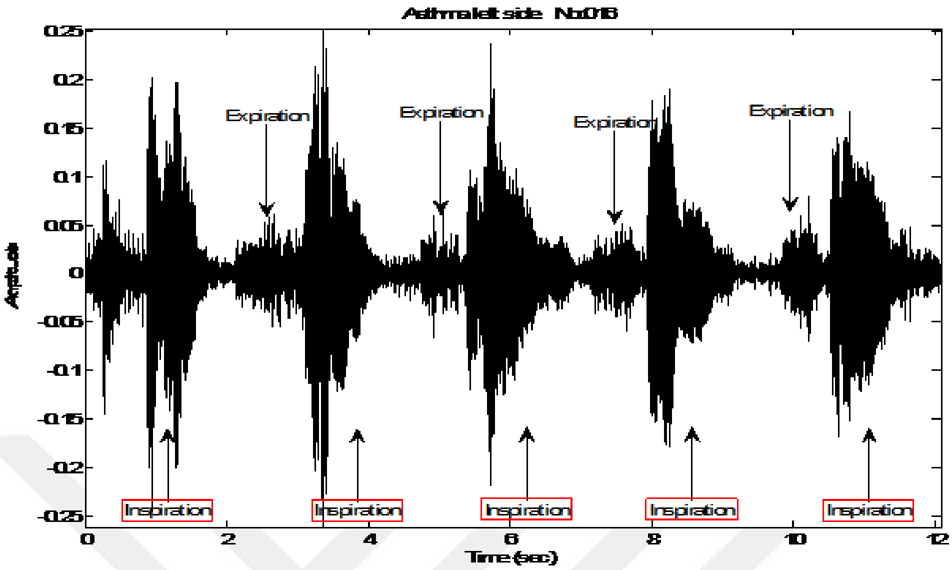
APPENDIX 1. Time-amplitude of the healthy subject.



APPENDIX 2. Respiratory phase time.

Breath Cycle	***Inhale starting***	***Inhale ending***	***Inhale total duration***	***Exhale***	***Exhale ending***	***Exhale total duration***
1	0.119	0.858	0.739	0.95	2.245	1.295
2	2.3	2.945	0.645	3.001	4.186	1.185
3	4.29	4.926	0.636	5.001	6.154	1.153
4	6.2	6.897	0.697	6.909	8.146	1.237
5	8.17	8.955	0.785	9.101	10.209	1.108
6	10.291	10.895	0.604	11	12.48	1.48

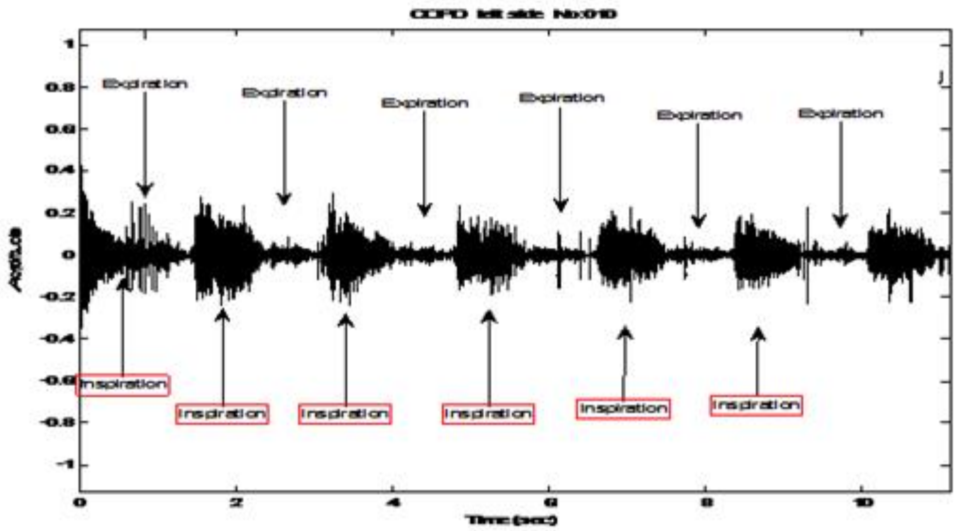
APPENDIX 3. Time - amplitude of the unhealthy subject.



APPENDIX 4. Respiratory phase time.

Breath Cycle	*Inhale starting*	*Inhale ending*	*Inhale total duration*	*Exhale Starting*	*Exhale ending*	*Exhale total duration*
1	0.845	1.625	0.78	1.7	3.027	1.327
2	3.08	3.993	0.913	4.113	5.311	1.198
3	5.367	6.407	1.04	6.502	7.911	1.409
4	8.001	8.867	0.866	9.001	10.438	1.437
5	10.501	11.588	1.087			

APPENDIX 5. Time - amplitude of the unhealthy subject.



APPENDIX 6. Respiratory phase time.

Breath Cycle	*Inhale starting*	*Inhale ending*	*Inhale total duration*	*Exhale starting*	*Exhale ending*	*Exhale total duration*
1	0.001	0.607	0.606	0.671	1.41	0.739
2	1.501	2.268	0.767	2.391	3.111	0.72
3	3.121	4.06	0.939	4.161	4.752	0.591
4	4.781	5.701	0.92	5.801	6.547	0.746
5	6.581	7.59	1.009	7.61	8.351	0.741
6	8.401	9.257	0.856	9.271	10.06	0.789
7	10.92	10.941	0.021	-	-	-

APPENDIX 7. Diagnosis values about the Asthma subjects'.

id	smoke	age	sex	indicator	diagnosis
N001	Yes	48	k	Bilateral wheezing	Asthma
N002	No	59	k	Bilateral common wheezing	Asthma
N003	Yes	62	k	Extended expiration	Asthma
N004	Yes	27	k	Bilateral rhonchi	Asthma
N005	Yes	60	e	Common wheezing	Asthma
N006	Yes	58	k	Normal	Asthma
N007	Yes	32	k	Crackles	Asthma
N008	Yes	40	e	Stridor	Asthma
N009	No	19	k	Bilateral crackles, stridor, rhonchi	Asthma
N010	No	49	k	Right lung sounds rare crackles ,in left lung sounds inspiration and expiration thin ral	Severe Asthma
N011	Yes	48	e	Lung wheezing both phases and but in right lung clear and right side bronchial respiration	Asthma
N012	No	60	k	Common wheezing	Asthma
N013	No	59	k	Inspiration diffusive wheezing	Asthma
N014	No	55	k	Wheeze	Asthma
N015	No	16	e	Wheezing	Mild Asthma
N016	No	55	k	Bilateral wheezing and right side thin crackles	Asthma
N017	No	34	k	Asthma	Asthma
N018	No	16	e	Left and right-side inspiration middle crackles'	Asthma
N019	No	55	k	In right side rare crackles	Asthma
N020	No	63	k	As clear as wheezing	Asthma
N021	Yes	49	e	Normal	Bronchitis-asthma
N022	No	60	k	Common wheezing	Asthma
N023	No	59	k	Inspiration diffusive wheezing	Asthma
N024	No	55	k	Rare wheezing	Asthma
N025	No	16	e	Wheezing	Mild Asthma

APPENDIX 8. Diagnosis values about the Healthy subjects'.

id	smoke	age	sex	indicator	diagnosis
N001	No	48	F	Normal	Normal
N002	No	41	M	Normal	Normal
N003	No	18	F	Normal	Normal
N004	No	40	F	Normal	Normal
N005	No	63	F	Normal	Normal
N006	No	39	M	Normal	Normal
N007	No	38	M	Normal	Normal
N008	No	37	M	Normal	Normal
N009	Yes	45	M	Normal	Normal
N010	No	30	F	Normal	Normal
N011	Yes	35	M	Normal	Normal
N012	Yes	30	F	Normal	Normal
N013	No	24	M	Normal	Normal
N014	Yes	41	M	Normal	Normal
N015	Yes	52	F	Normal	Normal
N016	No	55	M	Normal	Normal
N017	Yes	38	M	Normal	Normal
N018	Yes	29	F	Normal	Normal
N019	No	32	F	Norma	Normal
N020	No	45	M	Normal	Normal
N021	No	51	F	Normal	Normal
N022	No	29	M	Normal	Normal
N023	No	46	M	Normal	Normal
N024	No	52	M	Normal	Normal
N025	No	45	M	Normal	Normal

APPENDIX 9. Diagnosis values about the COPD subjects.

id	smoke	age	sex	indicator	diagnosis
N001	Yes	80	M	Bilateral expiration, Left lobe common wheeze both phase	Severe COPD
N002	Yes	52	M	Bilateral long expiration	COPD
N003	No	67	M	Long expiration	COPD
N004	No	50	F	Raller	COPD
N005	Yes	51	F	Bilateral long expiration, wheeze and thin raller	COPD
N006	Yes	67	M	Normal	COPD
N007	Yes	50	M	Long wheeze	COPD
N008	Yes	40	M	Stridor	COPD
N009	No	45	F	Bilateral wheeze	COPD
N010	No	51	F	Bilateral long expiration	COPD

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Publications

[1]. F. Z. Göğüş, B. Karlık, and G.Harman, " Identification of Pulmonary Disorders by Using Different Spectral Analysis Methods ", International Journal of Computational Intelligence Systems (IJCIS) ., Vol. 9, No.4 pp.595-611 June 2016

[2]. Güneş Harman, "Classification of Normal and Asthmatic Sounds Using Fuzzy Clustering Based Cascade Classifier Methods", Computer Methods and Programs in Biomedicine. (under review)

<u>Conference Proceedings</u>

[1]. Fatma Z. Göğüş, BekirKarlık, and Güneş Harman, "Classification of Asthmatic Breath Sounds by Using Wavelet Transforms and Neural Networks," International Journal of Signal Processing Systems, Vol. 3, No. 2, pp. 106-111, December 2015. doi: 10.12720/ijsps.3.2.106-111