ENHANCING MACHINE LEARNING ALGORITHMS IN HEALTHCARE WITH ELECTRONIC STETHOSCOPE

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Murat AYKANAT

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We have read the thesis entitled **"ENHANCING MACHINE LEARNING ALGORITHMS IN HEALTHCARE WITH ELECTRONIC STETHOSCOPE"** completed by **MURAT AYKANAT** under the supervision of **ASST. PROF. DR. ÖZKAN KILIÇ** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

Asst. Prof. Dr. Özkan KILIÇ

Supervisor

Asst. Prof. Dr. Rahime BELEN SAĞLAM

Jury Member

Prof. Dr. Emine Bahar KURT

Jury Member

Asst. Prof. Dr. Osman Serdar GEDİK

Jury Member

Asst. Prof. Dr. Gül TOKDEMİR

Jury Member

Prof. Dr. Fatih V. ÇELEBİ

Director

Graduate School of Natural and Applied Sciences

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Signature:

Date: 11/06/2018 **Name & Surname: Murat Aykanat**

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ENHANCING MACHINE LEARNING ALGORITHMS IN HEALTHCARE WITH ELECTRONIC STETHOSCOPE

ABSTRACT

In this study, our aim is to classify respiratory sounds and diseases via audio and text data recorded by an electronic stethoscope using convolutional neural networks (CNNs), support vector machines (SVMs), k-nearest neigbor (k-NN) and Gaussian Bayes (GB) algorithms on a dataset that contains 17,930 lung sounds that were recorded from 1630 subjects.

For classifying respiratory sounds, we employed; SVM, k-NN and GB with mel frequency cepstral coefficient (MFCC) features and CNN with 28x28 and 600x600 spectrogram images. We prepared 4 datasets to classify respiratory audio into: (1) healthy versus pathological; (2) rale, rhonchus, and normal sound; (3) singular respiratory sound type; and (4) audio type with all sound types classification. Accuracy results in percent were; (1) CNN 86 and 95, SVM 86, k-NN 85, GB 58, (2) CNN 80 and 93, SVM 80, k-NN 79, GB 42, (3) CNN 76 and 85, SVM 75, k-NN 76, GB 22 and (4) CNN 62 and 77, SVM 62, k-NN 61, GB 15 respectively.

For classifying respiratory diseases, SVM, k-NN and GB algorithms were run on 6 datasets to classify patients into; (1) ill or healthy with text data, (2) ill or healthy with audio MFCC features, (3) ill or healthy with the text data and audio MFCC features, (4) 12 diseases with text data, (5) for 12 disease with audio MFCC features, (6) for 12 disease with the text data and audio MFCC features. Accuracy results in percent for SVM were 75, 88, 64, 73, 63, 70; for k-NN 95, 92, 92, 67, 64, 66; for GB 98, 91, 97, 58, 48, 58 respectively.

To compare the electronic and traditional stethoscope, 3 chest physicians assessed 100 audio clips. We observed; good level consistency between physicians 2 and 3, average level consistency between physicians 1, 3 and 1, 2 via kappa statistic method.

Keywords: Convlutional neural netwoks, support verctor machines, lung diseases, lung sounds, electronic stethoscope

TIPTA ELEKTRONİK STETOSKOP KULLANARAK MAKİNE ÖĞRENMESİ ALGORİTMALARI GELİŞTİRİLMESİ

ÖZ

Bu çalışmada, 1.630 denekten elektronik stetoskop ile kaydedilen 17.930 ses ve metin verisinden oluşan bir veri kümesinde, konvolüsyonel sinir ağları (CNN), destek vektör makineleri (SVM), k en yakın komşuluk (k-NN) ve Gaussian Bayes (GB) algoritmaları kullanılarak, solunum seslerinin ve akciğer hastalıklarının sınıflandırılması amaçlanmıştır.

Solunum seslerini sınıflandırmak için; Mel frekanslı kepstral katsayısı (MFCC) özellikleri ile SVM, k-NN, GB ve ayrıca 28x28 ve 600x600 spektrogram görüntüleri ile CNN kullandık. Solunum seslerini sınıflandırmak için 4 veri kümesi hazırladık: (1) sağlıklı ve patolojik ses; (2) ral, ronküs ve normal ses; (3) tekil solunum sesi tipi; ve (4) tüm ses türlerini içeren sınıflandırma. Kesinlik sonuçları yüzde olarak sırasıyla; (1) CNN 86 ve 95, SVM 86, k-NN 85, GB 58, (2) CNN 80 ve 93, SVM 80, k-NN 79, GB 42, (3) CNN 76 ve 85, SVM 75, k-NN 76, GB 22, (4) CNN 62 ve 77, SVM 62, k-NN 61, GB 15 olarak bulundu.

Hastaları hastalıklarına göre sınıflandırmak için 6 veri kümesinde SVM, k-NN ve GB algoritmaları çalıştırıldı; (1) metin verisine göre hasta veya sağlıklı, (2) ses verisindeki MFCC özelliklerine göre hasta veya sağlıklı, (3) ses verisindeki MFCC özellikleri ve metin verileri ile hasta veya sağlıklı, (4) metin verilerine göre 12 hastalık, (5) ses verisindeki MFCC özelliklerine göre 12 hastalık, (6) ses verisindeki MFCC özellikleri ve metin verileri ile 12 hastalık. Kesinlik sonuçları yüzde olarak sırasıyla SVM için 75, 88, 64, 73, 63, 70; k-NN için 95, 92, 92, 67, 64, 66; GB için 98, 91, 97, 58, 48, 58 olarak bulundu.

Geleneksel ve elektronik stetoskobu karşılaştırmak için 3 uzman doktor, 100 sesi değerlendirdi. Kappa istatistik yöntemi ile 2. ile 3. doktor arasında iyi düzeyde, 1. ile 3. ve 1. ile 2. doktor arasında ise ortalama düzeyde tutarlılık gözlemlendi.

Anahtar Sözcükler: Konvolüsyonel sinir ağları, destek vektör makineleri, akciğer hastalıkları, akciğer sesleri, elektronik stetoskop

CONTENTS

NOMENCLATURE

Acronyms

AI	Artificial Intelligence
AIS	Artificial Immune System
ANN	Artificial Neural Network
AR	Autoregressive Model
BP	Back-propagation
C	Control
CA	Cancer
CAD	Coronary Artery Disease
CD	Cycles Duration
CDBN	Convolutional Deep Belief Network
CHF	Congestive Heart Failure
CNN	Convolutional Neural Network
COPD	Chronic Obstructive Pulmonary Disease
CORSA	Computerized Respiratory Sound Analysis
Cpm	Cycles per Minute
CPNN	Constructive Probabilistic Neural Network
CRD	Chronic Respiratory Diseases
CT	Computed Tomography
CWT	Continuous Wavelet Transform
DBM	Deep Boltzmann Machine
DBN	Deep Belief Network
DDA	Dynamic Decay Adjustment
DFT	Discrete Fourier Transform
DNN	Deep Neural Network
DPCN	Deep Coding Network
DQN	Deep Q-Networks
DSN	Deep Stacking Network
DTW	Dynamic Time Warping
DWT	Discreate Wavelet Transform
FD	Fractal-dimension
FEV	Forced Expiratory Volume

FEV1	Forced Expiratory Volume in 1st second
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
FRFT	Fractional Fourier Transform
FRWT	Fractional Wavelet Transform
FT	Fourier Transform
FV	Feature Vector
FVC	Forced Vital Capacity
GA	Genetic Algorithm
GANN	Genetic Algorithm-Neural Network
GB	Gaussian Bayes
GMM	Gaussian Mixture Model
GRNN	Generalized Regression Neural Network
HHS	Hilbert-Huang Spectrum
Hz	Hertz
HMM	Hidden Markov Model
I:E	Inspiratory-Expiratory Ratio
ICD-10	International Classification of Diseases
IDW	Initial Deflection Width
IIR	Infinite Impulse Response
ILD	Interstitial Lung Disease
ILSA	International Lung Sound Association
IOS	Impulse Oscillometry
IPF	Interstitial Pulmonary Fibrosis
ISNN	Incremental Supervised Neural Network
KFD	Katz's Fractal Dimension
k-NN	k-Nearest Neighbor
LDW	Largest Initial Deflection
LED	Long Expirium Duration
LFCC	Linear Frequency Cepstral Coefficient
LPC	Linear Predictive Coding
LVQ	Learning Vector Quantization
MA	Moving-average Model
MAR	Multivariate Autoregressive Model

MFC	Mel Frequency Cepstrum
MFCC	Mel Frequency Cepstrum Coefficients
MKM	Multilayer Kernel Machine
MLNN	Multilayer Neural Network
MLP	Multi-layer Perceptron
MRI	Magnetic Resonance Imaging
MSPCA	Multi-scale Principal Component Analysis
N	Subject
NMC	Nearest Mean Classifier
NN	Neural Network
P	Patient
PCA	Principal Component Analysis
PE	Pulmonary Embolism
PFT	Pulmonary Function Test
PN	Pneumonia
PNN	Probabilistic Neural Network
PTE	Pulmonary Thromboembolism
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
RBM	Restricted Boltzmann Machine
ReLU	Rectified Linear Unit
RMS	Root-Mean-Squared
RNN	Recurrent Neural Network
S	Sound
SBC	Subband Based Cepstral
SGD	Stochastic Gradient Descent
SNPT	Smear Negative Pulmonary Tuberculosis
SNR	Signal-to-Noise Ratio
ssRBM	Spike-and-Slab RBM
STFT	Short-time Fourier Transform
SVM	Support Vector Machine
SWT	Stationary Wavelet Transform
TB	Tuberculosis
T-DSN	Tensor Deep Stacking Network

TEWA	Time Expanded Waveform Analysis
VAR	Vector Autoregressive Model
VRI	Vibration Response Imaging
VQ	Vector Quantization
YW	Yule-Walker
WHO	World Health Organization
WPD	Wavelet Packet Decomposition
WT	Wavelet Transform

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CHAPTER 1

INTRODUCTION

1.1 Literature Summary

Pulmonary illness is one of the most encountered diseases all over the world [1]. Tens of millions of people suffer from lung disease in the U.S. Infections, smoking, contaminants and hereditary qualities are in charge of most lung illnesses [2]. Pneumonia, chronic obstructive pulmonary, asthma, tuberculosis, lung malignancy infections are the most vital chest ailments [3]. In Europe, chronic obstructive pulmonary disease (COPD) and asthma have been estimated to affect between 10 and 25% of the adult population [4,5]. Pulmonary infections such as acute bronchitis and pneumonia are common, and interstitial lung disease is increasing in incidence [4].

A few methods have been executed for perceiving lung disorders [6]. The diagnostic worth of any clinical test or examination depends upon its capacity to recognize plainly, precisely, and in a repetitive way between the normal and abnormal [6]. Separation between different sorts of abnormalities is an extra significant vantage [6]. The standard methodology for evaluating patients with respiratory system symptoms is medical history and physical examination [6]. The stethoscope has been used as a basic diagnostic tool among physicians and has been a successful device for diagnosing lung problems and abnormalities [7,8]. Auscultation is a procedure for hearing internal voices in the human body using a stethoscope [7]. Additionally, different investigations have demonstrated that the analytic precision and estimation of the stethoscope are arguable [6,9].

Auscultation contributes much to the physical examination [4,9,10]. But auscultation has numerous restrictions [4,10]. It is process that relies upon the physician's own listening ability, knowledge and capacity to separate between various sound examples [4,10]. Customary auscultation does not answer the necessities for a diagnostic test because of the impediments of human ear [11-13]. The ears are sensitive to deterministic sounds in the time or frequency domains, but are substantially less accurate in identifying, analyzing, and classifying the noise [4,12]. Another reason for human deficiency in the auscultatory analysis of lung sounds is their low signal-to-noise ratio [4,12]. Thoracic lung sounds have relatively low amplitude compared with background noise of heart and muscle sounds [4,12].

Auscultation contributes much to the physical examination [6,9], but auscultation has numerous restrictions [4,9].

It is difficult to deliver quantitative estimations or make a persistent record of an examination in recorded condition [4,14,15]. Observing or connection of lung sounds in long periods of time with other physiologic signs is likewise troublesome [4,14, 15]. In addition, the stethoscope has a periodicity reaction that reduces periodicity parts of the respiratory sound which is about 120 Hz higher [4,14,15]. Also human ear is not exceptionally susceptible to low-level recurrence band that remaining parts [4,14,15]. Auscultation process mainly relies on the physician. Thus, a professionally well-trained physician is required to recognize lung abnormalities and disorders using this process. The possibility of untrained physicians incorrectly recognizing abnormalities, which can be due to not calibrating the instrument and/or due to noisy environment, is very high using this method and has thus led to the development computer-assisted analysis systems of lung sounds [16,17].

Computer-assisted analysis of lung sounds**,** serves as a reliable tool for the diagnoses of lung abnormalities and disorders since early 1980s [18]. Several techniques have been implemented for recognizing lung disorders and abnormalities [18].

The utilization of computerized methods in analysis of lung sounds is an important advance in enabling to go beyond the stethoscope [16,19,20].

However, according to our literature survey, lung sound analysis continues to attract researchers because past researchers focused on identifying lung sounds and very few researchers concentrated on developing lung disorder diagnostic tools. Therefore, this research area appears incomplete and has attracted many researchers in recent years, which has led to the implementation of machine learning algorithms for the diagnosis of lung sound [21].

Machine learning has ended up being a powerful technique as of late [21-23]. Machine learning algorithms have been effectively utilized as a part of an extensive number of utilizations [21]. Machine learning algorithms possess Artificial Intelligence (AI) that learns from past experiences, which allow the tools to function more accurately) [17]. Many researchers suggest different techniques to analyze lung sounds as shown in Table 1.1. A number of methods, such as multi-layer perceptron (MLP), k-nearest neighbor (k-NN), hidden Markov model (HMM), Gaussian mixture model (GMM), Fuzzy and genetic algorithm (GA) are extensively utilized in computer-assisted analysis of lung sounds. The use of support vector machines (SVMs) is very limited in the literature [21].

Murphy et al. in 1977 executed an extrinsic sound investigation through the time extended waveform examination (TEWA) [24,25,26]. In TEWA, they showed that the crackles were a shorter and more complicated wave form when compared to the sinusoidal sound [24-26]. Afterward, Hoevers and Loudon portrayed crackles by time-domain parameters, for example, the underlying diversion width (IDW), the two cycle span (2CD) and the largest initial deflection (LDW) [24-26].

Investigations of Sestini et al. demonstrate that a relationship between acoustical signal and its image is gainful to the comprehension for understudies in medical field [27,28].

Forkheim et al. utilized neural networks (NNs) to process lung sounds and recognize wheezes is exhibited [29]. Every data portion was ordered physically as either including a wheeze or not including a wheeze [29]. A Fast Fourier Transform (FFT) was computed and the Fourier transform (FT) range was computed [29].

Table 1.1 Machine learning in computerized respiratory sound analysis systems [8].

Author	**Subjects**	**Classified Items**	**Material**	**Feature Extraction Method**	**Classification Method**	**Accuracy**
Forkheim 1995 [29]	Not specified	Wheeze and normal	Eight channel microphone	Raw Signal Data, FFT	MLP	The training sets 1 and 2 were 93% and 96%
Kahya 1997[30]	69n	Normal or abnormal	Electret microphone	AR Model	k-NN	69.59%
Rietveld 1999 [31]	60n	Normal and Asthma	Electret microphone	FT	MLP	43%
Oud 2000 [32]	10n	Asthmatic patients	Electret microphone	Spectral Analysis	k-NN	60% to 90%
Waitman 2000 [33]	17p, 17c	Normal or abnormal	Microphone	FT	MLP	73%
Bahoura 2003 [34]	24n	Wheeze	Electret microphone	MFCC, FFT, LPC, WPD, SBC	VQ	75.80% and 77.50%
Baydar 2003 [35]	20n	Normal or abnormal	Electret microphone	Periodogram, Welch, Yule-Walker, Burg	Nearest mean classifier	72% in expiration and 69% in inspiration
Kandaswamy 2004 [36]	Not specified	Lung sounds	Electret microphone	WT, STFT	MLP	94.02%
Folland 2004 [37]	Not specified	Lung sounds	Electret microphone	Spectral Computation Parametric Model, GenerationLinear Normalization	MLP, RBFN, CPNN ANN	97.8%
Güler2005 [10]	129n	Normal, wheeze and crackles	Electret microphone	Welch	MLP, GANN	ANN81–91%, GANN 83–93%
Martinez-Hernandez 2005 [38]	19n	Normal or abnormal	Electret microphone	Multivariate AR Model	MLP	87.68%
Kahya2006 [39]	20p, 20c	Rale	Air-coupled electrets microphone	WT	k-NN	46%
Lu.2008 [40]	Not specified	Fine and coarse crackles	Electret microphone	GMM	GMM VQ	95.1%
Alsmadi 2008 [41]	42n	Lung sounds	Microphone	AR Model	k-NN and minimum distance classifier	96%
Riella2009 [42]	Not specified	Wheeze	Electret microphone	FFT, STFT	MLP	92.86%
Riella2010 [43]	Not specified	Lung sounds	Electret microphone	DWT	RBFNN	92.36%
Matsunaga 2010[44]	114n	Normal or abnormal	Electronic stethoscope	Raw Data	HMM	84.2%
Charleston-Villalobos 2011 [45]	27n	Normal or abnormal	Electret microphone	AR Model	MLP	75% and 93%

p: Patient, c: Control, s: Sound, n: Subject, ANN: Artificial Neural Network, AR: Autoregressive, CHF: Congestive Heart Failure, COPD: Chronic obstructive pulmonary disease, CPNN: Constructive Probabilistic Neural Network, DWT: Discreate Wavelet Transform, FFT: Fast Fourier Transform, FT: Fourier Transform, GANN: Genetic Algorithm-Neural Network; GMM: Gaussian Mixture Model, HMM: Hidden Markov Model, k-NN: k-nearest neighbor, LFCC: Linear Frequency Cepstral Coefficient,LPC: Linear Predictive Coding, MFCC: Mel Frequency Cepstral Coefficient, MLP: Multi-layer Perceptron, RBFNN: Radial Basis Function Neural Network, SBC: Subband based Cepstral, STFT: Short-time Fourier Transform, SVM: Support Vector Machine, VQ: Vector Quantization, WPD: Wavelet Packet Decomposition, WT: Wavelet Transform

Table 1.1 (continue) Machine learning in computerized respiratory sound analysis systems

Author	**Subjects**	**Classified Items**	**Material**	**Feature Extraction Method**	**Classification Method**	**Accuracy**
Yamashita 2011 [46]	168n	Normal or emphysema	Electret microphone	Segmentation	HMM	87.4% and 88.7%
Jin 2011[47]	21n	Normal or abnormal	Electret microphone	Temporal-Spectral Dominace Spectrogram	k-NN	92.4%
Serbes 2011[48]	26n	Crackles	Electret microphone	WT, DWT	SVM	97.20%
Flietstra 2011 [49]	257n	Pneumonia and CHF	Multichannel lung sound analyzer STG 16	Manual Crackle Analysis	SVM	Pneumonia 86% and CHF 82%
Hashemi 2011 [50]	140p, 140s	Wheeze	Electronic stethoscope	WT	MLP	%89.28
Aras2015 [51]	27 pathological, 21 normal s	Rale, rhoncus, normal	Electronic stethoscope	MFCC LFCC	k-NN	The datasets 1 and 2 were96% and 100%
Chen2015 [52]	20p	Rale, rhoncus, wheeze, normal	Digital stethoscope	MFCC	k-NN	93.2%

p: Patient, c: Control, s: Sound, n: Subject, ANN: Artificial Neural Network, AR: Autoregressive, CHF: Congestive Heart Failure, COPD: Chronic obstructive pulmonary disease, CPNN: Constructive Probabilistic Neural Network, DWT: Discreate Wavelet Transform, FFT: Fast Fourier Transform, FT: Fourier Transform, GANN: Genetic Algorithm-Neural Network; GMM: Gaussian Mixture Model, HMM: Hidden Markov Model, k-NN: k-nearest neighbor, LFCC: Linear Frequency Cepstral Coefficient,LPC: Linear Predictive Coding, MFCC: Mel Frequency Cepstral Coefficient, MLP: Multi-layer Perceptron, RBFNN: Radial Basis Function Neural Network, SBC: Subband based Cepstral, STFT: Short-time Fourier Transform, SVM: Support Vector Machine, VQ: Vector Quantization, WPD: Wavelet Packet Decomposition, WT: Wavelet Transform

In the literature, lung sound classification was made for a maximum of 6 classes [8]. Kandaswamy et al. [36] implemented a system to classify the lung sounds to one of the six categories: normal, wheeze, crackle, squawk, stridor, or rhonchus. Forkheim et al. [29], investigated to detect only wheezes in isolated lung sound segments [8]. Bahoura et al. [34], Riella et al. [42] and Hashemi et al. [50] classified sounds as whether containing wheezes or normal respiratory sounds [8]. Lu et al. [40], classified fine crackles and coarse crackles [8]. Kahya et al. [39], Flietstra et al. [49] and Serbes et al. [48] classified the presence or absence of a crackle [8]. These studies are very narrow in scope, as they have limited number of classes. Their results are focused on only a few sound types [8].

Rietveld et al. [31] selected clean audio samples, and Baydar et al. [35] recorded their audio clips in a quiet room [8]. To explore the value of artificial neural networks (ANNs), the limits of NNs and human inspectors to categorize respiratory sounds were looked at in the investigation of Rietveld [31]. A feedforward network based on supervised learning was utilized on spectrogram images created by Fourier transform [31].

In investigation of Kahya et al., lung sounds recorded from patients and healthy people were identified as restrictive and obstructive respiratory tract infected and healthy people [30]. Highlight parameters were gotten from autoregressive (AR) models connected to covering sections of respiratory sounds [30]. Crackle parameters acquired from Prony model were additionally consolidated into the feature space for classification improvement [30]. Two distinctive multi-stage classifiers were created [30].

While Oud et al. [32] analyzed adventitious sounds of asthmatic patients, Waitman et al. classified [33] the breath sounds in the intensive care environment as normal or abnormal [33].

In the investigation of Bahoura et al., another approach in light of cepstral analysis is suggested to classify lung sounds [34]. This approach is tried and contrasted with other sort of feature extraction like the wavelet transform and the autoregressive representation [34]. The audio signal is partitioned into portions, portrayed by a diminished number of cepstral coefficients [34]. Then these fragments are named in the case of including wheezes or normal breath sounds, by utilizing the Vector Quantization (VQ) technique [34].

In the investigation of Baydar et al., the use of signal coherence technique for parametric portrayal and automatic breath sounds’ grouping is examined [35]. The different range estimation techniques, for example, Yule-Walker (YW), Welch's, periodogram and the Burg's strategies were utilized with the goal that both non-parametric and parametric strategies were thought about [35]. Prior to the count of the power range, DC end from the digitized signal was done [35]. The capabilities were then characterized by utilizing closest mean classifier with leave-one-out method [35].

Folland et al. evaluated the execution of the moderately new constructive probabilistic neural network (CPNN) against the more typical classifiers, to be radial basis function network (RBFN) and specific the multilayer perceptron (MLP), in classifying an expansive scope of tracheal-bronchial breath sounds [37].

Güler et al. exhibited an investigation for GANNs approach expected to help in lung sound characterization [10].

Martinez-Hernandez et al. proposed multichannel obtaining of respiratory sounds with a receiver exhibit, include extraction by a multivariate AR (MAR) demonstrate, the ability to reduce multiple dimensions of the feature vectors (FV) by SVD and PCA and, their arrangement by a managed neural NN [38].

In the investigation of Kahya et al., feature sets are utilized as a part of conjunction with k-NN and artificial neural network (ANN) classifiers to address the arrangement issue of lung sound signals [39].

Attempts to utilize computerized recordings of lung sounds as an aid for diagnosis and education have been previously described, with various complexities of systems [6].

Murphy et al. in 2000 assembled a framework for automatically giving an exact conclusion in view of an investigation of respiratory sounds recorded [8,53]. The sound is taken with the help of various receivers placed on the chest [8,53]. Framework likewise has a signal processing circuit to change analog data into digital data [8,53]. This information is then recorded, sorted out and showed on a PC screen utilizing an application program [8,53]. The gathered information is then physically broken down and analysed [8,53]. However this innovation is not utilizing a computerized investigation system to dissect the information they gathered [8,53]. In 2004 they developed a system to collect data and provide automated identification of wheezes, rhonchi, fine crackles, coarse crackles, and squeaks, in accordance with published definitions [54]. To record tracheal sounds of the patients, they used a multichannel lung sound analyzer (model STG-1602), in which 14 receivers are placed into a soft foam base [54,55]. The data collected was analyzed using time-expanded waveform analysis of each channel [54].

Hossain et al. think about the heart-noise lessening procedure utilizing wavelet transform which disintegrate frequency into various parts that is connected to various channels [24,26,56].

Şen et al. has built up a framework that discovers and procedures breathing sounds [57]. The respiratory sounds are recorded by means of fourteen amplifiers appended on the chest divider, with the concurrent estimation of the air flow for synchronization [57]. Fourteen channels are opened up, band-pass filtered and digitized to be prepared on PC, while flow signal is just low-pass separated before digitization [57].

Lu et al. built up an incorporated robotized framework for crackles acknowledgment [40]. This framework contains three serial modules with following capacities: (1) division of crackles from vesicular sounds utilizing a wavelet packet filter (WPST–NST); (2) location of crackles by fractal dimension (FD); (3) characterization of crackles in view of GMM [40].

Sello et al. investigated the respiratory sound difference amongst healthy and ill persons [58]. Consequently here they utilized an appropriate receiver coupled to the skin by a shut chamber, like a stethoscope bell, with chose size and shape keeping in mind the end goal to catch the general frequnecy scope of interest [58]. At that point they played out the wavelet analysis and the related factual calculation [58].

Rayes suggests the time-frequency model Hilbert-Huang spectrum (HHS) as a suitable examination apparatus for coarse and fine crackles [24,26,59].

Alsmadi et al. utilized a digital signal processor to plan a device fit for getting, parameterizing and characterizing respiratory sounds into two classes in order to assess them without bias in real time [41].

Riella et al. built up a method for automatic wheezing recogniton in digitally recorded lung sounds in 2009. This strategy depends on the extraction and preparing of spectral data from the respiratory cycle and the utilization of these informations for user feedback and automatic recognition [42]. They also built up a method for unusual lung sounds classification utilizing discrete wavelet transform (DWT) and a classifier situated in a radial basic function (RBF) NN in 2010 [43]. The proposed algorithm arranged unusual sounds into normal, wheeze, rhonchi, squeak, fine crackles, coarse crackles and stridor [43].

Ayman et al. built a system to classify cough and airflow sounds whether the patient is sick or not [60]. To collect the sounds a microphone, a pneumotachograph and a differential pressure transducer were used [60]. A product virtual instrument was planned utilizing Lab-VIEW to catch the sound weight and flow signals created by a coughing person to a microphone [60].

Matsunaga et al. suggested a new classification methodology for recognizing normal breathing and abnormal breathing sounds in view of a maximum likelihood approach utilizing HMMs [44,61].

Charleston-Villalobos et al. have assessed distinctive parameterization strategies for multichannel lung sounds procured all in all back thoracic surface for two class characterizations; normal breath sounds against abnormal breath sounds [45]. A feed forward MLP utilizing the backpropagation algorithm and the Levenberg– Marquardt adjustment rule was actualized with two hidden node layers and a solitary yield hub [45].

Yamashita et al. proposed an order methodology for recognizing a healthful person and a patient suffering from pneumonic emphysema on the premise of respiratory sounds [46]. The classification accuracies for the proposed method were found to be 87.4% and 88.7% utilizing the deterministic rule and the segment bigram rule, respectively [46].

Jin et al. proposed another signal recognizable proof and extraction strategy for different adventitious sounds in light of instantaneous frequency analysis [47].

Serbes et al. proposed a novel strategy for crackle recognition [48]. In this strategy, different capabilities are removed utilizing time-frequency and time-scale analysis [48]. The removed capabilities are input into SVMs both exclusively and as a group of systems [48].

Flietstra et al. was to decide if the crackles in patients with IPF (interstitial pulmonary fibrosis) contrast from those in patients with CHF (congestive heart failure) and PN (pneumonia) [49]. Crackle features were investigated utilizing machine learning strategies including NNs and SVMs [49].

Jamar et al. designed electronic stethoscope consisting of a main receiver box, with both speakers and a headphone jack for auscultating, along with two wireless microphones (MEMS microphones) that attach to the patient and detect the heart and lung sounds. The PurePath kit was chosen to implement the wireless capability of the prototype [62].

Hashemi et al. used Gauss Mixed Model (GMM) and MFCC for wheeze and normal sounds classification [50].

Morillo et al. aim to analyze respiratory sounds during COPD exacerbations [63]. The audio was registered via an electret receiver [63]. The sensor was placed on the trachea on the sternum and used by the patients themselves. [63]. Both clinical history and sound documents were doled out to a classified electronic patient record [63]. Factual examination was performed utilizing SPSS statistical analysis software [63]. What's more, PCA and bunching were likewise connected, and Matlab was utilized for signal processing [63].

Falk et al. outline a modulation filter to enhance the division of heart and lung sounds from breath sound chronicles recordings [24,64,65].

Le Belvedere et al. utilize adaptive wavelets for respiratory sounds examination and effectively recognize pathological changes of the lung [24,26,65].

Wang et al. think about the connection between the lung multi-source vibration and the delay time [24,26,65]. They utilized cepstrum analyzes [24,65].

In the study of Aras et al., lung sounds recorded by electronic auscultation, were classified as healthy and pathological [51]. Linear predictive coding coefficients (LPCCs), mel frequency cepstrum coefficients (MFCCs) mean and standard deviation were used as features [51]. Records are consists of two data sets containing different respiratory cycle. k-NN classification algorithm used and the performance obtained were discussed in the conclusion to the case of using different data sets and different attributes [51].

Chen et al. has built up a computerized stethoscope to enable doctors to overcome these issues when diagnosing anomalous respiratory sounds [52]. In this computerized framework, MFCCs were utilized to generate the features of respiratory sounds, and after that the K-means algorithm was utilized for feature clustering, to decrease the measure of information for calculation [52]. k-NN technique was utilized to classify the respiratory sounds [52].

The classification accuracy reported by Kandaswamy et al., was 100% for training and 94.02% for testing using ANN in classification of normal, wheeze, crackle, squeak, stridor, and rhonchus respiratory sounds [36]. This shows the effectiveness of ANN in classifying the lung sounds [66]. The ANN can adjust well with complex non-linear information and classify it precisely and adequately [66].

The work of Alsmadi and Kahya has reported a classification accuracy of 96% in realtime using k-NN classifier [39,41]. Their developed system can recognize normal and abnormal lung sounds and they trained the model with a large dataset comprising of 42 subjects [39,41].

There have been a few examinations detailed concentrating on chest disease diagnosis issue utilizing ANN structures concerning other clinical analysis issues [3]. These examinations have connected diverse neural networks structures to the different lung diseases diagnosis issue utilizing their different dataset [3], as can be found in Table 1.2.

Ashizawa et al. utilized the MLNN with one hidden layer and they utilized Back-propagation (BP) training algorithm for diagnosis of COPD [3,67]. They utilized twenty six features for the conclusion. The authors announced roughly 90% diagnosis accuracy [3,67].

El-Solh et al. utilized a generalized regression neural network (GRNN) utilizing clinical and radiographic data to anticipate active pulmonary tuberculosis [68,69].

The information patterns were framed by 21 distinct parameters which were separated into three groups: statistic factors, established indications, and radiographic discoveries [68,69]. The yield of the GRNN gave a gauge of the probability of active pulmonary tuberculosis [68,69]. The authors used a 10-fold cross-validation strategy to prepare the NNs. The authors announced roughly 92.3% diagnosis accuracy [68,69].

Table 1.2 Machine learning in computerized lung diseases analysis systems [8]

Author	Subjects	Classified Items	Number of Features	Feature Extraction Method	Classification Method	Accuracy
Kahya 1997[30]	51p 18n	COPD, restrictive lung disease,normal	14 (audio)	AR Model	k-NN	69.59%
Ashizawa 1999 [67]	110s	ILD	26 (text)	Manual selection	MLNN	90%
El-Solh 1999 [68]	682p	TB	21 (text)	Manual selection	GRNN	92.30%
Santos 2004 [70]	136p	SNPT	26 (text)	Manual selection	MLP	77.0%
Heckerling 2004 [71]	1160s	Pneumonia	35 (text)	Manual selection	MLP	82.8%
Barua 2004 [72]	131s	Pulmonary diseases	12 (text)	IOS	MLP	61.53%
Barua 2005 [73]	361s	Asthma	12 (text)	IOS	MLP	95.01%
Er 2008 [69]	100n 50p	TB	38 (text)	Manual selection	MLNN, GRNN	95.08%
Er 2008 [74]	100n 55p	COPD	38 (text)	Manual selection	MLNN	96.08%
Er 2009 [75]	100n 101p	Pneumonia COPD	38 (text)	Manual selection	MLNN, PNN, LVQ, AIS	94%
Er 2010 [3]	100n 257p	TB, COPD, Pneumonia, asthma, lung CA	38 (text)	Manual selection	MLNN, PNN, LVQ, GRNN, RBF	TB vs others 90% COPD vs others 88% Pneumonia vs others 91.67% Asthma vs others 90.91% Lung CA vs others 93.75% Normal vs others 99%
Yamashita 2011 [46]	101p 39n	Normal or emphysema	Not specified	Segmentation	HMM	87.4% and 88.7%
Amaral 2012 [76]	25p 25n	COPD	7 (text)	Manuel selection	k-NN, SVM, MLP	95%

p: Patient, c: Control, s: Subject, n: Normal, AIS: Artificial immune system, ANN: Artificial neural network, AR: Autoregressive, CA: Cancer, COPD: Chronic obstructive pulmonary disease, GRNN: Generalized regression neural network, HMM: Hidden Markov model, ILD: Interstitial lung disease, IOS: Impulse oscillometry, k-NN: k-nearest neighbor, MLNN: Multilayer neural network (MLNN), MLP: Multi-layer perceptron, PNN: Probabilistic neural network, RBF: Radial basis function, SVM: Support vector machine, LVQ: Learning vector quantization, TB: Tuberculosis

Heckerling et al. utilized the MLNN with one and two hidden layers and they utilized BP with momentum as the training algorithm for anticipating community-acquired pneumonia among patients with respiratory grievances [71,75]. They performed GAs to look for ideal hidden layer structures, availability, and training parameters for the

NN [75]. The authors revealed a ROC precision proportion of 82.8% for the pneumonia disease determination [71,75].

Santos, et al. [69], utilized an expectation display for determination of smear negative pulmonary tuberculosis (SNPT) [69]. They utilized indications and physical signs for building the NN modeling [69]. They detailed around 77% diagnosis precision. They utilized a MLNN structure with one hidden layer [69].

In the study by Barua et al. in 2004 [72], an ANN was utilized to perceive and classify the sicknesses of the airways. The authors utilized IOS estimations and a feedforward ANN that was trained by the BP algorithm [76]. In 2005 they [73,76], developed a classifier in light of ANN was fit for recognizing relatively constricted and nonconstricted airway conditions in asthmatic kids [76]. The 361 data set contained two unique classes [73].

Er and Temurtaş utilized a multilayer neural network (MLNN) for determination of COPD [3,74]. They utilized thirty eight features for the diagnosis and revealed roughly 96% diagnosis precision for MLNN with LM algorithm and two hidden layer [3,74]. In 2008, they [69] utilized MLNN for tuberculosis diagnosis. For this reason, two diverse MLNN structures were utilized [69]. A general regression neural network (GRNN) was additionally applied to acknowledge tuberculosis diagnosis for the comparison. Levenberg-Marquardt algorithms were utilized for the training of the MLNN [69]. In 2009, they utilized MLNN, PNN and LVQ NN for diagnosis of COPD and pneumonia illnesses [3,75]. They utilized thirty eight features for the diagnosis and reported around 93.92% diagnosis precision for PNN as the best outcome [3]. In 2010, they applied a relative chest ailments diagnosis by utilizing MLNN, PNN, LVQ, and GRNN [3]. The chest ailments dataset were set up by utilizing patient epicrisis records in the database of the chest diseases hospital [3]. All specimens had thirty eight features [3]. They also utilized MLNNs and GRNNs for classification of tuberculosis [3,77]. They utilized thirty eight features for the classification and found around 93.3% analysis accuracy for GRNN and 95% diagnosis precision for MLNN with LM algorithm and two hidden layer [3,77].

Hanif et al. utilized three diverse ANNs to characterize distinctive seriousness of asthma and the plausible precautions to accomplish it [3,78]. These NNs were connected to BPNN (MLNN), Elman BPNN and RBFNN [3,78]. The accuracy of the prepared designs was tried by entering novel series of data to a graphical user interface (GUI). They acquired best accuracy result (90%) utilizing the RBFNN [3,78].

Prasadl et al. designed the expert system for diagnosis of asthma [79]**.**

Amaral et al. built up a clinical decision support system in light of machine learning algorithms to help the diagnosis of COPD utilizing forced oscillation measurements [76]. The performances of classification algorithms in light of Linear Bayes Normal Classifier, ANN, k-NN, SVM and decision trees were compared to find the best classifier [76]. The conclusion of this investigation show that the suggested categorizers may add to simple the diagnosis of COPD by utilizing forced oscillation measurements [76].

Kononenko et al., compared two diverse ways to deal with machine learning in medicinal practices: the system for inductive learning of decision trees and the naive Bayesian classifier [80].

Medicine has framed a rich proving ground for machine learning experiments before, enabling researchers to create intricate and powerful learning systems [79,81]. While there has been much viable utilization of expert systems in hospital environments, currently, machine learning systems does not appear to be utilized as a routine part of the diagnosis process [79,81]. Machine learning systems can be utilized to build up the databases utilized by expert systems [79,81]. Given an arrangement of clinical events as samples, a machine learning system can create a precise depiction of properties unambiguously portray the status [79,81]. This learning can be communicated as basic rules [79,81]. There are a wide range of sorts of clinical assignment to which expert systems can be connected [79,82]:

- Diagnostic help: If the case of a patient is complicated, uncommon or the individual performing the analysis is just untrained, an expert system can come to up with probable findings in light of patient information [79,82].
- Therapy evaluating and designing: Systems can either search for irregularities, errors and exclusions in a current treatment design, or can be utilized to detail a treatment in view of a patient's particular condition and acknowledged treatment rules [79,82].
- Image recognition and interpretation: Many medical images would now be able to be automatically interpreted, from plain X-rays through to more complex images like angiograms, CT and MRI scans. This is of incentive in mass-screenings, for example, when the system can flag possibly anomalous images for definite human consideration [79,81].

ANN structures for classification systems in medicinal diagnosis are expanding gradually [3]. The MLNN, PNN, LVQ NN, GRNN, and RBFNN structures have been effectively utilized as a part of replacing conventional pattern recognition techniques for the disease diagnosis systems [3].

The utilization of computer innovation has given new perception into acoustic components and new estimations of clinical significance on lung sounds [16,19]. The utilization of digital signal processing techniques to extract information on average sounds were significant advances that have propelled the utility of lung sounds past the stethoscope [16,19]. In the previous decade, different advances, for example, expert systems were utilized to endeavor to take care of this issue [8]. However for critical systems the error in the decision was too high [8]. The most recent innovation that is endeavoring to take care of this issue is machine learning [6,8].

Also, there is a multinational effort, funded by the European Commission, to standardize computerized respiratory sound analysis [16]. This in turn has led to the creation of the International Lung Sound Association (ILSA), whose activities have consisted of a yearly international research conference and even the maintenance of a website, consisting of respiratory sounds that can be downloaded at no cost [83,84]. This renaissance of lung auscultation was confirmed by the European Commission's support of a multinational project to standardize computerized breathing sound analysis (CORSA project) [83,85-87].

Throughout the years various effective algorithms were created and now with the deep learning algorithms, error turned out to be exceptionally low [8]. Particularly in computer vision and speech recognition machine learning is coming to on human level of identification [6,8].

1.2 Aim of the Thesis

There are a variety of problems with clinical auscultation that make it difficult to reliably acquire the acoustic information that is associated with lung diseases [55]. One major problem is substantial observer variability [55]. There has been a lot of enthusiasm for utilizing computer based innovation to circumvent the deficiencies of auscultation [55,88]. Recent technical advances have led to the development of computer based respiratory sound analysis which serves as a powerful tool to diagnose abnormalities and disorders in the lung. [55].

To diagnose or classify something, we need to find patterns [8]. Be that as it may, more often than not, it is difficult to detect these examples, particularly if the information we have is huge [8]. Likewise as a rule information gathered from nature is non-linear, so we cannot utilize traditional techniques to discover patterns or make scientific models [8].

Computerised respiratory sound analysis comprises on recording subjects' lung sounds with an electronic device and afterward analysing and classifying the acoustic signal in view of particular qualities [89,90]. Its use could potentially enhance patients’ diagnosis treatment and monitoring [89,90].

This study tackles with the following questions:

- Can lung sounds be classified using convolutional neural networks using spectrogram images?

- Can the technique of classifying lung sounds with convolutional neural networks yield better or equal accuracy, precision and recall results compared to the traditional sound classification techniques?
- Can lung diseases be classified via lung sounds' MFCC features and text patient data using and support vector machine, k-nearest neighbor and Gaussian Bayes algorithms?
- Can the electronic stethoscope that was developed to collect lung sounds be successful in providing viable lung sound samples for the study?

The first goal of this project is to develop a non-invasive method of classifying respiratory sounds using convolutional neural networks and spectrogram images of the respiratory audio [8].

Our second goal is to classify respiratory diseases using both patient information and respiratory sounds [8]. This data consists of audio recordings and text data which was collected through survey and from the physician [8].

To collect patient data and respiratory sounds we designed and constructed a cheap, mobile and easy to use electronic stethoscope with associated software system that can transfer respiratory sounds to a PC for recording and subsequent computer aided analysis and diagnosis [8]. The hardware-software system was used to collect a dataset of patient information and respiratory sounds to train a machine learning system for the automated analysis and diagnosis [8].

We performed the following experiments on the collected data:

- Classification of healthy versus pathologic respiratory sounds (SVM, k-NN, GB and CNN) [8]
- Classification of respiratory sounds labeled with a singular type (SVM, k-NN, GB and CNN) [8]
- Classification of respiratory sounds labeled with only as type rale, rhonchus and normal (SVM, k-NN, GB and CNN) [8]
- Classification of respiratory sounds with all labels (SVM, k-NN, GB and CNN) [8]

- Classification of lung diseases using text data (SVM, k-NN and GB)
- Classification of lung diseases using audio data (SVM, k-NN and GB)
- Classification of lung diseases using text and audio data (SVM, k-NN and GB)
- Classification of healthy versus sick using text data (SVM, k-NN and GB)
- Classification of healthy versus sick using audio data (SVM, k-NN and GB)
- Classification of healthy versus sick using text and audio data (SVM, k-NN and GB)

Our third goal was to compare traditional audio classification algorithms such as SVM, k-NN and GB with a deep learning algorithm CNN, so that we can benchmark how deep learning performs.

Our final goal was to compare the difference of diagnosis between lung sounds that was auscultated by both by traditional stethoscope and electronic stethoscope.

1.3 Original Contribution

Stethoscopes currently in use are mainly mechanical, which does not allow digital recording of the sounds for later or remote access or for computer aided diagnosis. Electronic stethoscopes, on the other hand, convert the analog sound waves to digital signals which can be processed and recorded [91]. They are expensive and not yet in widespread use. Likewise, while traditional stethoscope auscultation is subjective and scarcely sharable, electronic stethoscopes should supply an objective and early diagnostic help, with a superior sensitivity and reproducibility of the outcomes [27,92]. Therefore, we believe electronic stethoscopes can be utilized as a diagnosis device for hard to diagnose lung sounds with traditional stethoscope [8]. To this end, we designed and constructed a cheap, mobile and easy to use electronic stethoscope with associated software system that can transfer respiratory sounds to a computer for recording, storing and subsequent computer aided analysis and diagnosis [8]. The hardware-software system was used to collect a dataset of patient information and respiratory sounds to train a machine learning system for the automated analysis and diagnosis [8].

We developed the software/hardware system so that it can be used in a clinical environment. This system allows chest physicans to record patient information and their lung sounds so they can compare patient’s progression. Therefore, in the future this system can form the base of a telemedicine platform.

According to the literature we surveyed, our database has the most number of patients (1,630) and most number of lung sounds (17,930). In the previous studies, researchers classified lung sounds at most into 6 classes; however we classified our database of lung sounds into 73 classes. Therefore, this study has the most comprehensive database of patient data and audio among the studies that were done before.

Respiratory sounds are used for non-invasive diagnosis of lung diseases. Stethoscopes are used to auscultate to the sounds and diagnosis of different diseases requires expertise. There is a lot of data in lung sounds that isn't effectively acquired by even the best of clinicians [55,88]. As of late, much research has been completed on modernized strategies for computerized recording and examination of respiratory sounds with a view to make respiratory sounds an important wellspring of data for analysis [39]. A large portion of the exploration on lung sound analysis has been focused on looking at the sound of a particular pathological condition versus ordinary lung sounds [10]. In the previous studies, researchers used either text data or audio data in diagnosis and lung sound classification. While, we experimented on text and audio separately, we also experimented on audio and text data combined and produced consistent results. In literature, researchers used traditional machine learning algorithms, however we experimented with CNN deep learning algorithm and we benchmarked our results with a commonly used SVM algorithm and found consistent results.

Finally, we compared the difference of diagnosis between lung sounds that was auscultated by both by traditional stethoscope and electronic stethoscope and found that some lung sounds which have a very low frequency and cannot be heard by human ear, contained diagnostic clues when it auscultated with 200 times amplified audio that is recorded by an electronic stethoscope.

In conclusion, we believe our method can improve the results of previous studies and help in medical research [8].

CHAPTER 2

LUNG DISEASE AND LUNG SOUNDS

2.1 Lung Diseases

The lack of proper medical attention for patients in developing nations has fatal consequences [2]. Lung diseases are some of the most common medical conditions in the world [2]. Tens of millions of people suffer from lung disease in the U.S [2]. Smoking, infections, and genetics are responsible for most lung diseases [2]. World Health Organization reported that 4 million people died in 2005 due to chronic respiratory diseases [2,93]**.** In particular, acute respiratory diseases are the main source of mortality in children under five years old in the world [94-96].

Distribution of causes of death at national level in 2015 according to Turkish Statistical Institute Death Predictors Statistics: 40.3% circulatory system diseases, 20% malign and benign neoplasms, 11.1% lung diseases, 5% endocrine system diseases, 4.9% nervous system diseases, 4.5% injury and poisoning, 14.2% others [97] Lung illnesses are: Chronic obstructive pulmonary disease (COPD), asthma, bronchitis, pneumonia, pulmonary edema, emphysema, interstitial lung disease (ILD), pulmonary embolism (PE), pulmonary arterial hypertension, pleural effusion, cystic fibrosis, tuberculosis, lung cancer etc.

- *Asthma* is a chronic disease [98]. It is frequently connected with extra mucus production [73,98]. As a result, this disease causes the lining of the airways to end up inflamed and swollen [98]. So airways constriction results in episodes of asthma [73]. The patient becomes more difficult to breathe [3,73]. In this case, wheezing, cough, tight chest, shortness of breath and airway obstruction can be seen [3,73]. Asthma can be hard to analyze, in light of the fact that the symptoms are some of the time like different conditions, including lung infection, allergic rhinitis, and even cardiac problems [73]. Asthma influences 3% to 5% of grown-ups and 7% to 10% of children [73]. Early diagnosis and appropriate treatment will facilitate the patient's life struggle with this disorder [73].

- *Chronic obstructive pulmonary disease* is a major worldwide health burden with increasing morbidity, mortality [75]. The disease is characterized by progressive airflow obstruction that is not completely reversible [3,74,99]. It is sometimes partially reversible with the administration of a bronchodilator [99,100]. COPD is usually associated with tobacco smoking or prolonged exposure to other noxious particles and gasses [3,74]. There is heterogeneity in disease activity and in the nature of symptomatic impairment experienced by patients [99]. The typical symptoms are cough, excess sputum production, and dyspnea [99]. There may likewise be wheeze [74,75,99]. The airflow obstruction is persistent [74,75,99]. As per the World Health Organization information, consistently rough 2.5 million people die due to COPD [75]. According to the data of the Turkish Thoracic Society COPD Working Group; in our society, COPD is one out of every 5 people over 40 years old. It is estimated that approximately around 2.5-3 million COPD patients are in our nation [74,101].
- *Pneumonia* is an inflammation of the lungs most usually caused by a microorganism [3,75,98]. Pneumonia can likewise be caused by inhaling foreign substances [3,75,98]. Air sacs of the lungs fill with mucous, pus and different fluids and can't work appropriately [75]. This implies oxygen can't rearch the blood and the cells of the body successfully [75,98]. This disease for the most part begins when you inhale the germs into your lungs [75]. Symptoms include; fever, fast breathing and feeling short of breath, cough, chest pain, fast heartbeat, fatigue, diarrhea, nausea and vomiting [75]. Pneumonia is the main source of infectious-disease related death [55]. It is a main source of mortality in people 60 years of age in the United States [55]. As per the World Health Organization information, every year consistently rough 2.4 million people die because of pneumonia [3]. According to the statistical reports of the Ministry of Health in 2005 90,000 patients have pneumonia and every year 2,500 persons die because of pneumonia in our nation [75].

- *Bronchitis* is inflammation of the bronchi in the lungs [98]. Symptoms include coughing up mucus, wheezing, shortness of breath, and chest discomfort [98]. Bronchitis is divided into two types: acute and chronic [98]. In more than 90% of cases the cause is a viral infection [102]. These viruses may be spread through the air when people cough or by direct contact [102]. Risk factors include exposure to tobacco smoke, dust, and other air pollution [98]. A small number of cases are due to high levels of air pollution or bacteria such as Mycoplasma pneumoniae or Bordetella pertussis [102]. Chronic bronchitis, a more serious condition, is a constant irritation or inflammation of the lining of the bronchial tubes, often due to smoking [103]. Acute bronchitis is one of the most common diseases [102]. About 5% of adults are affected and about 6% of children have at least one episode a year [102].
- *Emphysema* is a chronic obstructive pulmonary disease [98,104]. It is a destructive disease of the lung in which the alveoli that promote oxygen exchange between the air and the bloodstream are destroyed [98]. Smoking is the primary cause of emphysema, which makes it a preventable illness [98]. The primary symptom of emphysema is shortness of breath [102]. It is a progressive complaint by affected individuals, worsening over time [102]. Early in the disease, shortness of breath may occur with exercise and activity but symptoms gradually worsen and may occur at rest [102].
- *Pulmonary edema* is liquid amassing in the tissue and air spaces of the lungs [98,105]. It leads to impaired gas exchange and may cause respiratory failure [98]. Pulmonary edema can develop in two ways, cardiogenic pulmonary edema or noncardiogenic pulmonary edema. [98,105,106]. It is a cardinal feature of congestive heart failure [98]. The most common symptom of pulmonary edema is difficulty breathing, but may include other symptoms such as coughing up blood, excessive sweating, anxiety, and pale skin [106]. The development of pulmonary edema may be associated with symptoms and signs of fluid overload; other signs include end-inspiratory crackles on auscultation and the presence of a third heart sound [106].

- *Interstitial lung disease* (ILD) is a group of lung diseases affecting the interstitium [98]. It may occur when an injury to the lungs triggers an abnormal healing response [107]. Ordinarily, the body generates just the right amount of tissue to repair damage [107]. But in interstitial lung disease, the repair process goes awry and the tissue around the air sacs becomes scarred and thickened [98]. This makes it more difficult for oxygen to pass into the bloodstream [107]. In 2013 interstitial lung disease affected 595,000 people globally. This resulted in 471,000 deaths [107].
- *Pulmonary embolism* is the blockage of an artery in the lungs by a substance from the bloodstream of other parts of the body [98,108]. Symptoms may include shortness of breath, chest pain particularly upon breathing in, and coughing up blood [98]. Symptoms of a blood clot in the leg may also be present such as a red, warm, swollen, and painful leg [98,109]. Signs include low blood oxygen levels, rapid breathing, rapid heart rate, and sometimes a mild fever [109]. Severe cases can lead to passing out, abnormally low blood pressure, and sudden death [109]. Pulmonary emboli affect about 430,000 people each year in Europe [109]. In the United States between 300,000 and 600,000 cases occur each year, which results in between 50,000 and 200,000 deaths [109].
- *Pulmonary arterial hypertension* is an increase of blood pressure in the pulmonary artery, pulmonary vein, or pulmonary capillaries [98]. Other symptoms of the disease include dizziness, fainting or syncope, shortness of breath, leg swelling, chest pain, decreased exercise tolerance, fatigue, palpitations, poor appetite, swelling (legs/ankles) and cyanosis [98,109,110].
- *Pleural effusion* is excess fluid that accumulates in the pleural cavity, the fluid-filled space that surrounds the lungs [98]. This excess can impair breathing by limiting the expansion of the lungs [111].
- *Cystic fibrosis* is a genetic disorder that affects mostly the lungs, but also the pancreas, liver, kidneys, and intestine [98]. Long-term issues include difficulty breathing and coughing up mucus as a result of frequent lung infections [98]. Other signs and symptoms may include sinus infections, poor

growth, fatty stool, clubbing of the fingers and toes, and infertility in males [112]. Different people may have different degrees of symptoms [112].

- *Tuberculosis* is a potentially serious infectious disease [69]. In most cases, the disease is caused by microorganisms called Mycobacterium tuberculosis [69]. Tuberculosis for the most part influences the lungs, yet can likewise influence different parts of the body [69]. The disease spreads through droplets scattered from contagious humans [69]. Some symptoms of the disease: weight loss, chronic cough, night sweats, intermittent fever and coughing blood [69,78]. In 2006, 9.2 million new cases of tuberculosis and 1.7 million deaths were reported worldwide [69,78]. As per reports of the Ministry of Health in 2006, roughly 23,875 persons have tuberculosis and each year 3,448 persons die as a result of tuberculosis in our nation [69,78].
- *Lung cancer* is an uncontrolled cell development in tissues of the lung [98, 113]. Lung cancer is the most lethal type of cancer among the cancer types all over the world [98]. Lung tumor causes around 1.3 million deaths worldwide every year [114].

Turkey at the national level, in the distribution of the first 10 diseases causing the death (UHY-ME Study, 2003, Turkey) [2]: Ischemic heart disease 21.7%, cerebrovascular diseases 15.0%, chronic obstructive pulmonary disease (COPD) 5.8%, perinatal causes 5.8%, lower respiratory tract infections 4.2% and others 47.5% [2] (Figure 2.1).

The lungs can be influenced by various infections (eg COPD, pneumonia, bronchitis, emphysema and lung cancer) [115]. The changes in lung structure that happen in ailment influence the amplitude and timing of sound transmission [16,116].

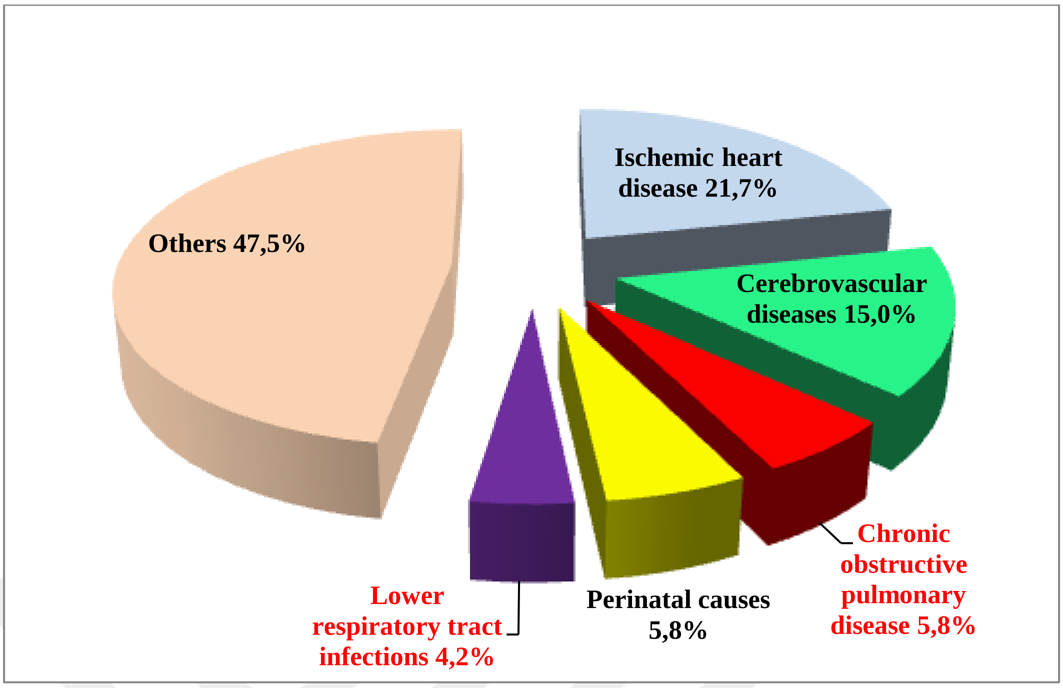

Figure 2.1 The distribution of the some diseases causing the death in Turkey at thenational level (UHY-ME Study, 2003, Turkey [2])

2.2 Structure and Function of the Lungs

The respiratory system is one of the most complex organ systems in the mammalian body [98]. The lungs are the primary organs of respiration in humans [98]. Humans have two lungs, a right lung and a left lung [115]. They are situated within the thoracic cavity of the chest [98]. The right lung is bigger than the left lung, as the left lung shares space in the chest with the heart [115]. The lungs are part of the lower respiratory tract that begins at the trachea and branches into the bronchi and bronchioles and which receive air breathed in via the conducting zone [115]. These divide until air reaches microscopic alveoli, which is where the process of gas exchange takes place (Figure 2.2) [115].

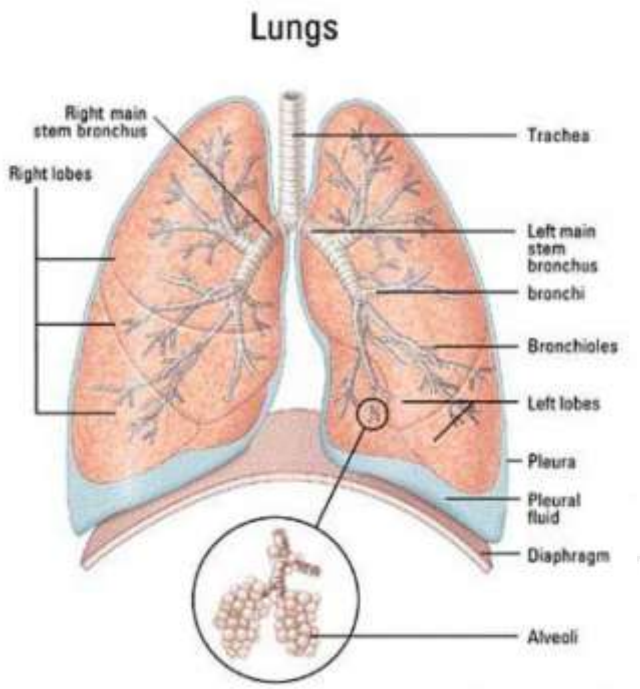

Figure2.2 The lungs, the trachea, bronchi, bronchioles and alveoli [116]

Their function in the respiratory system is to extract oxygen from the atmosphere and transfer it into the bloodstream, and to release carbon dioxide from the bloodstream into the atmosphere, in a process of gas exchange [98]. Respiration is driven by different muscular systems [115]. The diaphragm is a muscle below the lungs separating it from the rest of the organs below [98]. When the diaphragm contracts, the lungs expand and air is inhaled in a process called inspiration [98]. Conversely, expiration occurs when the diaphragm relaxes, air leaves the lungs, and the lungs return to their elaxed position [98]. Breathing, which in organisms with lungs is called ventilation and includes inhalation and exhalation, is a part of physiologic respiration [115].

Inspiration is the active part of the breathing process [117]. Fresh air on inspiration flows through the branching airways into the alveoli until the alveolar pressure is equal to the pressure on the airway opening [117]. Expiration is a passive event due to elastic recoil of the lungs [117]. However, when a great deal of air has to be removed quickly, as in exercise, or when the airways narrow excessively during expiration, as in asthma, the internal intercostal muscles and the anterior abdominal muscles contract and accelerate expiration by raising pleural pressure [117]. The processes of inspiration and expiration repeat throughout the breathing cycle. Respiration rate is defined as the number of breath cycles per minute (cpm), where a single cycle includes inspiration followed by expiration [117]. The respiratory rate ranges for normal healthy individuals are 12 to 20 cpm [117]. However, these values are rough estimates because there is no specific agreement in the literature on the acceptable ranges for respiratory rate among healthy people [117].

Pulmonary diseases result in changes in the lung structure; this in turn affects the amplitude and timing of the sounds heard over the chest wall [118].

2.3 Lung Sounds

Lung sounds, also called respiratory sounds or breath sounds (Figure 2.3), can be auscultated across the anterior and posterior chest walls with a stethoscope [119] Laennec enhanced their audibility with the stethoscope [119,120]. Normal lung sounds happen throughout the chest area [10,121]. Lung sounds are created by the flow of air as it goes with the branching system of bronchi and bronchioles [10].

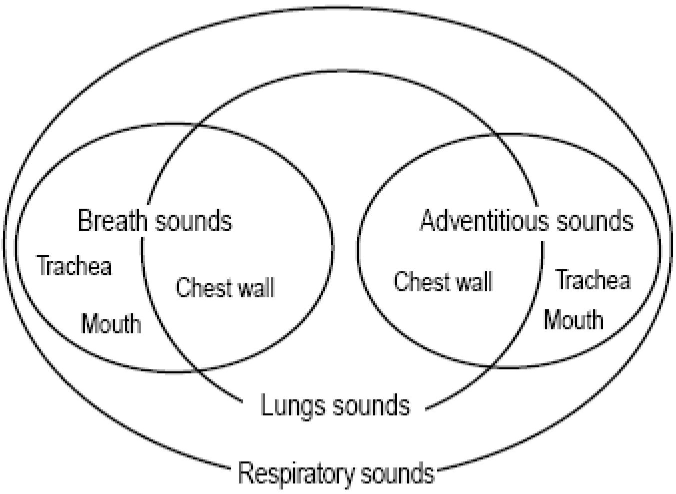

Figure 2.3 Relationship between the terms breath sounds, adventitious sounds, lung sounds and respiratory sounds [122]

Respiratory sounds serve as important indicators of respiratory related diseases [92]. Difference between normal lung sounds and anomalous sounds is critical for a precise medicinal conclusion [27,92]. Respiratory sounds incorporate important data about the physiology and pathology of the lungs [27,92]. In this way, the spectral density and amplitude of sounds can indicate the state of the lungs parenchyma, the dimension of the airways and their pathological modification [27,92]. Respiratory sounds may vary significantly from one individual to the next or to the same person over time [32,123].

The spectral attributes of respiratory sounds indicate varieties as indicated by the state and pathology of the lung [39]. Because of changes in the transmission characteristics of the lungs, the spectra of pathological sounds usually contain higher frequency components [39].

Respiratory sound has three characters; frequency, intensity, and timbre. These help us to separate two comparative sounds [124]. Single-tone sound vibrations have two main identifiers, frequency and amplitude [125]. We perceive frequency as pitch and amplitude as loudness [125]. Frequency measures the quantity of the sound waves or vibrations every second [124]. It is estimated in hertz (Hz) [124]. In general, lung sounds occur at low frequencies from 100 Hz to 1200 Hz. [124]. Frequency relies upon the quantity of wavelengths every second [124]. Pitch relies upon the frequency and is inside 5 Hz of the frequency typically [124]. The human ear can comprehend sound waves over a variety of frequencies, extending from 20 to 20,000 Hz [124]. Amplitude is identified with the energy of sound waves and is estimated by the height of sound waves from the mean position [124]. Sound estimated at 10 dB has an expansion in sound intensity of 10 times [124]. The most important feature that distinguishes two sounds of the same pitch and loudness is the timbre [124,125]. In a mixed sound, for example, the breath sounds, it is the availability of concurrent higher frequencies, specifically music, which give the sounds their particular character [125]. While we are auscultating to a mixed sound, we ordinarily hear the most minimal note [125]. The power of the lower note is enhanced as the amplitude of the sound arises [125]. For this reason, lower frequencies may mask higher frequency components [125].

The origins of lung sounds are not yet completely clear [126]. If there is no airflow, the lung cannot produce sounds [26,127]. Minimum of a flow is required [128]. It is accepted that the breath sound is incited by turbulence of air at the level of lobar or segmental bronchi [128,129]. Frequency band contains also components of respiratory muscles and heart [128]. Inspiration phase is louder and has much higher frequency components than expiration phase [128].

Respiratory sounds are all sounds related to respiration including breath sounds, adventitious sounds, cough sounds, snoring sounds, sneezing sounds, and sounds from the respiratory muscles [122,130]. Voiced sounds during breathing are not included in respiratory sounds [122,130].

The names of lung sounds were derived from the originals given by Rene Laennec and translated into English by Forbes [16,131]. Lung sounds are divided into 5 groups (Table2.1); (1) normal respiratory sounds, (2) abnormal respiratory sounds, (3) adventitious sounds, (4) speech voices, (5) pleural friction rub [98].

Table 2.1 Lung sounds are divided into 5 groups

LUNG SOUNDS		
Normal Respiratory Sounds	Normal Respiratory Sounds (Vesicular Sounds)	
	Tracheal breath sound	
	Bronchovesicular breath sound	
Abnormal Respiratory Sounds	Bronchial sound	
	Absent or decreased sounds	
	Aggravation of normal breath sounds	
Adventitious sounds	Rhonchus	
	Crackle (Rale)	Coarse crackle
		Fine crackle
	Wheeze	
	Squeak	
	Stridor	
	Cough sound	
	Snoring sound	
Speech voices	Whispered pectoriloquy	
	Bronchophony	
	Egophony	
Pleural friction rub		

1-Normal Respiratory Sounds:

a) Normal respiratory sounds (vesicular sounds): It is soft, low pitched, and rustling in quality [124]. The inspiratory phase lasts longer than the expiratory phase [124]. The inspiratory-expiratory ratio (I: E) during respiration is approximately 2: 1 [124]. The intensity of expiration is less than the intensity of inspiration [124]. Expiration is lower pitch than inspiration [124]. There is no cessation between inspiration and expiration during tidal breathing [124]. On the chest wall, the breathing sound is characterized by a low noise during inspiration, but is hardly audible during expiration [27,124]. On trachea, normal respiratory sound is characterized by a broader spectrum of noise. This sound can be heard both in the inspiratory and expiratory phases [27,92,124]. Sounds heard in the chest wall vary depending on the conductance and filtering effect of the lung tissue and the characteristics of the chest wall [125]. The parenchyma of the lung and the chest wall behave like a low frequency filter [125]. Thus, since the parenchyma reduces the higher frequencies, the sounds coming from the proximal airways are greatly weakened and they are composed of low frequencies [125]. The low frequency spectrum of breath sounds is further enhanced by frequencies below 300 Hz [124,132]. Because of these factors, the normal breath sounds recorded by the chest wall receivers are between 37.5 and 1000 Hz (Figure 2.4) and the fundamental energy is below 100 Hz [124,132]. Sound intensity drops forcefully in the vicinity of 100 and 200 Hz leaving little energy above 400 Hz [124,132]. Be that as it may, with sensitive transducers sound can even now be distinguished up to 1,000 Hz [124,132]. Most vesicular breath sounds are found at 37.5-1.000 Hz [16,125]. Their main energy is below 100 Hz [16,125]. The intensity of sound is continuously diminished between 100– 200 Hz with just little energy between 400– 1,000 Hz [125]. Higher frequency sounds do not disseminate [125]. The presence of high frequency but low amplitude sounds is important for the detection of underlying pathology [125]. The filtering of high frequencies is reduced in areas of consolidation of lung parenchyma [16,125]. This leads to an increase in high-frequency energy [16,125]. In addition, a decrease in low frequency sounds is seen [16,125]. This results in less masking of high frequency sounds [16,125]. Frequencies range from 240–1,000 Hz [125]. Added sounds can be continuous and melodic or discontinuous, explosive and non-musical [125,132]. They also contain strong peaks of energy [125,132]. The main energy of some common sounds is: wheezes (>400 Hz), rhonchi (<200 Hz), and crackles (750–1200 Hz) [125,132].

Vesicular sound has higher diagnostic value than tracheal sound, since this part of the lung is affected by serious lung diseases [128].

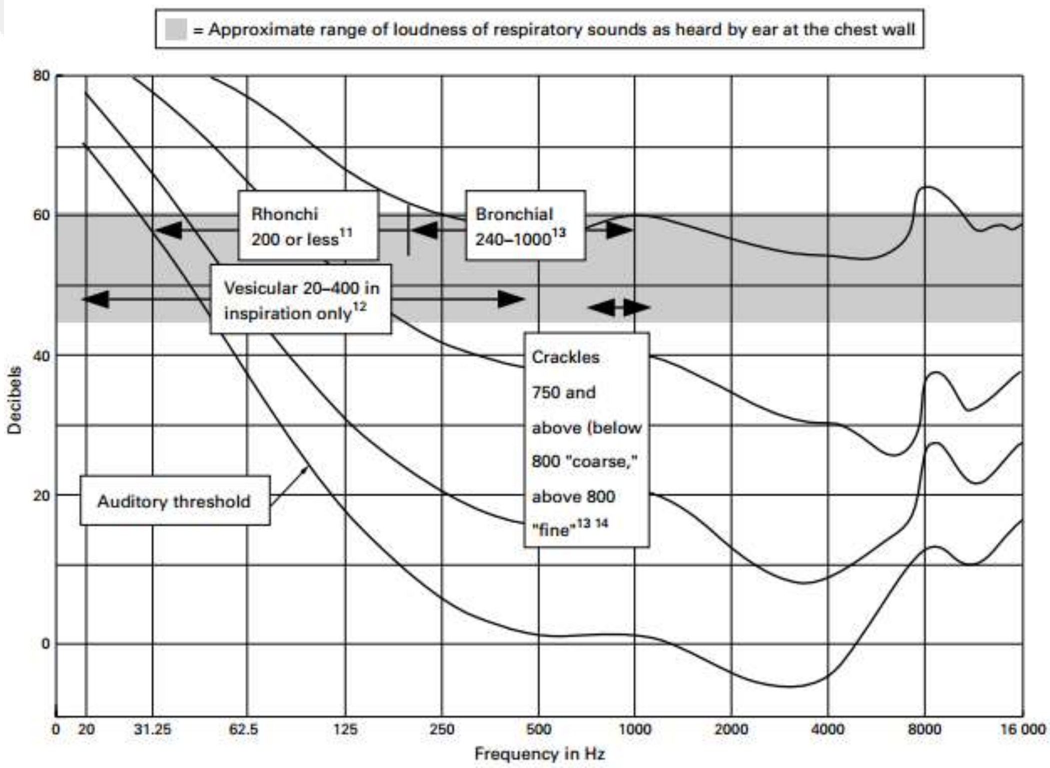

Figure 2.4 Equal loudness curves and frequency of respiratory sounds [132]

b) Tracheal breath sound: Tracheal breath sound is not or filtered in very small amounts [124]. It is hard, noisy, and high pitched sound heard over the trachea [124]. Frequency of tracheal breath sound shifts from 100 to 1500 Hz [124]. It shows a sharp decline over a cut-off frequency of about 800 Hz [124]. Difference of the power of inspiration and expiration varies greatly among the subjects [128]. Tracheal sound has a direct connection to the flow of air [128].

c) Bronchovesicular breath sound: It is a mixture of bronchial and vesicular sounds [133]. The inspiratory and expiratory phase times are the same [124]. The intensity and pitch of this sound are moderate [124]. It is normally heard over 1st and 2nd intercostal spaces anteriorly and between scapulae posteriorly [124]. In other locations, the hearing of these sounds is considered pathological [124].

2- Abnormal Respiratory Sounds:

a) Bronchial sound: The most widely recognized unusual breath sound heard at the chest wall is bronchial breathing [125,132]. Bronchial breathing contains considerably higher frequency segments than normal breath sounds [125,132]. It is loud, hollow, and high pitch [124,133]. The inspiratory phase is shorter than the expiratory phase (I:E changing from 3:1 to 1:2) [124]. There is a significant pause between inspiration and expiration phases [124]. The reason is that there is no alveolar phase [124]. The acoustic transmission qualities of the respiratory system in health and disease are complicated [132]. Bronchial sound is typical for many diseases (for example: Atelectasis) [128].

b) Absent or decreased sounds [98]: Absent or decreased sounds can mean [124,134];

- Air or fluid in or around the lungs (such as pneumonia, heart failure, and pleural effusion) [124,134],
- Increased thickness of the chest wall [124,134],
- Over-inflation of a part of the lungs (emphysema can cause this) [124,134],
- Reduced airflow to part of the lungs [124,134].

c) Aggravation of normal breath sounds: An increase in severity of the normal breath sounds is observed during exercise, fever, anemia, metabolic acidosis, or in the presence of one lung [98]. When a piece of the lungs are harmed, other parts are working more; the next zone may create overstated vesicular breath sounds [124].

3- Adventitious Sounds: There are a few kinds of unusual breath sounds [98,130]. Adventitious sounds relate to additional respiratory sounds superimposed on normal breath sounds [27,92,135]. The availability of such sounds usually demonstrates pulmonary disorders [27,92]. Many diseases can be classified by these adventitious sounds. The challenge in detecting abnormal lung sounds is that they do not occur in isolation. Often, respiratory diseases will involve multiple types of these abnormal lung sounds. Breath sounds contain a generally extensive variety of frequencies, are devoid of peaks, and are not melodic [132]. Adventitious sounds have powerful energy peaks [132]. These sounds may be in the form of continuous melodic sounds with frequencies between 100 Hz and 1000 Hz and and discontinuous explosive non-melodic sounds [132]. The most common sounds are [132]:

a) Rhonchus: Rhonchus is similar to wheeze, but dominant frequency is about 200 Hz or less [128]. They happen when air is blocked or air flow becomes rough through the large airways [92,130]. Rhonchus is heard in airway diseases such as asthma and COPD [27,133].

b) Crackles (Rales): These adventitious sounds, which are usually seen in the inspiratory phase, are explosive and discontinuous [27,133]. The specificity of the waveform, their duration and location in the respiratory cycle is characteristic [27,92]. Crackles can be found in many diseases (for example; heart congestion failure, pneumonia, bronchiectasis, pulmonary fibrosis, chronic diffuse parenchymal lung disease) [92,124]. They are an early sign for respiratory diseases, since fine crackles are originated in small air paths [128]. A crackle can be defined as fine (short duration) or coarse (long duration) [27,92,135]:

- Coarse crackles are of less intensity and of longer duration than fine crackles.
- Fine crackles instead are present in higher frequencies. Pitch range is from 10 to 2,000 Hz and duration < 20 ms.

c) Wheeze: This sound presents a musical character [27,133]. Acoustically, it is characterized by periodic waveforms with a dominant frequency usually over 100 Hz and with duration of ≥100 ms; hence, the sound must include at least 10 successive vibrations [92]. It is heard at expiration [128]. If the wheeze contains essentially a single frequency, the wheeze is called monophonic. If it contains several frequencies, it is termed a polyphonic wheeze. Wheezing and other abnormal sounds can sometimes be heard without a stethoscope [92]. Wheezes are usually associated with airways obstruction due to various causes. Wheeze can be found at many diseases (for example; congestive heart failure, asthma, pneumonia, chronic bronchities, emphysema, brochiectasis) [128].

d) Squeak: It is a short wheeze. It can be continuous or discontinuous [133]. With relatively short inspiratory adventitious sound having a musical characteristic, occasionally found in patients with interstitial lung disorders [92]. Acoustically, its waveform may resemble that of short wheezes, but they are often preceded by a crackle [92]. The duration of squeaks may vary between 50 and 400 ms [92]. The basic mechanisms of their origin probably differ from those of wheezes in obstructive lung diseases [92]. Squeak can be found for example in pneumonia [128].

e) Stridor: It is loud wheeze and high pitched [133]. It is a very low-frequency wheeze originating in the larynx or trachea. It appears most frequently during inspiration. It can be audible at the mouth, at the trachea and over the chest wall [92]. Usually stridor can be found for example in upper airway obstruction [128], in whooping cough, and in laryngeal or tracheal stenosis [92].

f) Cough sound: Transient sound induced by the cough reflex with frequency content between 50 and 3,000 Hz. The characteristics of cough sounds are different in several pulmonary diseases [92]. Cough sounds containing wheezes are typical in asthma [92].

g) Snoring sound: it is a respiratory low-frequency noisy sound with periodic components (fundamental frequency 30–250 Hz) detected usually during sleep induced by abnormal vibrations in the walls of the oropharynx [92]. It is typical inspiratory sound but a small expiratory component can appear especially in patients with obstructive sleep apnea [92].

4- Speech Voices: They are produced by the larynx [124]. There are three types of transmitted voice sounds: bronchophony, whispered pectoriloquy, egophony [124].

5- Pleural friction rub: If there is infection between two membranes that surround the lungs and chest wall, a sound similar to leather rubbing can be heard. Crackling sounds can be heard while the patient is inhaling and exhaling. If the patient holds his or her breath pleural rub becomes inaudible [92,124].

Lung sound signal has an assortment of superimposed segments [24,26]. Distinctive creations have their own specific time cycles [24,26]. In the meantime, normal and abnormal lung sounds demonstrate suitable changes in frequency range, time-domain waveform, the signal cycle, and the delay time [24,26]. The quantity of numerous sound sources and the time delay contain rich case data, and mirror the physical attributes of lung diseases [24,26].

2.4 Lung Tests

Lung tests [98]:

- Pulmonary function tests (PFTs): A series of tests to evaluate how well the lungs work. Lung capacity, the ability to exhale forcefully, and the ability to transfer air between the lungs and blood are usually tested [117]. Pulmonary function tests are very useful tests to diagnose several lung diseases [117]. The simplest but one of the most informative tests of lung function is a forced expiration [117]. Forced expiratory volume (FEV) is the volume of gas exhaled in one second by a forced expiration following a full inspiration (FEV1) [117,136]. The total volume of the gas exhaled after a full inspiration represents the vital capacity [117]. However, this value could be slightly smaller than the vital capacity measured with slow (normal speed) expiration

[117]. Therefore, this value is called forced vital capacity (FVC) [117]. The normal ratio of the FEV1 is 80 % of FVC [117].

• Spirometry: Part of PFTs measures how fast and how much air you can breathe out [98].

• Chest X-ray: An X-ray is the most common first test for lung problems [98]. It can identify air or fluid in the chest, fluid in the lung, pneumonia, masses, foreign bodies, and other problems [98].

• Computed tomography (CT scan): A CT scan utilizes X-rays and a computer to make detailed pictures of the lungs and nearby structures [98].

• Sputum culture: Culturing mucus coughed up from the lungs can sometimes identify the organism responsible for a pneumonia or bronchitis [98].

• Sputum cytology: Viewing sputum under a microscope for abnormal cells can help diagnose lung cancer and other conditions [98].

• Lung biopsy: A small piece of tissue is taken from the lungs, either through bronchoscopy or surgery [98]. Examining the biopsied tissue under a microscope can help diagnose lung conditions [99].

• Flexible bronchoscopy: An endoscope (flexible tube with a lighted camera on its end) is passed through the nose or mouth into the airways (bronchi) [98]. A physician can take biopsies or samples for culture during bronchoscopy [98].

• Rigid bronchoscopy: A rigid metal tube is introduced through the mouth into the lungs' airways [98]. Rigid bronchoscopy is often more effective than flexible bronchoscopy, but it requires general (total) anesthesia [98].

• Magnetic resonance imaging (MRI scan): An MRI scanner uses radio waves in a magnetic field to create high-resolution images of structures inside the chest [98].

CHAPTER 3

STETHOSCOPE

3.1 The History of the Stethoscope

Medical history and a detailed physical examination, including the sequence of inspection, palpation, percussion, and auscultation ought to be viewed as a fundamental piece of clinical examination [124]. The act of analyzing the body sounds produced by the mechanical vibrations of the organs is called auscultation [137,138]. The auscultation is one of the cheapest, noninvasive, safe, and easily applicable diagnostic methods for the diagnosis of pulmonary diseases [119,124]. Auscultation may be performed directly with the unaided ear, but most commonly a stethoscope is used to determine the frequency, intensity, duration, and quality of the sounds [119].

The stethoscope may be the one instrument common to all physicians [139]. The word stethoscope originates from the Greek words stethos, which means chest, and skopein, which means to explore [139,140]. Today, the stethoscope is a nearly universal symbol of medicine and health care [141]. The stethoscope is a safe, helpful, noninvasive, cheap device [141]. Sound abnormities demonstrate certain pathological conditions of airways or lungs [141]. Hearing of respiratory sounds at high frequency and intensity abnormally on the chest wall may show the presence of disorders [141].

In the early 19th century, auscultating to the chest sounds and heartbeat by pressing the ear to the chest wall was the ancient practice of direct or immediate auscultation [125,139]. Immediate auscultation was known to Hippocrates and practiced in ancient Greece, but was hardly an ideal way to examine patients because some patients did not bath, others were infested with vermin and modesty was an issue, especially with female patients [139].

3.1.1 Monaural Stethoscope

Rene Theophile Hyacinthe Laennec was a French physician who, in 1816, invented the stethoscope [139,142]. He rolled a piece of paper tightly [143]. He could clearly hear the heartbeat by placing one end of this roll on patient's chest and the other end on his ear [139]. Laennec discovered that heart sounds could be heard more clearly and loudly using mediate auscultation rather than immediate auscultation [139]. Laennec spent the next 3 years testing various types of materials to make tubes, perfecting his design and auscultating to the chest findings of patients with pneumonia [139]. He decided upon a hollow tube of wood, 3.5 cm in diameter and 25 cm long, which was the forerunner of the modern stethoscope [139] (Figure 3.1).

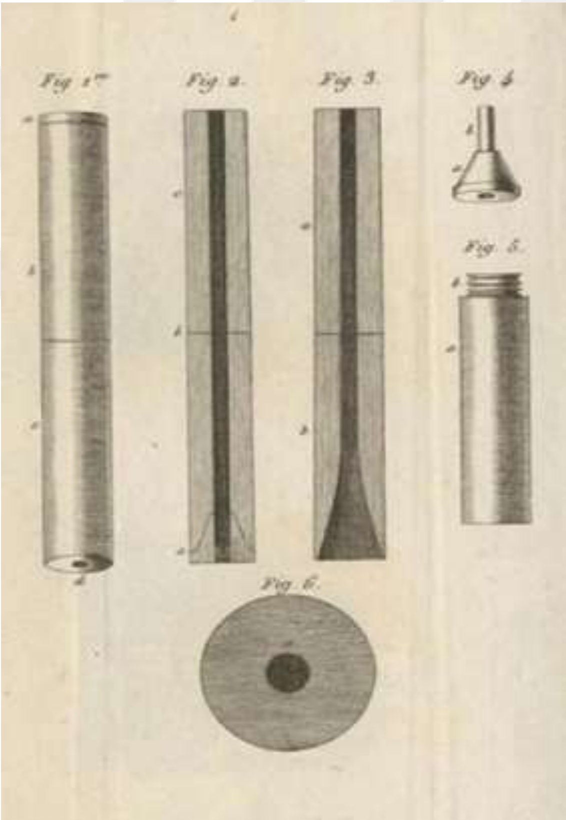

Figure 3.1 Laennec’s stethoscope: (1) instrument assembled, (2) and (3) two portions of the instrument in longitudinal section, (4) detachable chest piece, (5) ear piece unscrewed, (6) transverse section [139]

Laennec’s wooden tube was the first true stethoscope [139]. Wooden stethoscopes were used till the second half of the 19th century [143,144]. Then rubber tubing was developed and used [143,144]. Flexible monaural stethoscopes were introduced around 1832 [143]. These were tubes of coiled spring covered with woven silk, usually 14 to 18 inches long, with a chest piece at one end and usually a very short, straight earpiece at the other [143] (Figure 3.2). Flexible stethoscopes are often confused withconversation tubes, which looked the same, but were much longer than stethoscopes [139].

Figure 3.2 Flexible monaural stethoscopes [143]

3.1.2 Binaural Stethoscope

George Philip Cammann (1852) produced the first recognized usable binaural stethoscope. Cammann's model was made with ivory earpieces connected to metal tubes of German silver that were held together by a simple hinge joint, and tension was applied by way of an elastic band [145]. Attached to these were two tubes covered by wound silk [145]. These converged into a hollow ball designed to amplify the sound, and attached to the ball was a conical shaped, bell chest piece (Figure 3.3) [142,145].

Figure 3.3 Cammann stethoscope [145]

The design of stethoscopes changed little over the next 40 years or so, apart from the development of a differential stethoscope having two separate chest pieces, with tubing connected to each ear [125]. In the 1940's, Dr. Sprague, working with Maurice Rappaport, scientifically investigated the physical principles of stethoscopy, upon which much current knowledge is founded [125]. In 1961, David Littmann designed a streamlined, lightweight stethoscope, with a single tube binaural, which was available in both stainless steel and light alloy [125].

Figure 3.4 Littmann Stethoscope [146]

Since the introduction of the stethoscope in 1816, several modifications (Table 3.1) have been introduced, such as the binaural, the diaphragm, and the combined bell and diaphragm [139,147]. Further developments include teaching, electronic and differential (2 chest pieces) stethoscopes [139,147]. Present day stethoscopes have been created with changes to weight and appearance however utilizing similar standards described by Rappaport, Sprague and Groom [125].

Table 3.1 The evolution of the stethoscope

THE EVOLUTION OF THE STETHOSCOPE		
….-1816		The only method of auscultating to heart sounds was simply to press an ear to the patient's chest
Monaural Stethoscopes		
1816	Laennec	Roll paper, then a wooden tube (Figure 3.1) [139]
1821	McGrigor	The chest plug made entirely of wood and the ear plate made of horn [143]
1828	Piorry	A bell in funnel form, lighter handle, and very thin earpiece [148]
1832		Flexible monaural stethoscopes (Figure 3.2) [143]
1839	Hope	Made of cherry wood and ivory [149]
1843	Williams	The first binaural stethoscope with earpieces made of lead pipe [150]
Binaural Stethoscopes		
1851	Marsh	The membrane of the chest piece of the stethoscope had a flexible structure [151]
1852	Cammann	Flexible tubing (Figure 3.3) [125]
1894	Bianchi	First rigid diaphragm [152]
1925	Bowles and Sprague	Bell and rigid diaphragm combined.
1945–1946	Rappaport, Sprague and Groom	Work for the ideal properties of the stethoscope. [125]
1956-....	Various (for example, Leatham, etc)	The weight and appearance of the stethoscope has been improved [125]
1961	Littmann	Streamlined, lightweight stethoscope, with a single tube binaural, which was available in both stainless steel and light alloy (Figure 3.4) [146]
Electronic Stethoscopes		
1961	Amplivox	Microphone and amplifier technology did not match the physicians' needs.
1991	Clive Smith	Thinklabs Digital Stethoscope (Figure 3.5) [153]
1999	Littmann	3M Littmann Electronic Stethoscope: Noise dampening method in the environment, amplified friction noise reduction features, Bluetooth technology (Figure 3.6) [154]

3.1.3 Electronic Stethoscope

In 1961 an electronic stethoscope was developed by a company named Amplivox, taking advantage of the smaller vacuum tube technology then available [155]. This was intended purely as a teaching device, given its considerable weight and size [155]. Again, microphone and amplifier technology, did not match the physicians' needs, and this proved to be a rudimentary device soon abandoned in favor of traditional stethoscopes [155].

Thinklabs Digital Stethoscope was founded in 1991 by Clive Smith [153] (Figure 3.5). In the mid 90's, stethoscope acoustics had essentially not improved since Laennec built the first stethoscope in 1816 [153]. Physicians confirmed that even top-of-the-line traditional stethoscopes did a poor job of amplifying heart and lung sounds [153]. Thus began Smith's obsession to re-invent the stethoscope [153]. All the benefits of advanced electronic techonology would then accrue and the authentic sound of the stethoscope would be preserved. Physicians would not require any ear retraining [153]. A completely new transducer was needed [153].

Figure 3.5 Thinklabs Digital Stethoscope [153]

Littmann Electronic Stethoscope (Figure 3.6) (1999) combines Ambient Noise Reduction method and amplified friction noise reduction features [154,156]. The 3M Littmann Electronic models are specially designed to detect hard to hear heart and lung sounds [154].

Figure 3.6 3M Littmann Electronic Stethoscope [154]

3.2 Properties of Stethoscopes

A stethoscope is composed of 3 parts (Figure 3.7):

1) Headset
   Eartips
   Eartube

2) Tubing

3) Chestpiece
   Bell
   Stem
   Diaphragm

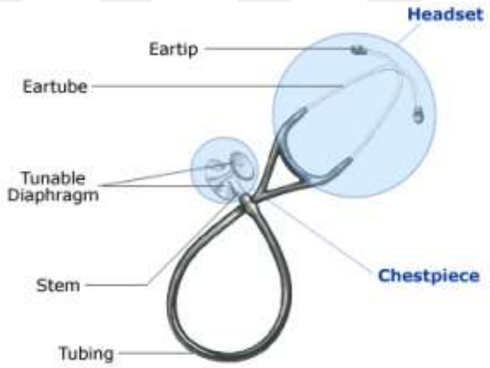

Figure 3.7 Parts of stethoscope

The most important parts to know are the diaphragm, which is larger, flatter side of the chest piece, and the bell, which has the smaller, concave piece with a hole in it [139,157]. The diaphragm is a sealed membrane that vibrates, much like your own eardrum [157]. When it does, it moves the column of air inside the stethoscope tube up and down, which in turn moves air in and out of your ear canal, and voila, you hear sound [157]. Since the surface area of the diaphragm is much greater than that of the column of air that it moves in the tube, the air in the tube must travel more than the diaphragm, causing a magnification of the pressure waves that leave the ear tip [157]. In your ear, larger pressure waves make louder sounds [125]. This is how stethoscopes amplify sounds [125].

The stethoscope bell may be utilized to distinguish respiratory sounds [125]. The diaphragm may also be utilized to define and easily situate both normal and abnormal respiratory sounds. [125].

The bell of a stethoscope is best used for auscultating to low-pitched sounds [141]. However, if the underlying skin is pressed too hard, the advantage of bell will be lost because the skin will become stretched too much [141]. The utilization of the stethoscope diaphragm for pulmonary auscultation is ideal because it enhances high frequency conduction [135]. The auscultation should be done over the bare skin, not over clothes, as there may be rubbing noises [141].

Laennec later published the first seminal work on the use of auscultating to body sounds, De L'auscultation Mediate [139]. Laennec is viewed as the father of clinical auscultation and composed the first depictions of bronchiectasis and cirrhosis and furthermore classified respiratory conditions from the sounds he heard with his innovation [139]. Laennec perfected the art of physical examination of the chest and introduced many clinical terms still used today [139].

Assessing lung sounds: You need to start above the clavicle, since lung tissue extends that high [141]. Always auscultate to left and right sides at the same level before moving down to the next level this way you get a side-by-side comparison, and any differences will be more apparent [141].

3.3 Acoustics of the Stethoscope

Using the stethoscope has some disadvantages: It is a subjective method which depends on physician's experience, ability, and auditory perception [50,158]. It lacks a method of recording, has insufficient sensitivity and offers no quantitative description [50]. Moreover, the stethoscope decreases frequency components of respiratory sound signal above 120 Hz [36, 50]. However, the human ear is not much delicate to the lower frequency band [36,48,50]. Abella et al. compared six different stethoscopes. They found that the sounds between 37.5-112.5 Hz were generally amplified by the stethoscope bells by about 5-10 dB and decreased by the stethoscope diaphragms [132]. All in all bells consistently outperformed diaphragms by expanding the amplitude of sounds, creating amplification of up to dB in the range 37.5– 112.5 Hz, however the conclusion is that stethoscope diaphragms were reliably better at decreasing the amplitude, specifically the amplitude of the lower frequencies [14,132].

Despite the high cost of many modern stethoscopes, these instruments remain simply conduits for sound conduction between the body surface and the ears [16]. They are less than ideal acoustic instruments because they do not supply a frequency-independent, uncolored transmission of sounds [16,159]. Amplification tends to occur below 112 Hz and attenuation at higher frequencies [16]. This feature is inherent in the design of the stethoscope that often places convenience and clinical utility ahead of acoustic fidelity [16]. Amplification at low frequencies is appreciated by cardiologists since heart sounds are in this frequency range, which is poorly perceived by the human ear [16]. Auscultation of the lung, however, could benefit from a more faithful representation of sounds than present stethoscopes provide [16]. There are many factors that affect the auscultation [16]. There is relatively little bilateral asymmetry of sound amplitude and that asymmetry indicates disease [16]. Sounds on the chest surface are primarily filtered versions of those detected over the trachea or neck [16]. Considerably more information of clinical utility can be gathered from respiratory sounds [16].

The sound perception of the human ear is complex [132]. We can concentrate on specific frequencies [132]. Concurrent higher frequencies and harmonics perceived at the ear give distinctive characters of sounds [132]. High frequency components of a complex sound are generally masked by low frequency components [132]. This masking is progressive and occurs when the amplitude is rising [132]. Depending on the age, progressive hearing loss is called Presbycusis [132]. But this situation may not be the disadvantage of the elderly physicians as it usually affects frequencies above 3,000 Hz, well above the frequency of sound that must be heard by a stethoscope [132].

Limits of human audition: Works were undertaken to measure the ability of the human ear to determine the crackles of the oscultation signal [27,92]. For this purpose, techniques involving simulated cracks overlapping with real breath sounds were used [27,92]. The most important detection errors were shown to be caused by the following factors [27,92,164]:

- Intensity of the respiratory signal: deep breaths mask more crackles than superficial breaths [126,160],
- Type of crackles: fine crackles are easily recognizable in so far as their waveform differs more from the waveform of classical lung sounds [192,160],
- Amplitude of crackles

The sound repertoire of the lung may indeed be limited when heard through a stethoscope, but it clearly exhibits a much wider range of information content when digitally analyzed [57]. Computer analysis is now reaching beyond the capabilities of the human ear to resolve changes in respiratory sounds [57] (Table 3.2).

Table 3.2 Advantages and limitations of auscultation by stethoscope [141]

Advantages and limitations of auscultation by stethoscope	
Advantages	**Limitations**
Effective	Information obtained is subjective
Non invasive	Information is dependant on the expertise of the examiner
Inexpensive	Auditory capability is also a factor
	There is not a permanent objective record
	Non continuous

Oscultation is often performed in an environment where noise can not be avoided. [161]. Limitations of acoustic auscultation are weak signal transmission due to noise, resonance, and further weakening of high frequency sounds [161]. These limitations are the most critical factors to take notice in pulmonary auscultation, as respiratory sounds are usually in the higher frequency spectrum, which ranges from 50 Hz to 2,500 Hz [161]. Conversely, electronic auscultation has the benefit of signal amplification and ambient noise lessening [161]. This results in an increase in the signal-to-noise ratio regardless of the sensitivity of the ear to various acoustic frequencies [161].

Auscultation technique:

1. It is important that the auscultation is done in a place without noise. Auscultation ought to be performed in a quiet place. Patients should preferentially be in a sitting position. When patients are in a lying position, turn them on the other side to examine their back [124].

2. Auscultation should never be done through the clothing [124, 141].

3. Patients are asked to breathe deeply while their mouths are open [124].

4. Since lung tissue is high, it is necessary to start over the clavicle [124].

5. Always auscultate to left and right sides at the same level before moving down to the next level [141].

3.4 Capture Techniques for Electronic Stethoscopes

The use of the stethoscope is strictly based on the physician's experience. [162]. For this reason it is considered to be subjective [162]. Recently, it has led to studies that can do lung sounds on a more objective basis [162]. The assessment of pulmonary sounds, because of their short duration, are hard to recognize [162]. Because the human ear can not recognize events that occur in the milliseconds [162].

There are problems that limit the wider use of lung sounds. One of the problems is the technical hardship of catching sound from the surface of the body [4, 58]. None of the sensors are thought to be ideal [4]. It is only in recent years that the responses of microphones when attached to the chest in various ways have been extensively analysed [4].

It is an important point to capture of the sound before the analysis phase [27,92]. The chest behaves as a reduction and low-pass filter. For this reason, placing the microphone is important [27,92]. Kraman et al. studied the effects of different microphones [163]. They deduce that the optimal electret microphone coupler chamber for lung sound obtaining ought to be conical shaped, between 10 and 15 mm in diameter [163].

Different techniques and devices have been defined to capture sound [27,92]:

- Utilizing a unique microphone: This method is widely utilized [27,164]. Electret microphone is often used as a sensor [27]. The sampling frequency utilized is the same as the one utilized for telephony codecs (8 kHz) [27], an analogue/digital conversion with a 16 bits resolution [164]. Others use an accelerometer whose performance is less than an electret microphone, but less sensitive to background noise [27,92].
- Use of a few microphones and three dimensional representations [27,92]: This technique is a dynamic method that allows structural and functional features for the diagnosis, making it possible to determine the origin of the sounds [27,92].
- Emission of a sound and analysis of its propagation [27,92]; This method processed the signal propagation characteristics through the respiratory tract and chest using a loudspeaker inserted into the mouth of the patient [27,92]. The analysed parameters are energy ratios, signal time delays, and dominant frequency [92].
- Measurement in closed loop controlled ventilation [27,92].

In our study, we focused on the utilization of a unique microphone [8].

3.5 Factors Affecting the Sound Acquisition Using Electronic Stethoscopes

The acoustical properties of stethoscopes used today vary widely [165,166]. At each stethoscope, resonances/antiresonances are seen [165,166]. This is due to differences in the choice of sensor and mechanical design [165,166]. When the stethoscopes are tested, no flat frequency response is seen [165,166]. This response is more suitable for calculating the acoustic signal [165,166]. None of them has an impedance that closely matches the skin structure [165,166]. There is no standard used to measure and compare the acoustic properties of electronic stethoscopes [165,166]

Traditionally, a stethoscope is used to acquire audio data from lungs. However, traditional stethoscopes have no ability to record audio into a device because they are designed to relay analog audio data to human ear. To record audio an electronic stethoscope must be used.

An electronic stethoscope consists of a traditional stethoscope chest piece connected to a condenser microphone with an elastic tube, which the microphone is connected to either directly into a device or an electronic circuit that filters and amplifies the audio data and then connects to the device so it can be stored to any device that has recording capabilities.

However to use recorded data, audio must be of high quality. We observed that the sound quality recorded during our research depends on various causes:

1) Environmental noise

   The environment of the recording is very important. It directly affects the recording quality by adding substantial noise to the recording. Environmental noise can be everything in the recording room such as computer fans or people speaking or sounds that come from outside such as vehicle engines or alarms.

2) Frictional noise

   The noise that is caused by human skin rubbing to the diaphragm or the handle of the stethoscope is called friction noise. Frictional noise also occurs when the tube that connects the chest piece to the microphone rubs to human skin. The reason for this is all materials, regardless of how smooth they are, generate this frictional noise when placed on human skin. The user of the electronic stethoscope may also cause this noise while holding the chest piece.

3) Electronic noise

   Electronic noise is caused by the electronic components that are connected to the microphone. Especially if the electronic stethoscope is using a high powered internal power source or connected directly to electricity, this noise can decrease the quality of the recording. Also, microphones by default also include electronic noise from their internal circuits while recording.

4) The material of the connector tube

The sound generated by the diaphragm travels through a tube to reach the microphone. Material selection when it comes to building this tube is very important because; it affects how much environmental and friction noise is relayed into the tube and it affects the amount of audio data lost while sound travels in this tube.

5) Quality of the microphone

Microphones have various properties which directly affects quality while especially recording body sounds.

First of all, the frequency range of the microphone determines what minimum and maximum frequencies can be recorded. Since body sounds are usually in low frequencies, if a microphone with a higher range is used while recording, not all audio frequencies can be stored leading to data loss.

Secondly, there are two main types of microphones; omnidirectional and directional. Omnidirectional microphones capture audio from all directions equally. However directional microphones capture audio usually from one direction best, and dampen the other directions. In electronic stethoscopes, omnidirectional microphones lead to poor quality recordings because they capture more environmental and frictional noise than directional microphones. So, usually directional microphones are used in electronic stethoscopes.

6) Quality of the recording device

Recording device can be anything from a computer, mobile device or specialized recording equipment. One thing they have in common is the audio card or audio circuits that the electronic stethoscope is connected.

Various devices have a wide range of audio cards that are installed on them. They have different properties, hence a huge number of different recording qualities when used with an electronic stethoscope. If we compare devices with default audio hardware; recording quality on default on-board audio cards on desktop computers are usually the best, closely followed by laptop computers. Mobile devices however, are not built to handle such low frequency audio data and perform worse than computers.

The best option for audio recording is to use an external audio card that are used to record music professionally. These devices are more expensive than the on-board audio cards, however they can be connected to most of the devices and can be used to record directly into the device. This also insures the level of recording quality stay the same on every device.

CHAPTER 4

CURRENT ANALYSIS METHODS OF RESPIRATORY SOUNDS

Respiratory sound analysis methods can be grouped into three groups. The three groups are briefly described below [167].

4.1 Statistical Methods

The first category is the use of statistical analysis methods to classify the respiratory sounds. Statistical analysis is used to process data sets to determine how usual an event occurs based on its historical data [168].

The methods used in this category are; higher order crossing discrimination analysis, analysis of variance (ANOVA), Fisher discriminant analysis, lacunarity‑based analysis, and linear discriminant analysis [169].

4.2 Visualization Analysis

The second category is to use visualizations of respiratory sounds and find the similarities or differences between them to classify and diagnose sound abnormalities [92]. These abnormalities are identified by the intensity of the signal visualizations [92]. This analysis results from the experience of the physician who is conducting the analysis [41]. Therefore, it requires the physicians to be well trained in their field [92]. However, this method suffers from the human error as the analysis and the end diagnosis is decided by a physician.

The circled area in Figure 4.1 shows the intensity changes which indicate the abnormalities in the respiratory system [169].

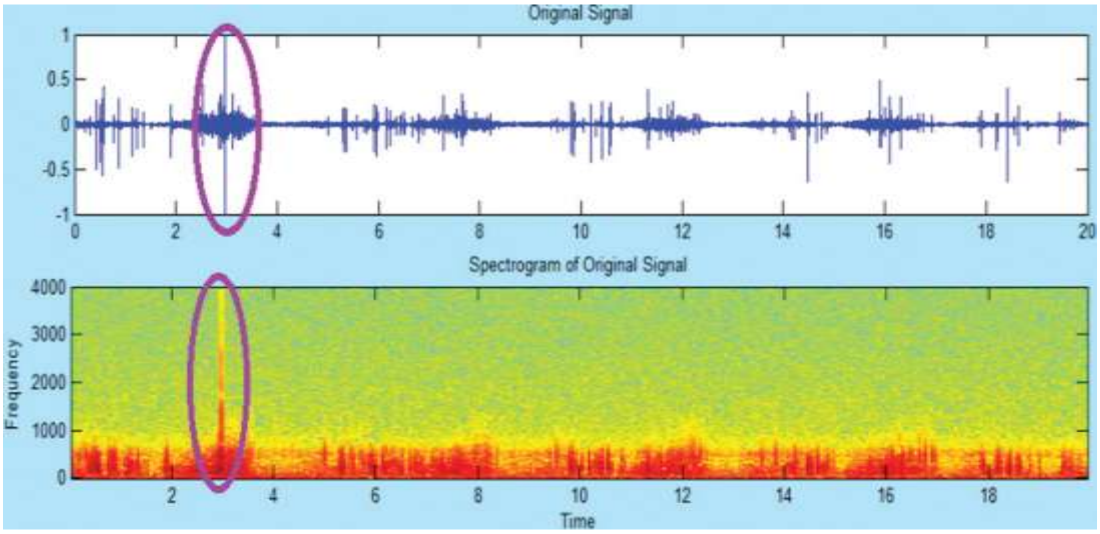

Figure 4.1 Example of spectrogram [169]

- Spectrogram is the representation of how frequency changes over time. The colors represent the intensity of the signal (Figure 4.2) [92].

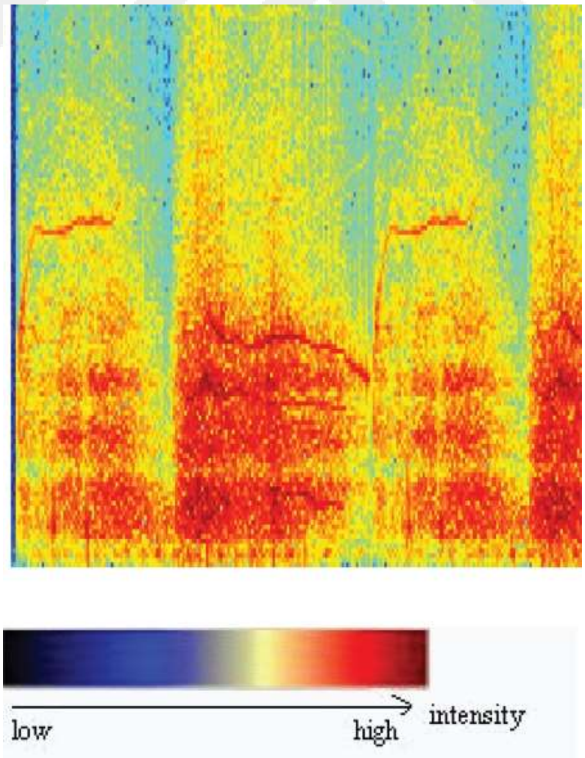

Figure 4.2 Spectrogram of a wheeze [92]

- Waveform represents how the amplitude of the signal changes over time. Below is a respiratory sound that was taken from a sick person (Figure 4.3) [92].

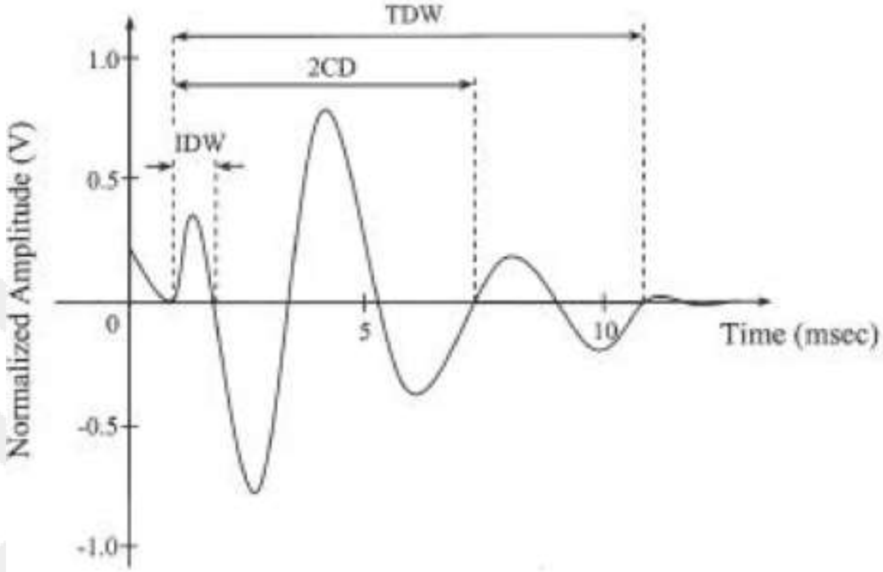

Figure 4.3 Example of waveform [92]

- Phonopneumogram is the overlapped plot of the waveforms of the respiratory sound and the airflow sound when a person is breathing (Figure 4.4) [92].

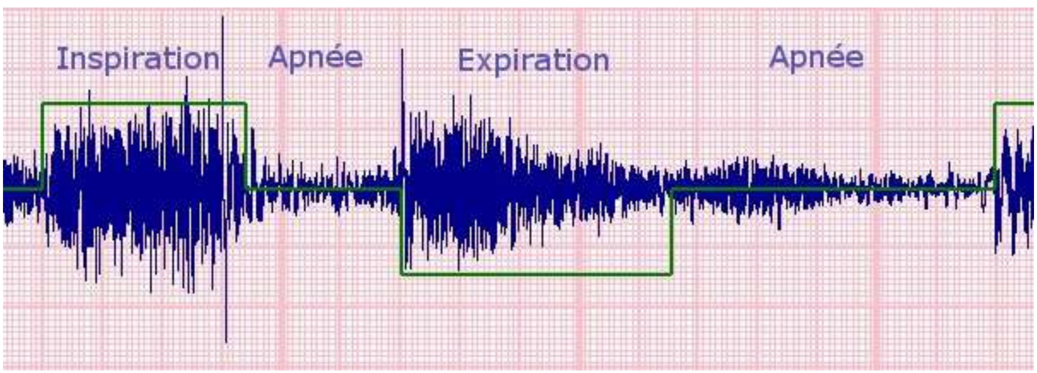

Figure 4.4 Example of phonopneumogram [92]

4.3 Computerised Audio Recognition Methods

The third category is the use of computers to analyze various properties of the sound to reach a conclusion.

Expert systems are the most commonly used way to analyse data and produce conclusions based on the input, knowledge-base of the system and the rules that help it reach a conclusion. Their knowledge-base is generated by an expert in the specific field that the system is used. Expert systems are usually very narrow in scope because they are programmed to perform a very specific analysis with a very specific knowledge-base and rule set [79].

The newest addition to the computerized analysis systems is machine learning systems. The most significant feature of machine learning systems is their capability to learn and produce a generalized conclusion. They are being used in almost every field in the past decade and their use have improved those fields a lot [170]. Machine learning techniques such as artificial neural network (ANN), Gaussian mixture model (GMM), hidden Markov model (HMM), k-nearest neighbor (k-NN), and fuzzy analysis were extensively used in computer based respiratory sound analysis by previous researchers [169,171,172].

Each respiratory sound has different properties and technology has made it simple now to improve the classification of lung disorders. The lung disorders have their corresponding respiratory sounds and corresponding dominant frequency range, using which the disorder can be identified employing signal processing techniques. Machine learning can be used further to classify the lung disorders more accurately.

The main advantage of computer‑based respiratory sound analysis is that it is non‑invasive and since extensive manual analysis by experts is not needed, less expensive, compared to other methods [169].

Before analyzing signals with a computerized audio recognition method, first, analog audio is converted into digital, and then using signal processing feature extraction is performed. Finally, these features are used in training the classifiers.

CHAPTER 5

FEATURE EXTRACTION METHODS

Feature extaction is the process to identify distinguishing properties of a signal, therefore it has a major role in classifying audio signals. The audio features are selected as follows [21,173,174]:

- Time domain
- Frequency domain
- Time-frequency domain

It is possible to consider frequently utilized feature extraction methods in classifying audio as follows [21, 175]:

- Autoregressive (AR) model
- Mel-frequency cepstral coefficients (MFCC)
- Energy
- Entropy
- Spectral features
- Wavelet

In the following subsections, all the feature extraction methods available in the field, are listed and explained in detail [176].

5.1 Raw Signal Data

Raw signal data means that the original signal is used without altered or processed by any means. When working with raw signal, the amplitude change over time data (which is the waveform plot) is extracted and used in analysis [177].

Advantages:

- Data is not modified in any way.
- Data loss is minimal.

Disadvantages:

- Raw signal data only provides the change of amplitude over time.

5.2 Autoregressive Models

Autoregressive model is a random process that describes a time-varying process. Its output variable is linearly dependent on its previous values, which makes it a stochastic difference equation [30].

5.3 Fourier Transform (FT)

The FT decomposes a signal into the frequencies that it contains therefore it generates the frequency domain model of the input signal [174]. The result contains the synthesis of contributions of various frequencies in the signal. We can also use the result to get the original signal back. This process is called inverse Fourier transform [178].

There are 2 different types of Fourier transform. These are:

5.3.1 Fast Fourier Transform (FFT)

FFT is a computer algorithm for rapidly calculating the frequency spectrum of a signal. A FFT algorithm calculates the discrete Fourier transform (DFT) of a sequence, or its inverse [179,180].

5.3.2 Short Time Fourier Transform (STFT)

STFT is a Fourier-related transform. STFT has been used to detect the sinusoidal frequency and phase content of a local part of a signal as the time changes [180-182].

5.4 Spectral Analysis

Spectral analysis is utilized to find the distribution of power over frequency (spectral content) of a time series from a finite set of measurements [32]. There are two methods to spectral analysis [183,184]. In the first method, the applied signal is performed to a bandpass filter with a narrow bandwidth so that the spectral content at the inlet of the filter is swept along the frequency band [183,184]. The second method is to propose a model for the data [183,184]. This allows parameterization of the spectrum [183,184]. Thus, the problem of spectral estimation is reduced to estimate the parameters of the assumed model [183,184].

5.5 Finite Impulse Response (FIR) Filtering

An FIR filter takes an input signal x[n], modifies it by the application of a mathematical rule, and produces an output signal y[n] [118]. This rule is a difference equation, and it tells us how to compute each sample of the output signal y[n] as a weighted sum of samples of the input signal x[n] [118].

5.6 Mel Frequency Cepstral Coefficients (MFCC) Features

Frequently used feature extraction method in automatic speech recognition (ASR) is MFCC [185,186]. MFCC mimics the logarithmic perception of loudness and pitch of human auditory system [190,191]. In audio processing, the MFC is a demonstration of the short-term power spectrum of a sound [185,186]. The MFC is based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency [185,186]. MFCCs are coefficients [185,186]. They jointly create an MFC [185,186]. They are obtained from a type of cepstral representation of the audio clip [34,185,186]. The fact that the frequency bands are equally spaced in the MFC is the most important difference between the cepstrum and the mel-frequency cepstrum [186]. This approximately indicates that the response of the human auditory system is more intimately than the linearly-spaced frequency bands utilized in the normal cepstrum [34,185,187].

Advantages:

- Provides better representation of compressed audio.

5.7 Linear Predictive Coding (LPC) Features

LPC is a method for signal source modelling in speech signal processing [188-190]. It has wide an application area. LPC analysis is usually most appropriate for modeling vowels which are periodic, except nasalized vowels. LPC is attributed on the source-filter model of speech signal [188-190].

Advantages**:**

- It is useful for encoding speech at a low bit rate [189,190].
- It makes extremely correct prediction of speech parameters [189,190].

5.8 Wavelet Packet Decomposition (WPD)

WPD is a wavelet transform. The discrete-time signal is passed through more filters than the discrete wavelet transform [192,193]. It incorporates numerous bases. Different basis will cause in different classification performance. It covers the shortage of fixed time–frequency decomposition in the discrete wavelet transform [192,194,195].

5.9 Subband Based Cepstral (SBC)

SBC coefficients were derived with the application of discrete cosine transformation on the subband energies [196].

5.10 Periodogram

In signal processing, a periodogram is a prediction of the spectral density of a signal. Periodograms are used to identify the dominant periods of a time series [197]. The periodogram is a component of more sophisticated methods [197]. It is the most common tool for examining the amplitude vs frequency characteristics of FIR filters and window functions [187].

5.11 Welch Method

Welch's method is asymptotically a method to spectral density prediction [198]. The method is an improvement on Bartlett's method [198]. The method depends on the idea of utilizing the periodogram spectrum estimates that are generated as a result of converting a signal from time domain to the frequency domain [198]. It lessens noise in the estimated power spectrum in return for diminishing the frequency resolution [198,199].

Advantages:

- Provides noise reduction [198].

5.12 Yule-Walker Methods

Yule-Walker Method (or autocorrelation method) block estimates the power spectral density of the input [200,201]. To accomplish this, the Yule-Walker autoregressive (AR) method is used [200,201]. This method applies window to data [200,202]. It minimizes the forward prediction error in the least squares sense [200,202].

5.13 Burg Methods

Burg Method block estimates the power spectral density of the input frame [203,204]. To accomplish this, the Burg method is used [203,204]. This method complies with an autoregressive (AR) model to the signal [202,203,205]. It does not perform window to data [203,204]. It diminishes the forward and backward prediction errors in the least squares sense, with the AR coefficients restricted to compensate the Levinson-Durbin recursion [202,203,205]. Burg method abstains calculating the autocorrelation function, and instead directly guesses the reflection coefficients [203,204].

5.14 Gaussian Mixture Model (GMM)

A GMM is a probabilistic model [206,207]. It assumes all the data points are produced from a mixture of a finite number of Gaussian distributions with unknown parameters [206,207]. Mixture models can be defined as generalizing k-means clustering toinclude information about the covariance structure of the data as well as the centers of the latent Gaussians [206,208]. They are used intensively for density estimation [206,207].

5.15 Wavelet Transform (WT)

WT is an appropriate technique for getting the time-frequency distribution of signals [36,209]. WTs are based on small wavelets with limited duration [210]. It is in fact an infinite set of various transforms [210].

The basic idea behind WTs is that the transformation should only let changes in time extension; however it should not shape it [210,211]. It selects the appropriate basic functions that allow it and is influenced by it [210,211]. WT computes the inner products of a signal with a family of wavelets [210].

The mathematical function utilized to divide a given function or continuous-time signal into parts of different scales is called wavelet [210,212]. Generally, a frequency range can be assigned to each scale part [210,212]. Then each scale part can be studied [210,212]. A wavelet transform is the presentation of a function by wavelets [210,212].The wavelets are scaled and translated copies of a finite-length or fast-decaying oscillating waveform [210,212].

Advantages:

- Provides good quality image compression [210].

The wavelet transform is categorized into continuous wavelet transform and discrete wavelet transforms 210,213].

a. Continuous wavelet transforms (CWTs): CWT is utilized to divide a continuous-time function into wavelets [214,215]. Compared to the Fourier transform, CWT has the capability to generate a time-frequency presentation of a signal providing very good time and frequency localization [215,216]. The CWT is a convolution of the input data sequence with a set of functions produced by the mother wavelet [216,217]. This convolution can be calculated by utilizing a fast Fourier transform algorithm [217,218].

   Advantages:

   - Resistant to the noise in the signal [214].

- Very efficient in determining the dampening ratio of an osscilating signal [214].

b. Discrete wavelet transforms (DWTs): DWT is an implementation of the wavelet transform that is a discrete sampling of wavelets [219,220]. Similarly as with other wavelet transforms, the most important advantage over Fourier transforms is temporal resolution: they capture both frequency and position information [219,220]. The DWT is not time-invariant yet extremely sensitive to the alignment of the signal in time [218,221]. The reason for this is the rate changing operators in the filter bank [218,221]. Mallat and Zhong suggested a new algorithm for wavelet representation of an unchanging signal in time shifts for each point in time [218,221].

5.16 RMS-SNR Envelope Calculation

Noise of a signal is evaluated by the root-mean-squared (RMS) value of the fluctuations over time [222]. The signal-to-noise ratio (SNR) is denoted as the average over time of the peak signal divided by the RMS noise of the peak signal over the same time [222]. To get a precise outcome for the SNR it is generally required to measure over 25 -50 time samples of the spectrum [222].

5.17 Katz Fractal Dimension (KFD) Calculation

KFD calculation is derived from the waveform and is a bit slow [223,224]. This computation eliminates the binary sequence creation phase [223,224].

5.18 Time Expanded Waveform Analysis

Time-expanded wave-form analysis gives reproducible visual displays [25]. This allows different properties of sounds to be documented and increase diagnostic utility of sounds [25].

5.19 Spectrogram

A visual representation of the sound or other signal frequency spectrum is called spectrogram [225,226]. Other nomenclatures for spectrograms are spectral waterfalls, voiceprints, or voicegrams [225,226]. Frequently utilized areas of spectrograms are to detect spoken words, phonetically, and to analyze the various calls of animals [225,226].

5.20 Vibration Response Imaging (VRI)

VRI records the intensity and distribution of respiratory sounds during the respiration cycle [227,228]. VRI, a novelty computer based technology takes the concept of the stethoscope to a more progressive level [227]. The technology is based on the physiologic vibration generated during the breathing process when flow of air distributing through the bronchial tree creates vibration of the bronchial tree walls and the lung parenchyma itself [227]. The VRI technology represents changes as a grey scale-based dynamic image [227]. The darker the higher the vibration intensity and the lighter the lower the vibration intensity is [227]. The foremost information that the VRI provides on vibration energy, is how lung sounds behave and function during inspiration and expiration [227].

5.21 Linear System Analysis

Linear system analysis is the study of equilibrium and change in dynamical systems, that contain variables which may change with time [229]. These variables include system inputs, outputs, as well as variables describing internal states of the system [229]. To perform the analysis, relationships between these variables are described by a set of equations known as the model [229]. For linear system analysis to be applicable, the model must possess the linearity property [229].

5.22 Dynamic Time Warping (DTW)

DTW is one of well-known algorithms for find an optimal alignment between two temporal sequences, which may vary in speed [230,231]. Initially, DTW has been utilized to analyze different speech patterns in automatic speech recognition [230,231].

5.23 Segmentation

Audio segmentation is the procedure of dividing a digital audio into multiple segments [232,233]. The goal of segmentation is to simplify and/or change the representation of audio into something that is more meaningful and easier to analyze [232,233].

5.24 Multi-scale Principal Component Analysis (MSPCA)

Principal component analysis (PCA) is an essential tool in investigating data [234,235]. PCA prompts to a solution which supports the structures with large variances [234,235]. It looks for the subspaces that maximize the sum of squared pairwise distances between data projections [234,235]. PCA is a linear technique which transforms data to a new coordinate system using linear orthogonal transformation such that the new coordinates are ordered by variance [236,237]. The coordinate with highest variance is the first principal component; the second principal component is the coordinate with the second highest variance and so on [236].

CHAPTER 6

CLASSIFICATION METHODS

ANN, k-NN, GMM, HMM, Fuzzy and GA classification methods are generally utilized in computerized lung sound analysis [21]. The use of support vector machines (SVMs) was found to be very limited in the literature [21]. The most commonly used machine learning methods used for lung sound analysis are ANN and k-NN [21].

Different types of classification methods in this area will be summarized under two headings as shown below.

6.1 Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are deliberately established computing systems that allow the use of neural organizational principles inspired by biological neural networks to perform certain tasks such as clustering, classification, pattern recognition ets [92,238,239]. Especially, ANN mimics electrical activity in nervous system [92,240,241]. In ANN, knowledge is deployed between neurons and connections [36,92,240]. The neurons are generally composed in a layer or vector [241]. The output of a layer is the input to the next layers [241]. Each connection between artificial neurons can transmit a signal from one to another [241]. The nodes can take input data and perform simple operations on the data [241]. The result of these operations is passed to other neurons [241]. The output at each node is called its activation or node value [241]. Each link is associated with weight [241]. All of the weight-adjusted input values are then summed with a processing element utilizing a function that converts a vector to scalar such as summation, average, maximum input or mode value to generate a single input value in the neurode [241]. After the input value is computed, the processing element then utilizes a transfer function to generate its output [241]. The transfer function transforms the neurode's input value [241]. This transformation includes sigmoid, hyperbolictangent, or other nonlinear function [241]. This procedure iterates itself between layers of processing elements until the final output value or vector of values, is generated by the neural network [241].

Although there are single-layer networks, most of the applications are networks with three normal layers [241]. These layers are input, hidden, and output [241]. In real-time applications, data source of the input neuron layer is generated by either input files or directly from electronic sensors [241]. The output layer conveys the information either to the outside, other processing or other apparatus [241]. The hidden layer is between input and output layers [241]**.** It may consist of several layers. [241]. These inner layers form neurons that are connected to each other by a variable power connection [241]. While some neurons perform addition on its inputs, others perform subtraction [241]. There are also feedback connections [241]. In the feedback, the output of the corresponding layer is sent to the previous layer [241]. One gives rise to the next neuron to be added, whilst the other causes it to be removed [241].

ANNs are capable of learning, which takes place by altering weight values [241]. Weighted data signals entering a neuron form the electrical stimulation of a nerve cell [241]. The neural network learns by adjusting its weights and bias iteratively to yield desired output [241]. For learning to take place, the neural network is trained first [241]. The training is performed using defined set of rules also known as the learning algorithm. [241]. ANNs are used for complicated pattern recognition and classification [36].

The multilayer feed forward neural networks have the following characteristics [242-244]:

- It is a mathematical model inspired by the nervous system [243,244].
- It is formed from multitude tightly connected processing elements [243,244].
- Depending on its local knowledge, a processing element may answer dynamically to the input stimulus [243,245].
- It can learn, recall, and generalize from training data by assigning or adjusting link weights [242,245].
- Its connections hold the knowledge [242,245].

- The power of calculation is based on its collective behavior [244,245].

Multi layered feed forward neural networks are widely utilized in many areas because of these features [242,245].

ANNs are commonly utilized in medicine for modelling, diagnostic classification, and data analysis [36]. The backpropagation (BP) algorithm is the most frequently utilized training algorithm in classification problems [36].

Neural networks may be categorized as shown below [241]:

- Binary-valued input
    - Supervised learning
    - Unsupervised learning
- Continuous-valued input
    - Supervised learning
    - Unsupervised learning

Supervised learning algorithms utilize the distinction between the wanted and true output to regulate the suitable weights for the ANN [241]. In supervised learning, all data is labeled and algorithms learn how to guess the output from input data [241]. Some supervised learning algorithms are notified whether the output is compatible with the input and that the weights are adjusted to obtain correct results [241].

Unsupervised learning algorithms only take input stimuli [241]. In unsupervised learning, all data is unlabeled and the algorithms learn to estimate it from input data [241]. The network does not need any data related to output accuracy [241].

The developer must make many decisions to design an ANN [241]. For example, input values, training and test data set dimensions, learning algorithm, network architecture or topology, and transformation function [241]. Many of these decisions are interdependent [241]. For instance, the type of input value will be determined by the ANN architecture and learning algorithm [241]. For this reason, it is imperative to identify and apply a methodology when designing ANNs [241]. It is possible to list these steps as shown below [241]:

- Define data to utilize.
- Define input variables.
- Divide data into training and test sets.
- Determine the network architecture.
- Choose a learning algorithm.
- Convert variables to network inputs.
- Perform the training by repeating until the ANN error falls below the acceptable value.
- Perform the testing on the holdout sample to verify the ANN generalization.

If values for design factors are chosen improperly, poorly performing ANN applications may emerge [241].

It is possible to count medical, engineering, business, and scientific problems within the areas of ANN practice [241]. There are studies that report that ANN performance is better than traditional statistical methods and other standard machine learning methods [241,246].

The different ANN types are described below.

6.1.1 k-Nearest Neighbor Algorithm (k-NN)

One of the most frequently used prospective statistical classification algorithms is k-NN [92,247]. It is a method utilized to classify objects based on the nearest training instances in the property area [92,247]. The k-NN method gathers all events and classifies new events on the basis of similarity [926,248].

The basic idea of the k-NN method is to appoint new unclassified samples to the class to which most of the closest neighbors belong [92,249]. This algorithm has been shown to be more efficacious in decreasing false classification errors in the case of numerous examples are found in the training data set [92,249]. One of the most important advantages of this method is that it may readily cope situations when there are three or more class sizes [92,249,250].

It is expressed as having a lazy learning algorithm because all the calculations are delayed until the classification [92,247]. No learning is done throughout the training stage [92,247]. But a training data set is needed [92,247]. The class is used to create an instance of the search field with known instances [92,247]. All the training data is required throughout the testing stage [247,250].

The steps of the k-NN algorithm are the training and classification phases [92,248]. In a multidimensional feature area of the training phase, vectors with a class label in each are samples of training [92,251]. The class labels and feature vectors of the training samples are kept at this phase [92,251]. In all the classification techniques based on k-NN, the classification correctness to a great extent relies upon the value of K and the kind of range measurements utilized for calculating closest range [252, 253]. K can be said to be a user-defined constancy in the classification phase [251]. Among the K training samples nearest this query point, the most repeated label is identified and classified as the test point [251]. Briefly, the library of reference vectors is compared either to the query point or to an input feature vector [251]. The query point is then labeled with the closest class of library feature vector [251]. The method to classify query points by distance from points in a training set is a simple but effective method to classify new points [250,251].

When an unknown class is evaluated, the algorithm computes its K nearest neighbors and the class is assigned between these neighbors [248]. The k-NN algorithm's testing phase is costly in both time and memory, but the training phase is very fast [248,250].

Advantages [254]:

- Computationally simple.
- Provides good results for small sized datasets.

Disadvantages [254]:

- Does not provide good results for larger sized datasets.
- Causes difficulty where the sample sets overlap in the dataset.

- If a class is appointed an input vector, then there is no sign of strength of being a member of that class [255].

6.1.2 Quadratic Classifier

Quadratic classifier, one of the methods used for machine learning and statistical classification, is a general version of linear classifiers [256,257]. This method is utilized to divide the measurements of two or more object classes or events by a quad surface [256,257].

With statistical classification, a set (called the training set) of observation vectors of an object or event is considered [257]. Defining what the best class should be for a given new observation vector is the biggest problem with this method [257]. It is expected that the accurate solution for a quadratic classifier in the measurements should be quadratic [256,257].

Advantages [256]

- Parameters of each class are estimated independently using the samples of one class only.

6.1.3 Multi Layer Perceptron (MLP)

MLP can be said to be an artificial neural network model that is feed-forward [258,259]. It matches the input data sets to the appropriate output data set [258,259]. The MLP includes multiple of node layers in a graph oriented that each layer is completely attached to the next layer [258,259]. Nodes outside the input nodes are neurons with a non-linear activation function [258,259]. MLP uses a supervised learning technique to train the network [258,259]. This technique is called backpropagation [258,259]. MLP is an improved version of the standard linear perceptron [258,259]. It can discriminate linearly non-separable data [258,259].

Advantages:

- MLPs are universal function approximators. This makes it possible to obtain approximate solutions or classifications for complicated problems using MLPs [258,261].

6.1.4 Genetic Algorithm-Neural Network (GANN)

Hybrid systems have been created by combining neural networks with genetic algorithms (GANN) [262]. GANNs have strong problem solving abilities in classification and estimation problems [262]. With the aid of parameters, the success of training in neural networks is determined**.** The parameters must be adjusted before the training starts. GA is utilized to determine the appropriate parameters [262].

When an array of chromosomes is given, an optimal ANN classifier is searched by the GA [262]. The determination of the appropriate chromosome selection and the combination of the most appropriate classification of each choice is the most important goal of GA [262]. The target of the process is to provide an optimal selection of chromosomes, rather than an optimal classification [262].

Advantages:

- The process is the coevolution of both GA and ANN to find the optimum result [262].

Disadvantages:

- GA can, if properly configured, fulfill targets of a GANN algorithm without the addition of an ANN [262].

6.1.5 Nearest Mean Classifier (NMC)

NMC is based on pattern creation process and identification process [263,264]. Identification process uses training set and identification set [263,264]. The NMC just holds the mean of each class, i.e., one prototype for every class [263,265]. It classifies unseen items with the label of the nearest class prototype [263,265]. The

NMC can be used in biomedical applications or in relatively high dimensional feature spaces or small sample sizes [263,266].

6.1.6 Probabilistic Neural Network (PNN)

PNN formation ensures a resolution to pattern classification problems [3]. The classification approach utilized by PNN is Bayesian classifiers [3]. The creation of a series of multivariate probability densities originating from the training vectors in the network constitutes the working principle of PNN [3,37]. The PNN utilizes a supervised training set [3,267]. The first layer provides the input patterns to the network [37]. These input vectors are disseminated to the pattern layer [37]. Here a new neuron is formed [37]. Calculation of the distances between the input vector and the training input vectors is provided by the first layer [37]. Next, a vector is generated that determines how far the input is to a training input [37]. In the second layer, the density of each model unit of the class is calculated [37]. The third layer, known as the total layer, then provides estimates of the probability density [37]. The fourth layer performs Bayes decision rules in calculating the output classification [37]. The feature space symbolizes the available training data. Gaussian functions in feature space are generated by PNN [37]. The Gaussian mixture model in PNN is used to calculate posterior probabilities [37]. The use of PNN has been reported to be appropriate for disease diagnostic systems [3].

6.1.7 Constructive Probabilistic Neural Network (CPNN)

CPNN is architecturally similar to the PNN [37]. It utilizes the dynamic decay adjustment (DDA) algorithm [37]. CPNN uses the Gaussian mixture model to calculate probabilities such as PNN [37]. But there are some differences [37]. This difference is due to the fact that the algorithm used to adjust the densities evaluates avaible Gaussian mixtures to determine whether additional neurons are needed [37].

CPNN has three main advantages over PNN [37]:

First; it has CPNN clustering capability. So, good event detection performance can be achieved with a small network size [37].

Secondly; every Gaussian component in the CPNN has its own softening parameter, which can be get by the DDA algorithm with a few epochs of training [37].

Thirdly; the size of the network is kept in check since it has the property of pruning old Gaussian components [37].

6.1.8 Radial Basis Function Neural Network (RBFNN)

RBFN consists of a hidden layer of radial kernels and the output layer of linear neurons [37]. Although the architecture of RBFNs and MLPs is similar, the input-output mapping and training algorithms differ [37]. Every hidden neuron in an RBFN is adjusted to communicate to a regional area of feature space with the aid of a radially symmetric Gaussian function [37]. The Gaussian component densities used with the Gaussian Mixed Model (GMM) are produced by radial basis functions [37]. RBFNN consists of an input layer, a hidden layer and an output layer [37]. In the input layer there is a neuron for every predicted variable [37]. The whole input vector is demonstrated to every of the RBF neurons [37]. These neurons in the hidden layer include Gaussian transfer functions [37]. The output layer consists of one node per category or data class [37]. The training of RBFNs is done with the aid of a hybrid algorithm [37]. Here, unsupervised learning is used in the hidden layer whereas supervised learning is used in the output layer [37]. First, the radial basis centers and spreads are selected by means of the orthogonal least squares algorithm, which forms the suitable number of hidden neurons [37]. The output is then trained [37]. The radial basis activations are utilized as regressors to predict the class target outputs [37]. The spreading constant value must be appointed with the aid of the training algorithm [37]. With the aid of the radial basis functions, the duration of training is drastically decreased and related analyzes become easier [3]. RBFNNs can be used in multi-class and high-dimensional classification problems [3].

6.1.9 Incremental Supervised Neural Network (ISNN)

ISSN consists of two layers [268]. Node count is defined by the learning algorithm [5]. The ISSN assigns the number of nodes with an index counter [5]. Each new node causes the index counter to increase by one [5]. Node count is checked by the histogram generated during the training phase [5]. The values of the nodes near the bounds of the classes in the utilization counters are lower than the internal nodes [5]. For this reason, these nodes are disconnected from the ISNN [5]. The user specifies the threshold value [5].

ISNN algorithm makes sure that there is always only a single node that is active [5]. Different information is expressed in each output node [5]. The nodes are labeled on the output layer [5]. ISNN is based on supervised learning and has a gradual structure [5]. With the help of the feature vectors in the training set, the nodes in the input layer are repeatedly generated [5]. Each vector has its own class label [5]. The learning algorithm finds the minimum distance by calculating the Euclidean distances between the input layer nodes and the input feature vector [5]. The the winner-node and the classes of the input vector are checked [5].

6.1.10 Hidden Markov Model (HMM)

HMM is a probabilistic sequence model [44,269]. The system is supposed to be a Markov process with not observed states [44,269]. Among the machine learning models, HMM is the most commonly used method of speech and language processing [44,269]. In simpler Markov models, state transition probabilities are only parameters and can be seen directly by the observer [44,269]. In HMM, only the output is visible, but the state is not directly visible [44,269]. There are probability distributions for each case on the possible output specifiers [44,269]. For this reason, the sequence of specifiers created by an HMM offers some knowledge about the state sequence [44,269]. Hidden word expresses the sequence of state that the model passes, not the parameters [269]. Although the parameters are known, the model is called the HMM [44,270].

HMMs are particularly recognized for their practice in temporal pattern recognition (for example handwriting, gesture recognition, speech) [271,272]. HMMs can be implemented in many areas, which are to bring back a data sequence that is not directly observable [271,273].

It can be assumed that HMM is a generalization of a mixture model [270,271]. The secret variables controlling the mixture elements for each observation are associated with an independent Markov process [270,271].

6.1.11 Support Vector Machine (SVM)

SVM is a supervised machine learning model and is often utilized [21]. Related learning algorithms analyze data utilized for classification and regression analysis [274,275]. However, it is mostly utilized in classification problems [274,275]. If a training sets, every labeled as one or the other in two categories, is considered, the support vector machine training algorithm generates a pattern that appoints the new arriving instances to one or the other of the categories [274,275]. This is not based on probability and is a binary linear classifier [274,275]. In the SVM model, samples are shown as points in space [274,275]. These points are shown in separate categories divided by a plain gap as wide as possible [274,275]. Then, new samples are placed in the same space and expected to enter a categorization according to which side of the gap is appropriate [48,274,275].

SVMs can also effectively make nonlinear classification [274,275]. They can make this classification by utilizing the kernel trick [274,275]. So they map their inputs to high-dimensional feature spaces [274,275]. If the data can not be labeled, an unsupervised learning application is needed which naturally accumulates the data to the groups as supervised learning is not possible and then works to pair new data to these groups [274,275]. Industrial practices use a clustering algorithm called the support vector clustering, which makes amelioration to the SVM when either no data is marked or only some data is labeled as a preprocessing for a classification passing [274-276].

Advantages:

- SVMs obtain considerably higher search accuracy than traditional query improvement schemes [49,277].

6.1.12 Deep Learning

Deep learning is a new field of machine learning [278,279]. It was conceptualized on learning data models [278,279]. Its algorithms try to model high-level abstractions [278,279]. This is done using complicated structures or otherwise model architectures consisting of multiple nonlinear transformations [278,279]. Deep learning models can reach high levels of correctness [279]. Occasionally, situations that exceed human performance can be seen [279].

Deep learning takes into account computer models [280]. These models contain multiple layers of processing to learn models of data and are trained utilizing a large set of labeled data and neural network architectures with multiple layers [280]. These methods have strikingly developed the advanced technology in speech recognition, visual object recognition, object perception and many other fields such as drug discovery and genomics [280]. Deep learning detects complex patterns in great data sets by utilizing the backpropagation algorithm [280]. The backpropagation algorithm is used to specify how the interior parameters utilized to calculate the presentation of each layer from the presentation in the previous layer should be modified [280]. Deep convolutional nets are more useful in video, image, speech, and sound processing areas. Recurrent nets provide improvements in consecutive data like text and speech [280].

In a simple case, there might be two sets of neurons: ones that receive an input signal and ones that send an output signal [278,279]. When the input layer receives an input it passes on a modified version of the input to the next layer [278,279]. A deep network has many layers between input and output [278,279,281]. Thus, the algorithm is allowed to utilize multiple process layers consisting of multiple linear and non-linear transformations [278,279,281].

An image-like observation can be presented in many ways. For instance; a vector of intensity values per pixel, or areas of specific shape and various other features [8,282,283. Some models facilitate to learn tasks (e.g. face recognition or facial expression recognition) from samples [8,282,283].

The purpose of the workings in this field is; to outperform models, to compose models to learn wide-ranging unlabeled data [8,284]. Neurological progresses have developmental effects on these representations [8,279,285]. Some representations are established upon hermeneutics of data processing and transmission models in a nervous system [8,279,285]. Neural encodings attempting to define the relationship between electrical activity of neurons in the brain and neuronal responses can be an example [8,279,285].

With the appropriate transformational composition it becomes possible to learn highly complicated functions [280]. Higher layers of representation reinforce the directions of the imput which is important for differentiation and also suppress unrelated modifications [280]. For instance, features learned in the first impression layer in an image that comes in a number of pixel value formats often present the existence or nonexistence of edges and positions in the image in some directions [280]. The second layer typically defines patterns [280]. It does this by detecting special edits of the edges, without without considering, minor changes in edge locations [280]. The third layer can collect patterns into bigger combinations that match components of familiar objects [280]. Following, layers would define objects as combinations of these components [280].

Deep learning has made great strides in solving resistant problems that the artificial intelligence society is challenging [280]. It was seen to be very successful in discovering complex texture in high-dimensional data [280]. For this reason, it can be used in many fields such as science, business and government [280]. Additionally its great success in image recognition and speech recognition, in many areas it has proven to be superior to other machine learning techniques [280]. These areas are; to anticipate the efficiency of potential drug molecules, to reconstruct brain circuits by analyzing particle accelerator data and to anticipate the influences of gene mutations in non-coding DNA on gene expression [280]. Deep learning has constructed highly encouraging results for diverse tasks [280]. Among these tasks, it is possible to count deep language learning, especially in natural language understanding, subject classification, emotional analysis, question answering and language translation [280]. Deep learning is expected to achieve far more success soon, because of the fact that it requires little manual intervention and can easily benefit from increases in the quantity of current calculations and data [280]. Today's learning algorithms and architectures contribute to accelerating the progression of deep neural networks [280].

There are various deep learning architectures such as deep neural networks, deep belief networks, convolutional deep neural networks and recurrent neural networks [278,286,287]. They have been used in areas such as computer vision, automatic speech recognition, natural language processing, voice recognition and bioinformatics, and it has been observed that these tasks achieve extremely good results [278,286,287].

Advantages

- Replaces handmade features with efficient algorithms for feature learning and hierarchical feature extraction [288,289].
- The layers of the features are created not by engineers but by learning from the data utilizing the procedure that is the learning target [280].

Disadvantages

- Needs large amounts of data to produce good results [280].

Types of deep learning architectures:

- Deep Neural Network (DNN)
- Deep Belief Network (DBN)
- Convolutional Neural Network (CNN)
- Convolutional Deep Belief Network (CDBN)
- Deep Boltzmann Machine (DBM)
- Restricted Boltzmann Machine (RBM)
- Stacked (Denoising) Auto-Encoders
- Deep Stacking Network (DSN)
- Tensor Deep Stacking Network (T-DSN)
- Spike-and-Slab RBM (ssRBM)

- Compound Hierarchical-Deep Models
- Deep Coding Network (DPCN)
- Multilayer Kernel Machine(MKM)
- Deep Q-Networks (DQN)
- Memory networks

6.1.12.1 Deep Neural Network (DNN)

Deep neural network is a multilayered network. There are many hidden layers that show complexity at a certain level [290-292]. The weights of the hidden layers are completely dependent and are frequently initiated by pre-training, utilizing a stacked restricted Boltzmann machine or deep Boltzmann machine [290-292]. Deep neural networks utilize advanced mathematical modeling to process data in complicated ways [290- 292].

6.1.12.2 Deep Belief Network (DBN)

Deep belief nets are probabilistic generative models created of multiple layers of stochastic, hidden variables [278,290,292]. Between the top two layers have nondirectional and symmetric links [278,290,292]. The following layers receive links from top to bottom [278,290,292]. When data are given as data to train the next layer, deep belief networks are learned from one layer at once, treating the values of hidden variables in a layer [278,290,292].

6.1.12.3 Convolutional Neural Network (CNN)

The CNN architecture is an all-round, but simple paradigm [8,293]. It can be performed to a wide range of perceptual duties [8,293]. Convolutional Networks architecture contains trainable stages [8,293].

ConvNets are used to compute data that get in the shape of multi-arrays [8,280]. ConvNets is based on four basic ideas. These are local connections, shared weights, pooling and the utilization of many layers [8,280]. ConvNet's architecture has a gradual structure [8,280]. It consists of two layers: convolutional layers and pooling layers [8,280]. The convolutional layer is created by feature maps [8,280]. Every unit is linked to a local patch on the feature maps in the previous layer with a weight sequence [8,280]. Then the outcome of this local weighted sum is transferred to a nonlinearity like a ReLU [280,294]. When all units in the feature map utilize the same filter bank, diverse feature maps in the layer utilize distinct filter banks [280,295]. This architecture has two reasons [280,295]. Primarily, in a series of data, as in images, local value groups are frequently correlated at a very high rate and create different local patterns that are readily identifiable [280,295]. Secondly, the local properties of input data do not change according to location [280,295]. That is to say, if a pattern can show up in one section of the data, it can show up anywhere, therefore units at distinct places having the same weights and defining the same pattern in distinct sections of the dataset [280,295]. From a mathematical aspect, the filtering operation made by a feature map is a discrete convolution [280,295].

Pooling layer combines same properties into one in the manner of semantic, while the convolutional layer plays a role in uncovering the local conjunctions of the features on the previous layer [280,295]. Since the relative positions of features forming a pattern can change slightly, it is possible to reliably perceive the pattern by making each feature position coarser [280,295]. A typical pooling unit calculates a local unit area as a maximum in the feature map [280,295]. Areas changed by more columns and rows inputs contiguous pooling units [280]. Thus, it decreases the size of the presentation and composing invariant to small slips and distortions [280]. These layers are then followed by more convolutional, pooling and finally fully connected layers [280].

The CNN is very effective and widely used in computer vision and image recognition [8,290]. While the CNN precedence is used in image analysis, it has also been used effectively for speech recognition by making changes based on specific features of speech [8,290].

6.1.12.4 Convolutional Deep Belief Network (CDBN)

The utilization of convolutional deep belief networks has provided new success in deep learning [287,290]. The training of CDBN is similar to that of deep belief networks [287,290]. For this reason, while using the 2D structure of images such as

CNNs, they use pre-training similar to deep belief networks [287,290]. They have a structure that can be utilized in a large number of image and signal processing duties [287,290].

6.1.12.5 Deep Boltzmann Machine (DBM)

A special type of Boltzmann machine (BM), deep Boltzmann machines, consist of many hidden variable layers with no connection between variables on the same layer [290,292]. It is a network that makes stochastic decisions about whether symmetrically linked units are open or closed [290,292]. Working with general BMs whose learning algorithm is very simple is very complicated, and calculating is very slow in learning [290,292]. In DBM, each layer has complex, high-order correlations between the actions of hidden features in the lower layer [290,292]. DBMs have the potency to learn increasingly complicated internal models to solve object and speech recognition problems [290,292]. Further, by utilizing unlabeled sensory inputs, advanced models can be created [290,296]. Limited labeled data can then be utilized to make small adjustments to the model for a particular task [290,296].

6.1.12.6 Restricted Boltzmann Machine (RBM)

RBM is known as a private kind of Markov random field [290,292,297,298]. It is organized into two layers; stochastic hidden units and stochastic visible units [290,292,298]. The visible units corresponding to the observation components form the first layer [290,292,298]. The hidden units, which can also be expressed as nonlinear feature detectors, show model dependencies between the observation components [290,292,298]. RBMs are also referred to as bidirectional graphs [290,292]. These are graphs showing that all visible units are linked to all hidden units and that there are no visible-visible or hidden-hidden links [290,292].

6.1.12.7 Stacked (Denoising) Auto-Encoder

Denoising autoencoders are the stochastic type of the basic autoencoder [290,292,297]. First, denoising autodetectors randomly distort inputs [290,292,297]. This can be done by randomly selecting a portion of inputs and making it to zero [290,292,297]. Then the autoencoder needs to be rebuilt [290,292,297]. The hidden encoding nodes are then designed utilizing factors like the distance between the original inputs and rebuilt inputs to reconstitute the original, uncorrupted input data [290,292,297]. The following nodes of the denoising autoencoder are utilized as input for uncorrupted encoded presentations [290,292,297].

6.1.12.8 Deep Stacking Network (DSN)

The basic idea of deep stacking network conseption concerns the notion of stacking [278,292]. First, simple modules of functions or classifiers are created and then connected together to learn complicated functions or classifiers [278,292]. Connection operations were generated in various forms in the past, typically making use of supervised information in the simple modules [278,292]. New features of the stacker classifier at the higher level of the stacker architecture include from aggregation of a lower modular classifier and the raw input features [278,292]. The basic component utilized for stacking was a conditional random field [278,292,299]. In addition, DSN architecture has been further developed for natural language and speech recognition applications [278,292,299].

6.1.12.9 Tensor Deep Stacking Network (T-DSN)

The T-DSN is formed of multiple stack blocks enclosing bilinear mapping to the output layer from two hidden layers where a weight tensor is used [278,292]. T-DSN is the tensorized type of the DSN architecture [278,292]. It has the same scalability as DSN in terms of parallelizability in learning, but T-DSN advances and expands the DSN architecture [290,292]. The mechanism of T-DSN is based on the philosophy of stacked generalization [290,292]. The architecture of the T-DSN is similar to the architecture of the DSN in terms of the manner in which the stacking process is applied [290,292]. That is, modules of the T-DSN are stacking up in a similar way to form a deep architecture [290]. The differences of T-DSN and DSN lie mainly in how each module is constructed [290].

6.1.12.10 Spike-and-Slab RBM (ssRBM)

The need for deep learning with real valued inputs motivates the spike and slab RBM, which models continuous-valued inputs with strictly binary latent variables

[300]. Similar to basic RBMs and its variants, a spike and slab RBM is a bipartite graph, while like GRBMs, the visible units (input) are real valued [300]. The difference is in the hidden layer [300,301]. Every unit of the hidden layer consists of a spike and a slab variant [300,301]. The slab is intensity over continuous field, while the spike is a separate probability mass at zero [300,302].

6.1.12.11 Compound Hierarchical-Deep Models

Compound hierarchical deep models compose deep networks with non-parametric Bayesian models [290]. This provides a better representation, allowing faster learning and more accurate classification with high-dimensional data [290]. However, these architectures are poor at learning novel classes with few examples [290].

6.1.12.12 Deep Coding Network (DPCN)

Deep coding network is a predictive coding scheme where top-down information is used to empirically adjust the priors needed for a bottomup inference procedure by means of a deep locally connected generative model [290]. This works by extracting sparse features from time-varying observations using a linear dynamical model [290]. Then, a pooling strategy is used to learn invariant feature representations [290]. These units compose to form a deep architecture, and are trained by greedy layer-wise unsupervised learning [290]. The layers constitute a kind of Markov chain such that the states at any layer only depend on the preceding and succeeding layers [290]. DPCNs can be extended to form a convolutional network [290].

6.1.12.13 Multi Layer Kernel Machine (MKM)

The multi layer kernel machine method was suggested to learn highly nonlinear functions with the iterative application of weakly nonlinear kernel methods [297].

6.1.12.14 Deep Q-Network (DQN)

A deep Q-network is a type of deep learning model developed at Google DeepMind which combines a deep convolutional neural network with Q-learning, a form of reinforcement learning [303]. Unlike earlier reinforcement learning agents, DQNs can learn directly from highdimensional sensory inputs [303].

6.1.12.15 Memory Network

Memory networks are another extension to neural networks incorporating long-term memory, which was developed by the Facebook research team [290]. The long-term memory can be read and written to, with the goal of using it for prediction [290]. These models have been applied in the context of question answering where the memory effectively acts as a database, and the output is a textual response [290].

6.2 Others

6.2.1 Continuous Wavelet Transform (CWT)

The CWT is utilized to split (partition, split, divvy) a continuous-time signal into wavelets [215,218]. The CWT calculates the interior products of a continuous signal with a series of continuous wavelets [215,218]. In contrast to the Fourier transform, CWT can produce a time-frequency presentation of a signal with extremely good time and frequency localization [215,218]. CWT is the convolution of the input data array consisting of a series of functions created via the mother wavelet [217,218]. A fast Fourier transform algorithm can be used to calculate this convolution [217,218]. The use of CWT can be very effective in defining the reducing rate of the release signals [214,216,218].

6.2.2 Time Expanded Waveform Analysis

Time expanded waveform analysis allows the documenting of different features of sounds [25]. It also provides visual images with the possibility of repetition increasing the usefulness of the sounds for diagnosis [25].

6.2.3 Vector Quantization (VQ)

VQ is a technique used to quantize signal vectors [304]. With this technique, probability density functions can be modeled [304]. This is done by distributing the prototype vectors [304]. The principle on which VQ is based is the block coding rule

[305,306]. VQ is also expressed as a lossy data compression method [305,306]. It was formerly utilized for data compression [307]. The compression process is two steps [307]. These steps are codebook training and codevector matching [307]. In the first step, similar vectors at the time of training are grouped into clusters [307]. Then a codevector is appointed to every cluster [307]. In the second step, every input vector is pressed by displacing it with the closest codevector referred to by a cluster series [307]. Then the index of the suitable codevector in the codebook is transfered to the decoder [307]. This is utilized it to get the same codevector from an identic codebook by the decoder [307]. This is the reconstituted replica of the suitable input vector [307].

VQ separates a group of points by the number of the nearest point [307]. Every group is shown by its centroid point [307]. VQ is the procedure for mapping vectors from a big area to a limited number of zones in that area [40,209,308].

The intensity pairing feature of VQ is very strong in finding the density of big and high-dimensioned data [40,309]. For this reason, VQ is considered to be appropriate for lossy data compression [40,310]. It can also be used for lossy data correction and density estimation [40,310]. VQ is greatly utilized in signal and image processing [311,312].

VQ is associated with the competitive learning model [311,312]. For this reason, it is intimately associated to the self-organized map model and to sparse coding models used in deep learning algorithms such as autoencoder [311,312].

6.2.4 Gaussian Mixture Model (GMM)

The GMM is a probabilistic model [206,313]. It is supposed that all data points are produced from a combination of a few Gaussian distributions with unknown parameters [206,313]. It can be considered that the mixture models are a universalization of the k-means cluster, which contains data about the covariance structure of the data and hidden Gaussian centers [206,313].

6.2.5 Linear System Analysis

Linear system analysis is concerned with the study of equilibrium and change in dynamical systems, that is, in systems that contain variables that may change with time [229]. These variables include system inputs, outputs, as well as variables describing internal states of the system [229]. To perform the analysis, relationships between these variables are described by a set of equations known as the model [229]. For linear system analysis to be applicable, the model must possess the linearity property: it must be a linear model [229].

6.2.6 Fuzzy Logic

The idea underlying the fuzzy system theory is to approach system behavior where no analytic functions or digital correlations occur [314,315]. For this reason, fuzzy systems can be called complex systems with high potential to understand systems without analytical formulations [314,315]. Complicated systems may be related to human conditions [314,315]. For example; it is possible to count biological and medical systems, or social, economic, or political systems that can not be analytically controlled by large input and output sequences [314,315]. Fuzzy system theory can be useful to evaluate more traditional, less complicated systems [314,315]. These systems are thought to be very useful in two cases [316]: where there are extremely complicated systems where actions are not comprehended well, and where a rough, but rapid resolution is required [314,317]. A fuzzy system tries to comprehend a system without any models, and it performs so with indefinite, fuzzy or incomplete or completely deficient information [314,317].

Fuzzy systems are strong [314,318]. The system has both uncertainties in inputs and output [314,318]. These uncertainties have been used to formulate the system structure based on a set of assumptions needed to form a mathematical form [314,318]. The ambiguities of both the input and output of the system are utilized in the formulation of the system organization, which is attributed on a series of assumptions necessary to form a mathematical form [314,318]. Realistically, fuzzy systems can be defined as shallow models [315,319]. Since the fuzzy system output is a consensus of all the inputs and all the rules, fuzzy logic systems can be well behaved when input values are not available or are not trustworthy [319]. Weightings can be optionally added to each rule in the rulebase and weightings can be used to regulate the degree to which a rule affects the output values [319]. These rule weightings can be based upon the priority, reliability or consistency of each rule [319]. These rule weightings may be static or can be changed dynamically, even based upon the output from other rules [319].

CHAPTER 7

MATERIALS AND METHODS

7.1 Building the Electronic Stethoscope

Before we started working, we decided that a device could be used to record lung sounds was necessary. Therefore, we examined all possible electronic stethoscopes that are commercially available [8]. There were two models that are being utilized in medicine; Littman 2100 Electronic Stethoscope and Thinklabs One Electronic Stethoscope [8]. These devices receive the audio from the head of the stethoscope through a microphone and a set of electronic circuits [8]. This digital signal can be transferred to the computer via a 3.5 mm microphone jack, which is widely available on computers and mobile devices [8].

Because of its proprietary software, the platforms on which the Littman 2100 electronic stethoscope software can operate are limited [8]. On the contrary, Thinklabs One electronic stethoscope can transmit an audio signal to any device utilizing any software [8,320].

However at the time we were researching, these devices' prices range from 396–500 dollars. Therefore, after analyzing the specifications of these stethoscopes, we determined to create our own custom electronic stethoscope [8].

The invention "Stethoscope having microphone therein" by Dieken et al. provides a stethoscope having a chest piece where the transducer resides within the acoustic pathway in the chest piece [321]. We used this invention's chest piece design in the device we built. Chestpiece was taken as secondhand. We improved on it by adding an option to connect the stethoscope to another device by an audio cable.

First prototype was a large device with audio out for headphones and a microphone input for the stethoscope with microphone. However this device was recording too much environmental noise that suppressed the respiratory sounds. Also it was too big to carry around in a hospital environment. So we decided not to use it.

Second prototype was a smaller version of the first one. This one had two inputs; one for stethoscope microphone signal and one for recording. It also had the audio output for headphones. The device was recording stereo audio, one channel for respiratory sounds and the other channel for environmental noise. The idea behind the device was to record both audio and extract the noise from the respiratory signal. However, we found out that the noise in the respiratory signal was not equivalent to the noise signal coming from the second channel, hence when it is extracted, there was a hug data loss on the respiratory audio signal because of the low frequency nature of the respiratory audio signal. So we decided not to use the second one either.

Also we found out that the environmental noise contains electronic noise from the components of the device, so the more complex it gets we get more electronic noise in the final signal.

For the final device, we decided to go back to the original simplest idea; a microphone strapped inside the head of the stethoscope with a 3.5mm microphone jack. In our electronic stethoscope design, we only used the chestpiece of an existing 3M™ Littmann® Classic II S.E. stethoscope. To ensure minimizing the environmental and friction noise, we needed to use material that has noise suppression properties. We found out that silicone is such a material [322]. Therefore, we used a 10cm silicone tube as the body of our stethoscope. For the microphone, we used a directional microphone connected to a 3V zener diode at one end of the silicone tube. We enclosed the other end with silicone sealant along with the microphone’s cable. We connected these cables to a standart 3.5mm audio jack (Figure 7.1). Finally we fixed the silicone tube’s microphone end to the chestpiece of a stethoscope with silicone sealant (Figure 7.2). To make a recording with our design; we simply need to connect the 3.5mm audio jack into the microphone input of a computer. In this study we used a Lenovo Thinkpad E550 laptop with a Dolby Digital audio card.

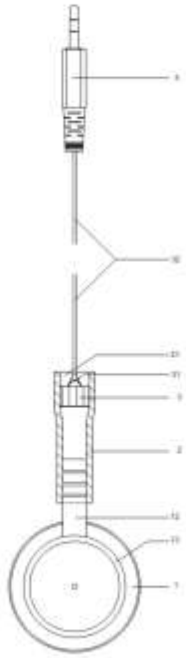

Figure 7.1 Technical drawing of electronic stethoscope (1: Stethoscope bell, 12: Stethoscope metal connection tube, 13: Silicone holder of stethoscope bell, 2: Silicone pipe, 21: Silicone material, 3: Unidirectional condenser microphone capsule, 31: 3V zener diode, 32: Shielded cable, 4: 3.5mm stereo audio jack)

Figure 7.2 Image of the final prototype electronic stethoscope

Since we were removing the signal enhancing hardware, a good, small and a directional microphone was necessary to receive high quality signal [8]. Nevertheless, the sound was still noisy due to the following reasons [8]:

- Hospitals are naturally noisy due to reasons such as the conversation of people in the vicinity, phone bells, noise of used devices, ambulances and police sirens [8].
- When the stethoscope diaphragm touches skin and body hairs during the auscultation, scratching noise may occur [8].

It is not easy to solve the first problem, because it can be said that it is impossible to make patients' rooms sound-proof [8]. Also, since we wanted to collect and test real (unclean) data we kept the rooms as quiet as we possibly can without any special equipment or changes in the room.

It is possible to solve the second problem by lubricating the area that the stethoscope diaphragm contacts before the auscultation [8]. We have also noticed that during preliminary work we do, this method also improves ability to receive of low frequency audio by the microphone [8].

The chracteristics of this stethoscope:

- Ability to minimize noise
- Sensitive
- Cheap
- Basic design
- Mobile and light weight
- Easy to use

The final design was approved by three professional physicians individually after auscultating to lung sound recordings captured with the stethoscope prototype.

The components in this stethoscope prototype are intended to be sufficiently modular such that the parts can be substituted for materials that are locally available in the deployment sites, making construction and maintenance simple and rapid. Another advantage of having the device easily disassembled is that it can be cleaned to prevent spread of disease from one patient to another. Wiping the plastic diaphragm and rubber rim of the device with rubbing alcohol can be done in between patients, as physicians normally practice for cleaning their traditional stethoscope chest pieces.

As a result, the second-hand chest piece and the other materials cost us 100 TL to build this device.

7.2 Software for Data Acquisition

We required a computer program to record audio and save patient data [8]. For this reason, we developed a .NET Windows Presentation Foundation (WPF) application, using C# programming language in Visual Studio 2015 that constitutes patient records and utilizes open source audio library NAudio to record, play and modify audio [8]. This application also allows the amplification of the recordings 200 times for better hearing [8]. It has 8 main sections:

1) Patient information: First name, last name, age, gender, smoking habits, sport habits [8] (Figure 7.3).
2) Preliminary questions: Shortness of breath, cough, color of mucus, coughing of blood, chest pains (Figure 7.4).
3) Symptoms: High fever, weight loss, swelling in legs, night sweating, palpitation (Figure 7.5).
4) Audio recording: Audio recordings from 11 areas of patient’s chest [8] (Figure 7.6).
5) Lung function test results: Forced vital capacity (FVC), forced expiratory volume in 1st second (FEV1), FEV1 / FVC (Figure 7.7).
6) Blood test results: White blood cell count, C-reactive protein count and neutrophils count (Figure 7.8).
7) X-ray results: X-ray comments from 6 regions of lungs (Figure 7.9).
8) Final Diagnosis (Figure 7.10).

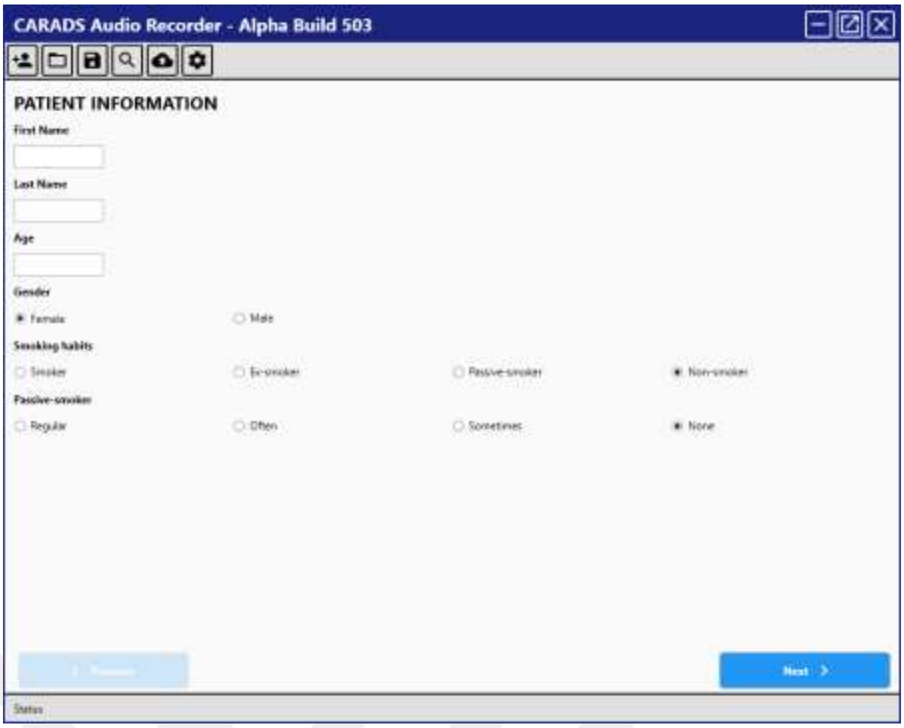

Figure 7.3 Patient information

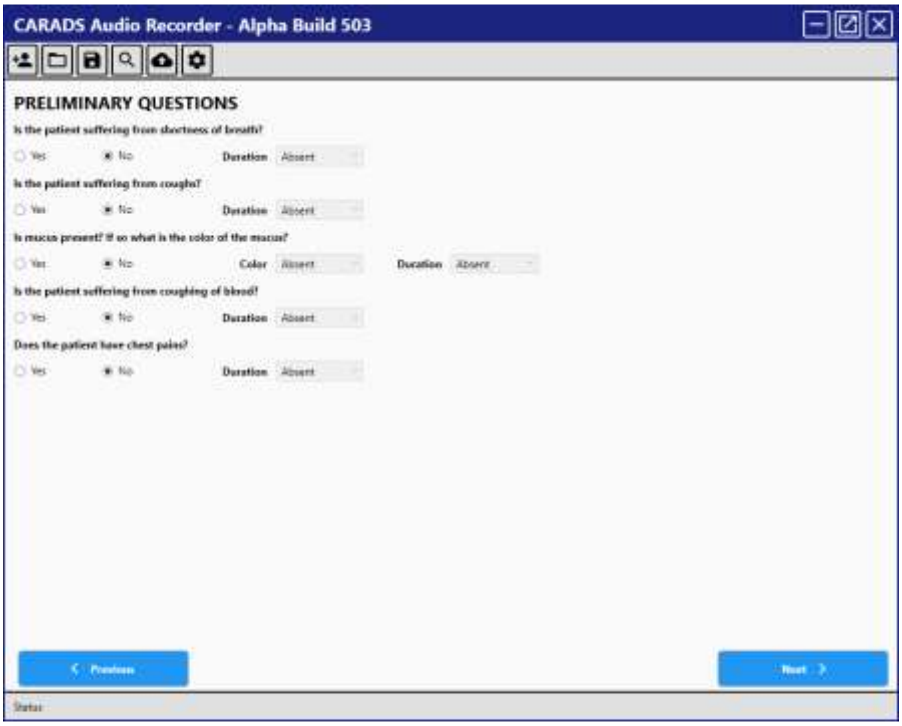

Figure 7.4 Preliminary questions

Figure 7.5 Symptoms

Figure 7.6 Audio recorder interface

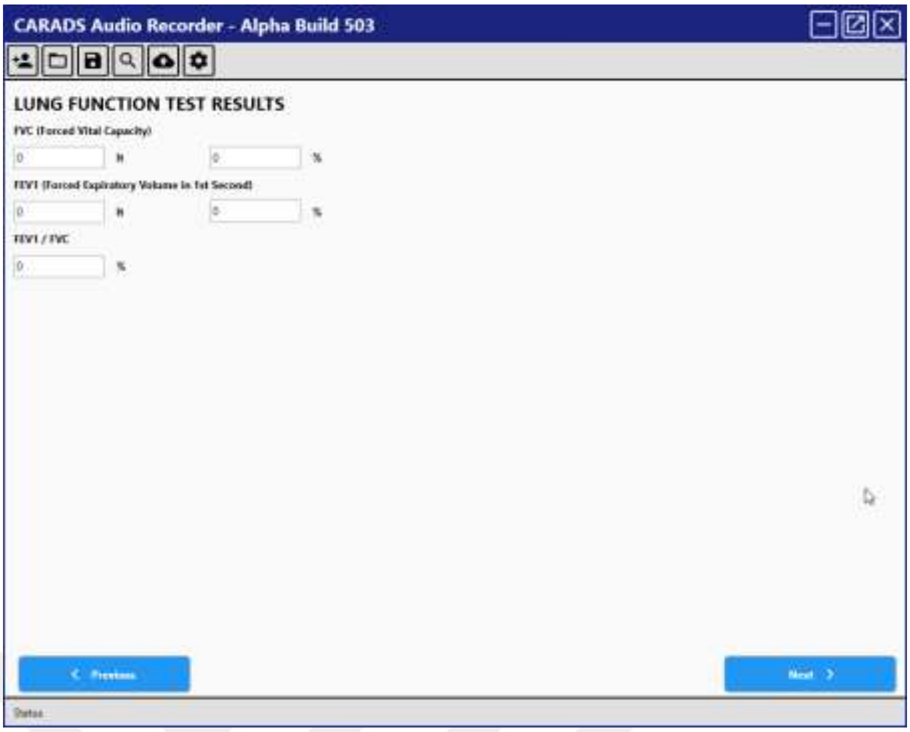

Figure 7.7 Lung function test results

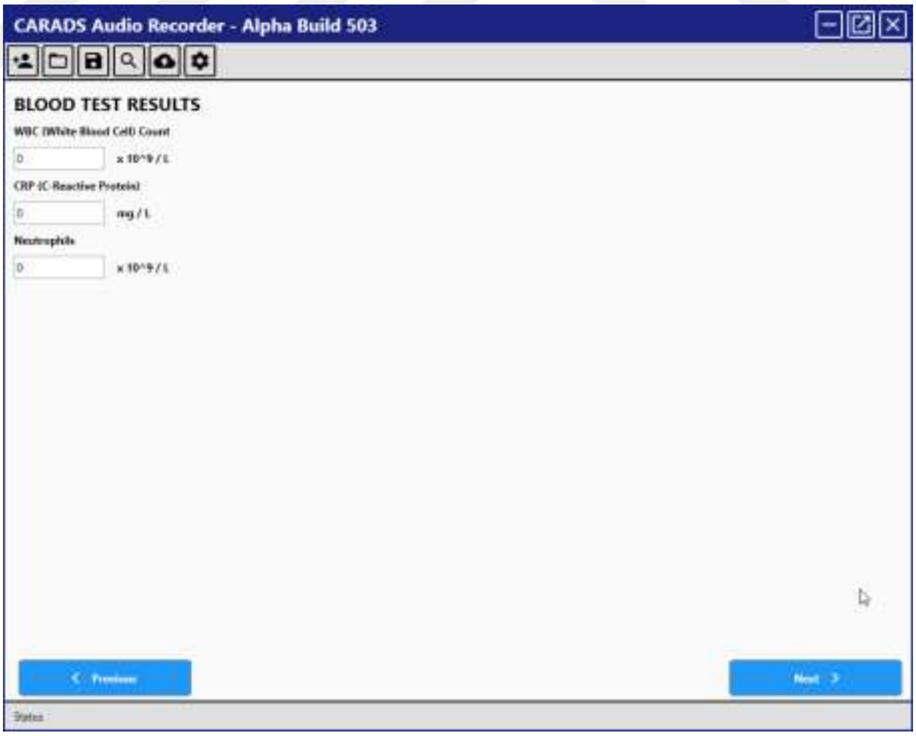

Figure 7.8 Blood test results

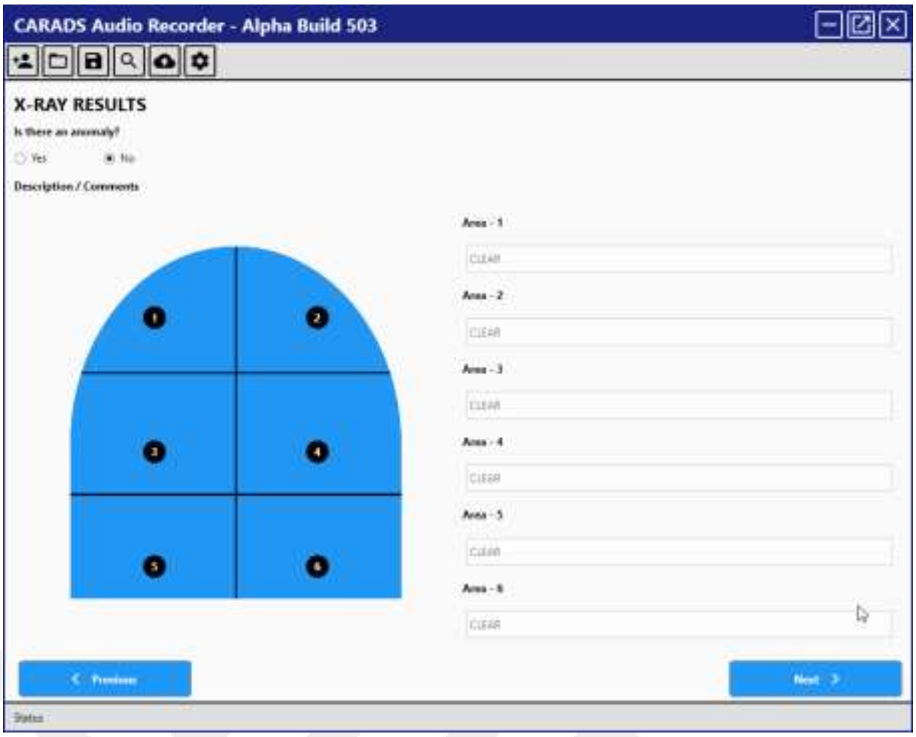

Figure 7.9 X-ray results

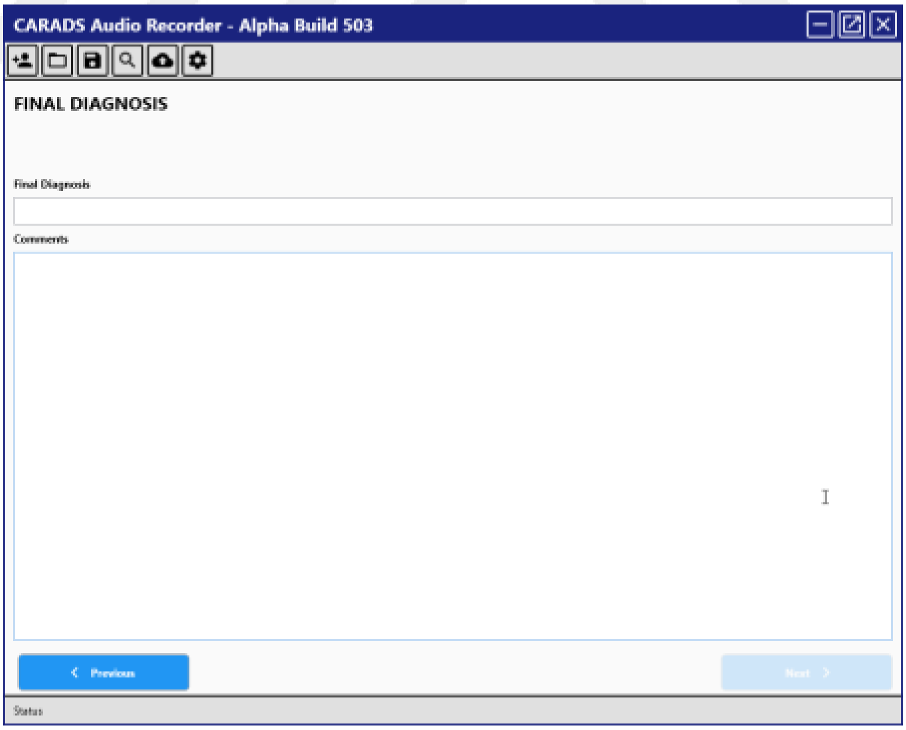

Figure 7.10 Final diagnosis

As a result, we designed and constructed an electronic stethoscope with associated software system that can transfer respiratory sounds to a PC for recording and subsequent computer aided analysis and diagnosis [8].

Our overall system can be seen in Figure 7.11.

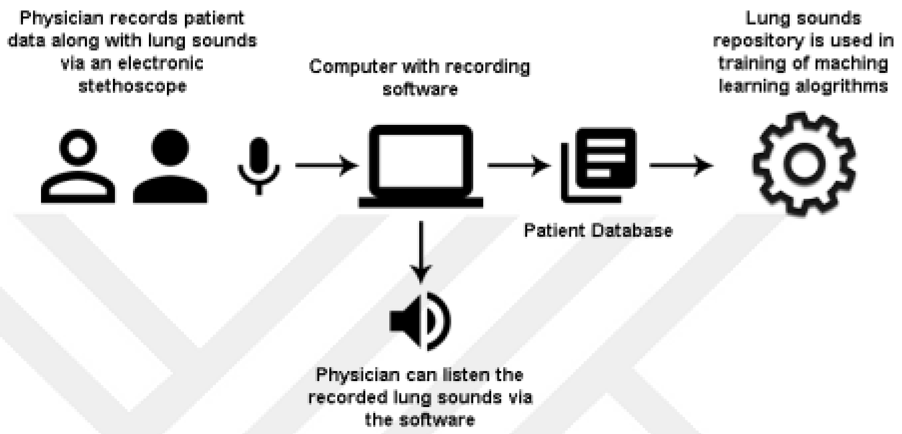

Figure 7.11 Workflow schema

7.3 Data Acquisition

The application and the hardware are tested together by recording respiratory audio and showing the results to chest physicians [8]. After we received positive feedback from all the physicians, we concluded that we could move forward to data acquisition [8].

In the end, three hospitals accepted that we could do our research in their respiratory diseases department [BC]:

- Ankara University, Chest Diseases Hospital
- Yıldırım Beyazıt Education and Research Hospital
- Yıldırım Beyazıt University Chest Diseases Clinic

To start the data acquisition we needed a laptop with a good audio card [8]. So we did a research and found out that Lenovo ThinkPad E550 Laptop has the best audio card for our purposes [8]. So we purchased that computer [8]. We also purchased two Seagate Expansion 1TB external hard drives for backup storage [8]. Once we are set with equipment we started the data acquisition [8].

The voluntary declaration form was read to the patient and signed with approval for participation in the study [8] (Appendix A).

We also prepared questionnaires including patient information, preliminary questions, symptoms, lung function test results, blood test results, x-ray results and final diagnosis (Table 7.1). After the procedures were completed, the questionnaires were filled in by the physician (Appendix B, Appendix C).

Table 7.1 Disease frequencies in dataset

Disease Name	ICD-10	Frequency
Normal		805
COPD	J44.9	211
Pneumonia	J18.9	134
Asthma	J45.9	75
Bronchiectasis	J47.0	30
IPF	J84.9	40
PTE	I26.9	43
COPD + Bronchiectasis	J44.9+ J47.0	28
COPD + Pneumonia	J44.9+ J18.9	85
Lung Cancer	D44.3	42
COPD + Emphysema	J44.9+J43.9	14
Pleural Effusion	J90	34
Pneumonia + PTE	J18.9+ I26.9	9
COPD + PTE	J44.9+ I26.9	8
Bronchitis	J41.0	53
Pneumonia + Lung Cancer	J18.9+44.3	19
Total		1630

COPD: Chronic Obstructive Pulmonary Disease
ICD-10: International classification of diseases [2]
IPF: Intesitial Pulmonary Failure
PTE: Pulmonary Thromboembolism

Table 7.2 Lung sound frequencies

SOUND	N	SOUND	N
Normal	**8937**	Decreased + LED + Rales	**190**
Rales	**3766**	LED + Rales + Rhonchus	**183**
Decreased	**646**	Decreased + Rales + Rhonchus	**83**
Rhonchus	**540**	Decreased + LED + Rhonchus	**69**
LED	**303**	Aggravation + LED + Rhonchus	**61**
Aggravation	**261**	Aggravation + Rales + Rhonchus	**55**
Squeak	**39**	Aggravation + LED + Rales	**53**
Bronchial	**7**	Aggravation + Decreased + Rales	**10**
Absent	**6**	Aggravation + Decreased + LED	**5**
Frotman	**2**	Normal + Rales + Rhonchus	**5**
Wheeze	**1**	Absent + Rales + Rhonchus	**4**
Decreased + Rales	**598**	Aggravation + Decreased + Rhonchus	**4**
Rales + Rhonchus	**583**	Aggravation + LED + Squeak	**3**
LED + Rales	**321**	LED + Rhonchus + Wheeze	**3**
Aggravation + Rales	**242**	Aggravation + Rales + Squeak	**2**
Decreased + LED	**204**	Aggravation + Rhonchus + Squeak	**2**
Led + Rhonchus	**196**	LED + Rales + Squeak	**2**
Decreased + Rhonchus	**134**	LED + Rhonchus + Squeak	**2**
Aggravation + Rhonchus	**120**	Rales + Rhonchus + Squeak	**2**
Aggravation + LED	**44**	Rales + Rhonchus + Wheeze	**2**
Rales + Squeak	**19**	Aggravation + Bronchial + LED	**1**
Normal + Rales	**15**	Aggravation + Bronchial + Rhonchus	**1**
Normal + Rhonchus	**12**	Decreased + Normal + Rales	**1**
LED + Squeak	**11**	Decreased + Rales + Squeak	**1**
Absent + Rales	**10**	LED + Rales + Wheeze	**1**
Rhonchus + Wheeze	**9**	Decreased + LED + Rales + Rhonchus	**42**
Aggravation + Decreased	**7**	Aggravation + Decreased + Led + Rales	**10**
Bronchial + Rales	**5**	LED + Rales + Rhonchus + Wheeze	**2**
Rhonchus + Squeak	**5**	Aggravation + LED + Rales + Squeak	**4**
Absent + Frotman	**4**	Aggravation + LED + Rales + Rhonchus	**43**
Aggravation + Frotman	**4**	LED + Rales + Rhonchus + Squeak	**1**
Decreased + Squeak	**4**	Aggravation + Decreased + Rales + Rhonchus	**4**
Aggravation + Squeak	**3**	Aggravation + Rales + Rhonchus + Squeak	**1**
LED + Wheeze	**3**	Decreased + LED + Rales + Squeak	**5**
Absent + Rhonchus	**2**	Aggravation + Decreased + LED + Rhonchus	**5**
Bronchial + Decreased	**2**	Aggravation + Decreased + LED + Rales + Rhonchus	**1**
Decreased + Normal	**2**		

Waveform and spectrogram images of various lung sounds types can be seen through Figure 7.12 to Figure 7.22.

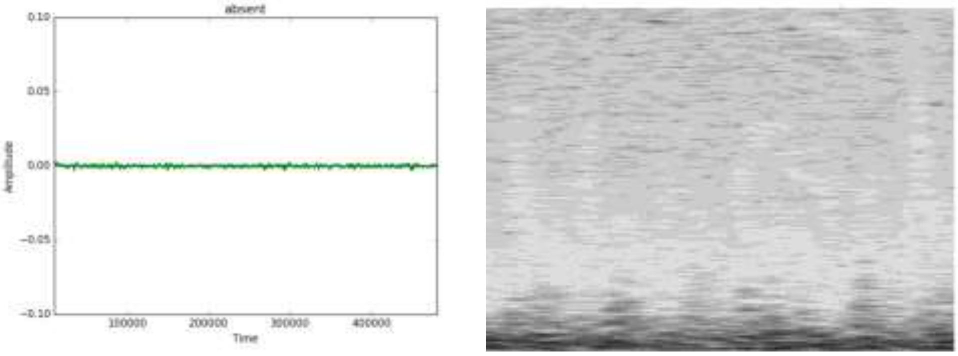

Figure 7.12 Absent waveform and spectrogram image

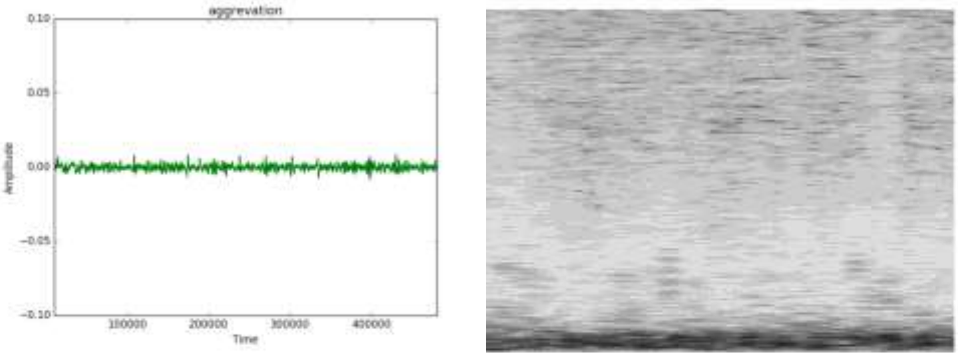

Figure 7.13 Aggrevation waveform and spectrogram image

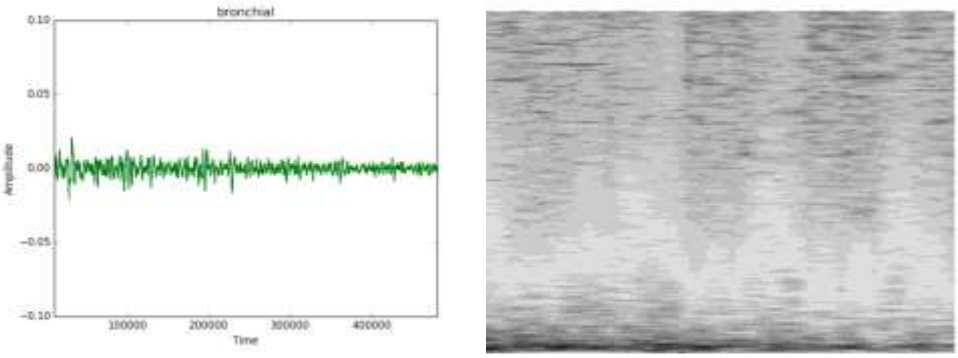

Figure 7.14 Bronchial waveform and spectrogram image

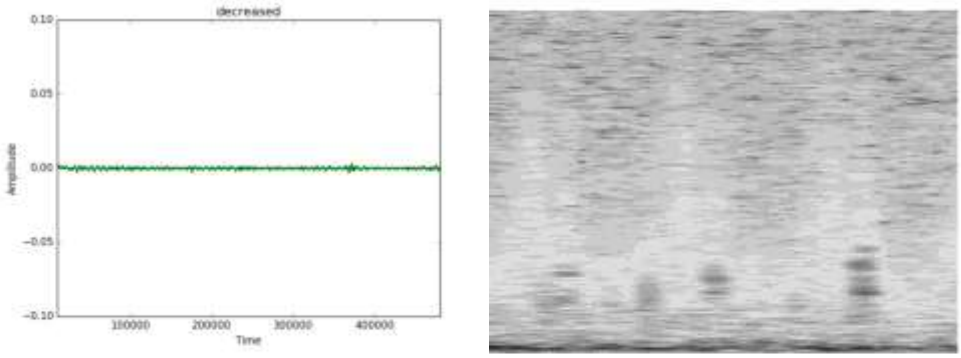

Figure 7.15 Decreased waveform and spectrogram image

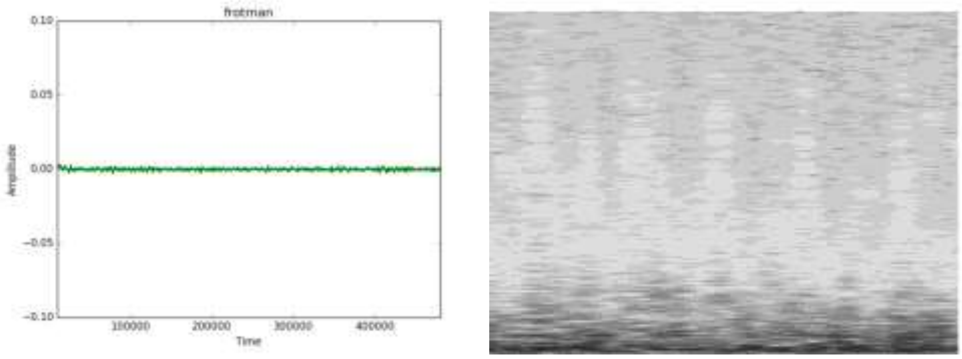

Figure 7.16 Frotman waveform and spectrogram image

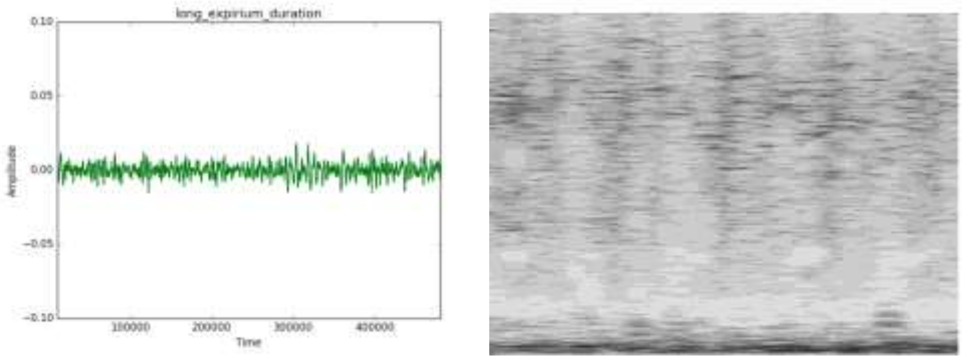

Figure 7.17 Long expirium duration waveform and spectrogram image

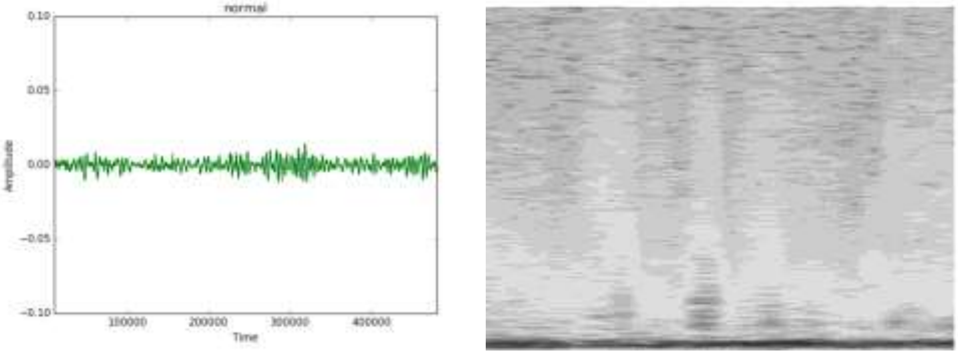

Figure 7.18 Normal waveform and spectrogram image

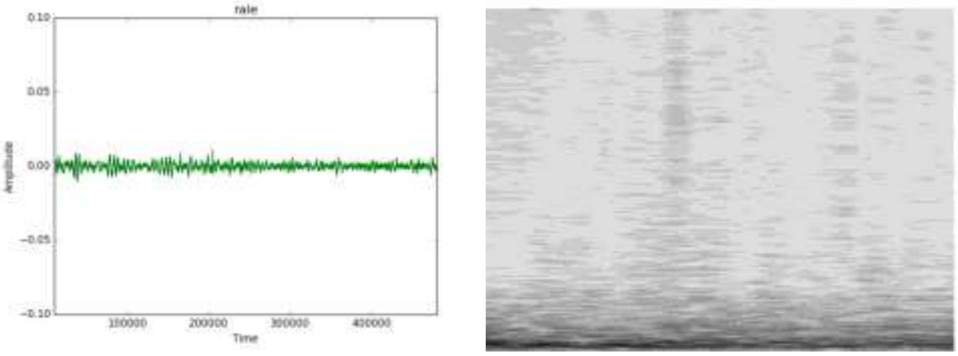

Figure 7.19 Rale waveform and spectrogram image

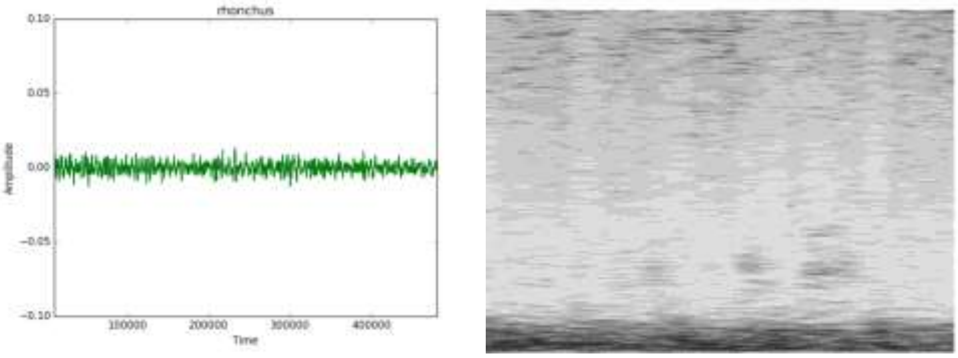

Figure 7.20 Rhonchus waveform and spectrogram image

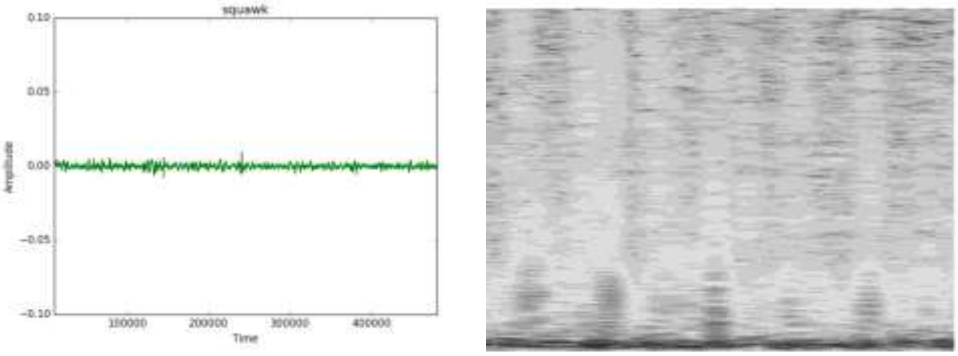

Figure 7.21 Squeak waveform and spectrogram image

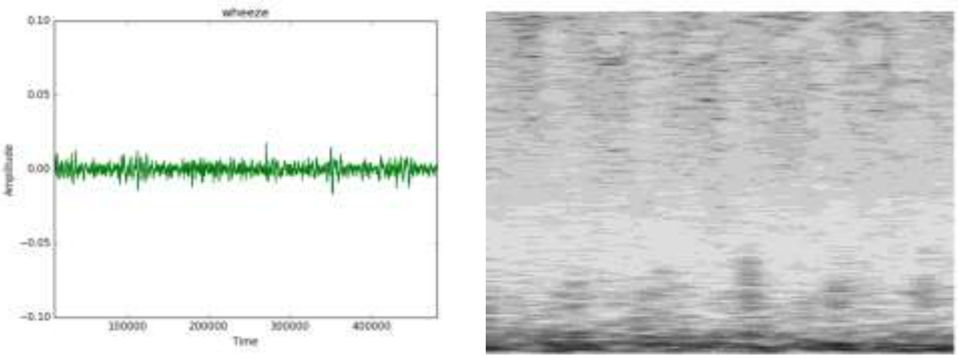

Figure 7.22 Wheeze waveform and spectrogram image

In this study, we recorded audio data from 1,630 subjects (825 sick and 805 healthy subjects) (Table 7.1 and 7.2) and 11 positions from each patient's chest, totaling to 17,930 audio clips [8] between 01.01.2016 – 23.09.2016 from Ankara University Chest Diseases Hospital, Yıldırım Beyazıt University Chest Diseases Clinic, Yıldırım Beyazıt Education and Research Hospital Chest Diseases Clinic. Each subject was allocated a unique numeric identification number and no personally identifiable information was recorded to maintain the subjects' anonymity. Healty subjects were volunteers from hospital staff, graduate students in hospitals, family members and friends.

In order to demonstrate the feasibility of capturing lung sounds audio data was collected with device from 10 test subjects to a laptop. Based on experience from chest physicians the optimal eleven locations on the chest for lung sound recording were selected, as depicted in Figure 7.23. In order to determine the length of each lung sound recording, physicians manually counted the number of breath cycles completed by the test subject in the 5, 10, 15, 20 seconds of the recording. Finally, it was decided that a 10 second data record from each location was sufficient because it was 3-4 cycles.

The recording locations selected for auscultating to lung sounds were Figure 7.23:

- On posterior chest: the upper left, upper right, center left, center right, lower left, and lower right.
- On anterior chest: the upper left, upper right, center left, center right, and lower right.

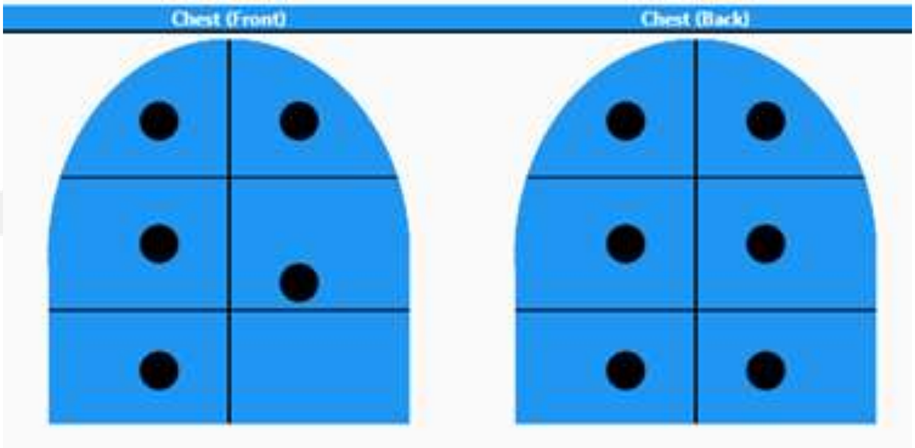

Figure 7.23 11 areas that the lung sound data was recorded

During auscultation, physicians start above the clavicle, since lung tissue extends that high. They auscultate in five areas on the chest, and six paired areas on the back (Figure 7.23). They always auscultate to left and right sides at the same level before moving down to the next level – this way they get a side-by-side comparison, and any differences will be more apparent. Thus, we also needed to follow the same pattern when auscultating with our electronic stethoscope. After physicians were done with the examination of the patient, we also recorded from the same spots that the physician auscultated from and input the lung sound classification physicians told us about each lung area such as rhoncus, rales etc (Appendix C).

The lung sounds recording protocol was as follows:

1) The subject was seated in a chair.
2) They were asked to relax for three minutes while this procedure was explained to them.
3) The subject was also asked not to talk or change posture.
4) The subject was asked to lift their shirt. The stethoscope device was first placed on the subject's back at position 1. The diaphragm of the device wereheld against the patient's back with direct skin contact and slight pressure. The stethoscope was not placed directly on the scapula because the bone mass would muffle the lung sounds. However, if no other locations offered audible lung sounds, a partial section of the stethoscope diaphragm could be placed over areas with bone.
5) The subject was instructed to breath deeper than normal.
6) Lung sounds were recorded for 10 seconds on the computer and associated with the correct audio file.
7) Steps were repeated for each position.

We recorded lung sounds in hospital environments without special sound isolation. But to reduce the noise as much as possible, we recorded these sounds inside patient rooms and/or examination rooms.

Our patient demographic information can be seen in Table 7.3.

Table 7.3 Patient demographic information

PATIENT INFORMATION	
Number of males	710
Number of females	920
Average age	43
Maximum age	92
Minimum age	18

This study was approved by the local Human Experiments Ethical Committee of Turgut Özal University (29.12.2015 – 0123456/0023).

7.4 Experiments

7.4.1 Experiment 1

In this experiment, 17,930 lung sounds have been recorded from 825 sick and 805 healthy (total 1,630) subjects. Each sound clip was 10 seconds long and included three to four respiration cycles.

A total of 6 chest physicians contributed to our study, 3 from Ankara University Chest Diseases Hospital, 2 from Yıldırım Beyazıt University Chest Diseases Clinic and 1 from Yıldırım Beyazıt Education and Research Hospital Chest Diseases Clinic.

We used our electronic stethoscope to digitally record and analyze lung sounds [8]. For the traditional stethoscope in our experiment, we used a 3M™ Littmann® Classic II S.E. stethoscope.

We started on experimenting with the data we collected. We aimed to build neural networks for the following experiments. For audio classification, we need to extract key features and run them over a network. However, how features extracted is a very important question.

There are two ways to extract features:

- Spectrogram Method
- MFCC Method

A spectrogram is a visual representation of the spectrum of frequencies in a sound or other signal as they vary with time or some other variable [8] (Figure 7.24). Therefore, spectrograms are a very common visualization method for audio. The idea behind the spectrogram method is that since convolutional neural networks (CNN) work best on images, we take the audio signal and turn it into an image so we can use it in the CNN.

Figure 7.24 Example of respiratory sound spectrogram

In this experiment we used two feature extraction methods [8]; Mel frequency cepstral coefficient (MFCC) feature extraction and spectrogram generation using short-time Fourier transform (STFT) [8]. MFCC features are widely used in audio detection systems and the experiments we ran using the MFCC features enabled us to find a base value for accuracy, precision, recall, sensitivity and specificity [8] (Figure 7.25, 7.26). Spectrogram images are also used in audio detection [8]. However, they were never tested in respiratory audio with CNNs [8]. We wanted to see if we can match or exceed the audio detection accuracies with MFCC features [8].

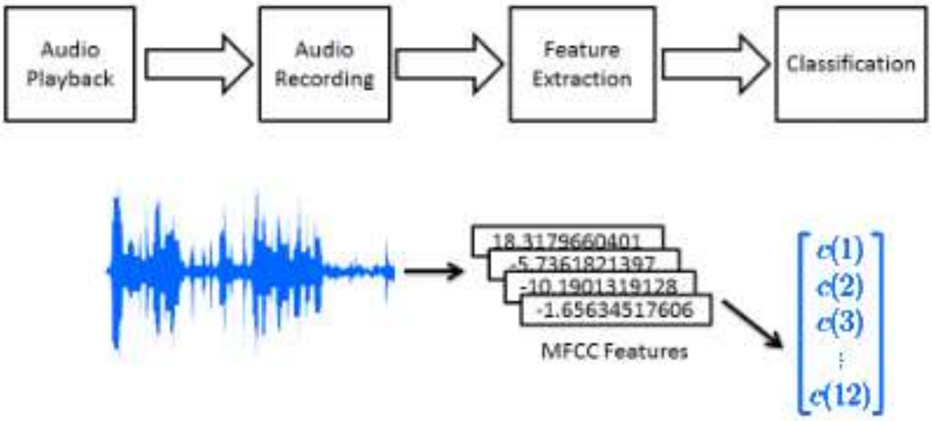

Figure 7.25 MFCC classification

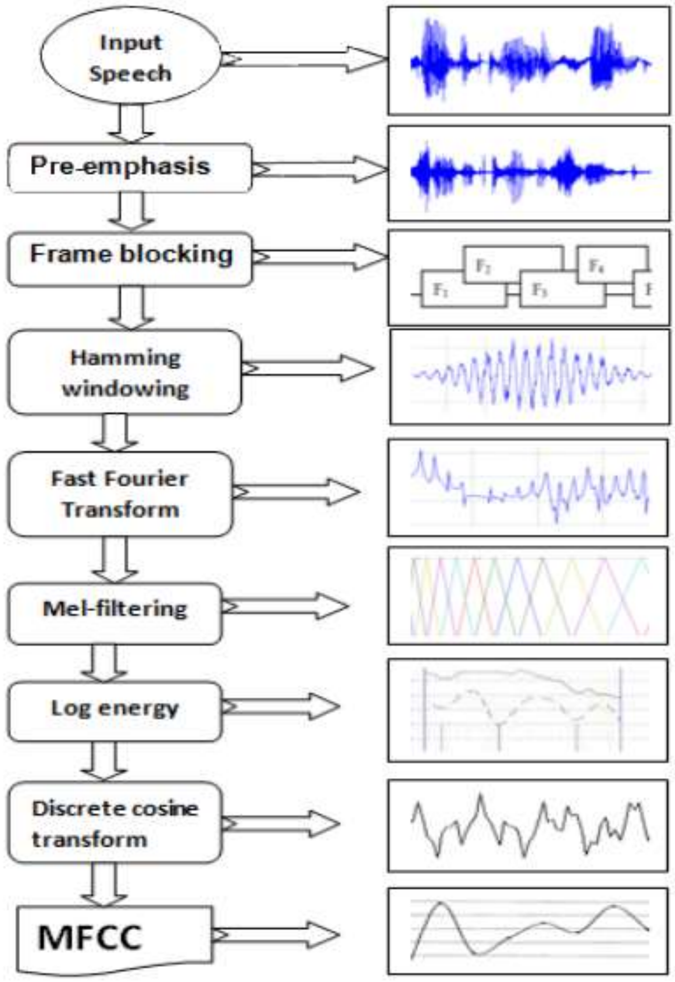

Figure 7.26 MFCC steps [323]

MFCC datasets were built using SciPy library [8]. We used support vector machine (SVM), k-nearest neighbor (k-NN) and Gaussian Bayes (GB) to process these datasets [8] (Figure 7.27, 7.28). Spectrogram dataset was built using a combination of open source graph generation library Pylab and various open source image processing libraries [8]. We generated 28x28 and 600x600 grayscale images to fit them into the memory for CNN to process [8].

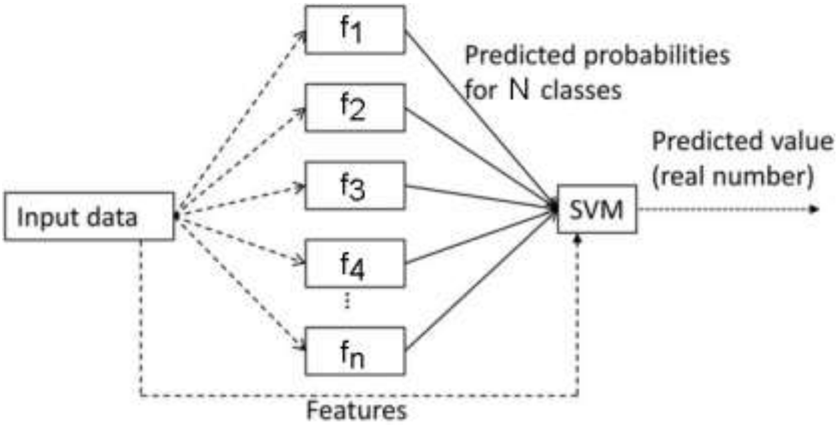

Figure 7.27 SVM steps

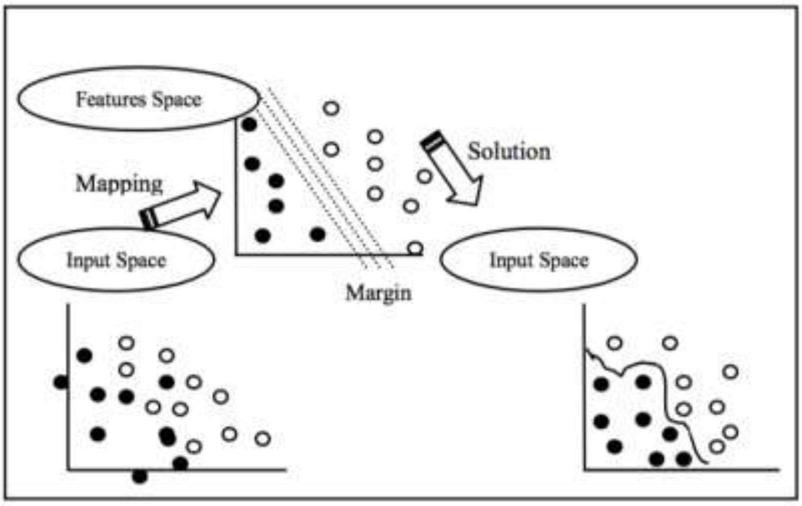

Figure 7.28 Classification principle of SVM [324]

We built 16 datasets, 4 for SVMs, 4 for k-NNs, 4 for GBs and 4 for CNNs:

- 4 datasets for prediction of respiratory sounds whether it is a normal respiratory sound or a pathological one. (17,930 audio clips, 2 classes) [8]
- 4 datasets for classification of respiratory sounds labeled with a singular type: Normal, rhonchus, squeak, stridor, wheeze, rales, bronchovesicular, frotman, bronchial, absent, decreased, aggravation, long expirium duration (LED). (14,453 audio clips, 13 classes) [8]

- 4 datasets for classification of respiratory sounds labeled with only as type rale, rhonchus and normal. (15,328 audio clips, 3 classes) [8]
- 4 datasets for classification of respiratory sounds with all labels including ones with multiple labels. (17,930 audio clips, 73 classes) [8]

In the CNN experiments, we used Theano and Keras frameworks. We resized the spectrograms to 28x28 and 600x600 images and input them into a CNN that has 2 convolutional, 2 max-pooling, a hidden and an output layer that is shown in Figure 7.29, 7.30, 7.31, and 7.32. We used categorical crossentropy as the loss function, optimizer as AdaDelta and weight initializer as glorot uniform.

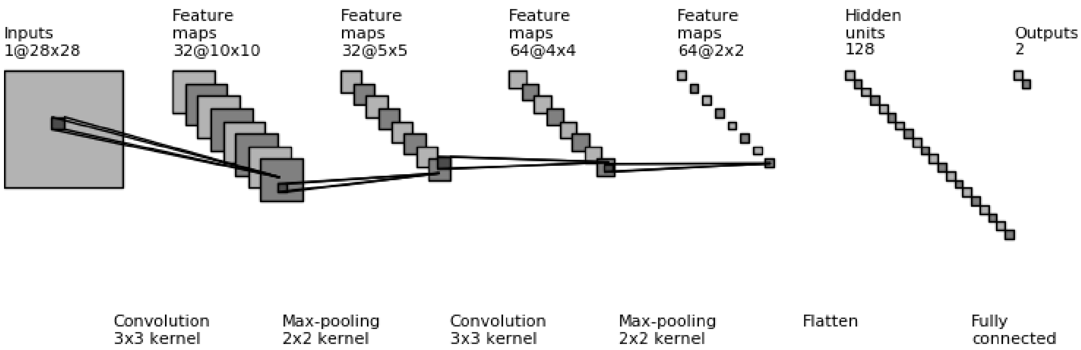

Figure 7.29 CNN structure for classifying pathologic and normal sound types [8]

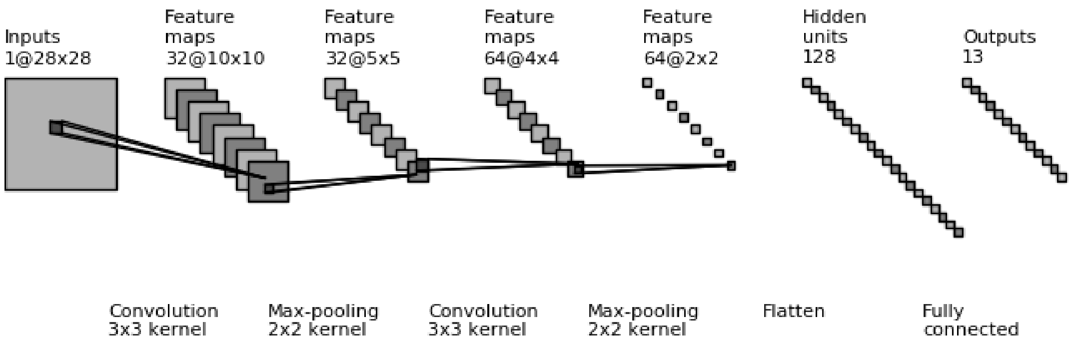

Figure 7.30 CNN structure for classifying all singular sound types [8]

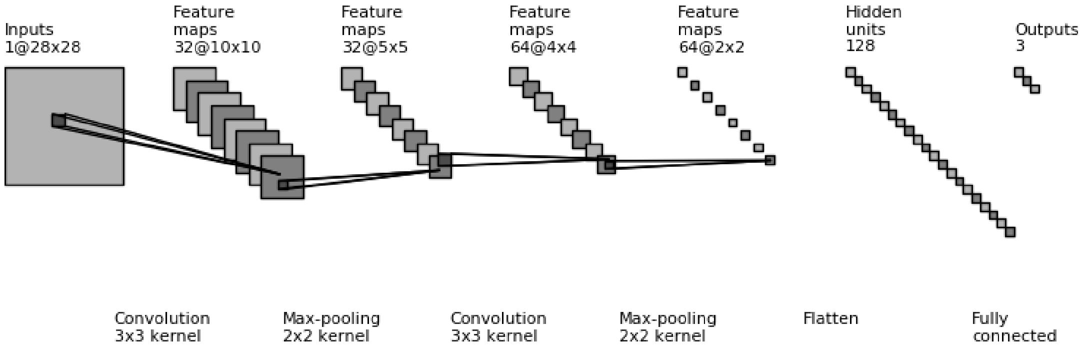

Figure 7.31 CNN structure for classifying rale, rhonchus and normal sounds [8]

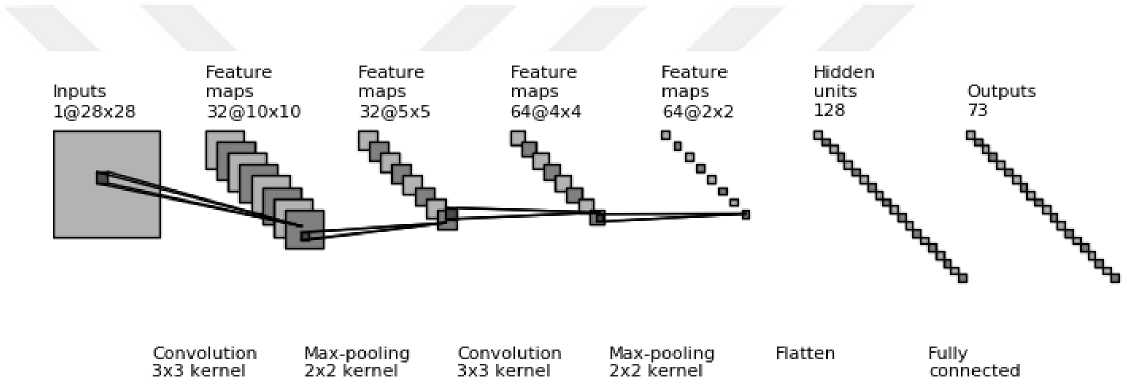

Figure 7.32 CNN structure for classifying all lung sounds [8]

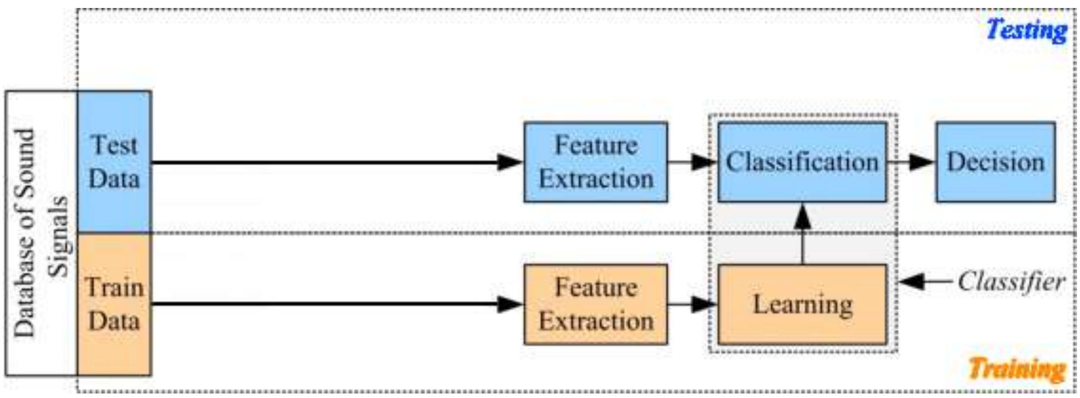

Figure 7.33 Experiment overview

In SVM experiments we used:

- Non-linear SVM with C as 1, gamma as 0.01 in classification of healthy versus pathologic respiratory sounds.
- Non-linear SVM with C as 1, gamma as 0.1 in classification of respiratory sounds labeled with a singular type.
- Non-linear SVM with C as 1, gamma as 0.01 in classification of respiratory sounds labeled with only as type rale, rhonchus and normal.
- Non-linear SVM with C as 1, gamma as 0.01 in classification of respiratory sounds with all labels.

In k-NN experiments we used:

- Weights as uniform, algorithm as auto, leaf size as 30, p as 1 and number of neighbors as 2 in classification of healthy versus pathologic respiratory sounds.
- Weights as distance, algorithm as KDTree, leaf size as 10, p as 1, and number of neighbors as 6 in classification of respiratory sounds labeled with a singular type.
- Weights as distance, algorithm as auto, leaf size as 30, p as 2, and number of neighbors as 6 in classification of respiratory sounds labeled with only as type rale, rhonchus and normal.
- Weights as distance, algorithm as auto, leaf size as 30, p as 2 and number of neighbors as 4 in classification of respiratory sounds with all labels.

In GB experiments we didn’t use any prior probabilities.

As can be seen from Figure 7.33, we divided the dataset into two parts; training and test. Then extracted either MFCC features or generated spectrogram images of sounds. Finally we used SVM, k-NN, GB and CNN algorithms to classify the sounds and display the end result.

7.4.2 Experiment 2

In this experiment, 17,930 lung sounds have been recorded from 825 sick and 805 healthy (total 1,630) subjects. Each sound clip was 10 seconds long and included three to four respiration cycles.

A total of 6 chest physicians contributed to our study, 3 from Ankara University Chest Diseases Hospital, 2 from Yıldırım Beyazıt University Chest Diseases Clinic and 1 from Yıldırım Beyazıt Education and Research Hospital Chest Diseases Clinic.

We used our electronic stethoscope to digitally record and analyze lung sounds [8]. For the traditional stethoscope in our experiment, we used a 3M™ Littmann® Classic II S.E. stethoscope.

In this experiment, apart from the manually selected features (age, gender, smoking habits, sport habits, shortness of breath, cough, color of mucus, coughing of blood, chest pains, high fever, weight loss, swelling in legs, night sweating, palpitation, FVC, FEV1, FEV1/FVC, white blood cell count, C-reactive protein count, neutrophils count and X-ray results from 6 regions of lungs), we used mel frequency cepstral coefficient (MFCC) feature extraction method [8] (Figure 7.25, 7.26).

MFCC datasets were built using SciPy library [8]. We used support vector machine (SVM) (Figure 7.27, 7.28), k-nearest neighbor (k-NN) and Gaussian Bayes (GB) to process these datasets [8].

We built 18 datasets with 1,630 subjects:

- 3 datasets for prediction of whether the subject is ill or healthy with our manually selected text features
- 3 datasets for prediction of whether the subject is ill or healthy with MFCC features extracted from combined audio data from each subject’s 11 locations on their chest
- 3 datasets for prediction of whether the subject is ill or healthy with combining our manually selected text features with MFCC features extracted from combined audio data from each subject’s 11 locations on their chest

- 3 datasets for 12 class diagnosis classification with our manually selected text features
- 3 datasets for 12 class diagnosis classification with MFCC features extracted from combined audio data from each subject's 11 locations on their chest
- 3 datasets for 12 class diagnosis classification with combining our manually selected text features with MFCC features extracted from combined audio data from each subject's 11 locations on their chest.

In SVM experiments we used:

- Linear SVM with C as 0.1 in 12 class classification of lung diseases using text data.
- Linear SVM with C as 0.0001 in 12 class classification of lung diseases using audio data.
- Linear SVM with C as 0.001 in 12 class classification of lung diseases using text and audio data.
- Non-linear SVM with C as 0.1 and gamma as 0.01 in classification of healthy versus sick using text data.
- Non-linear SVM with C as 0.1, gamma as 0.001 in classification of healthy versus sick using audio data.
- Non-linear SVM with C as 0.1, gamma as 0.001 in classification of healthy versus sick using text and audio data.

In k-NN experiments we used:

- Weights as distance, algorithm as brute, leaf size as 30, p as 1 and number of neighbors as 9 in 12 class classification of lung diseases using text data.
- Weights as distance, algorithm as auto, leaf size as 30, p as 1 and number of neighbors as 9 in 12 class classification of lung diseases using audio data.
- Weights as distance, algorithm as auto, leaf size as 30, p as 1 and number of neighbors as 5 in 12 class classification of lung diseases using text and audio data.

- Weights as uniform, algorithm as auto, leaf size as 30, p as 1 and number of neighbors as 2 in classification of healthy versus sick using text data.
- Weights as uniform, algorithm as brute, leaf size as 30, p as 1 and number of neighbors as 2 in classification of healthy versus sick using audio data.
- Weights as uniform, algorithm as auto, leaf size as 30, p as 1 and number of neighbors as 2 in classification of healthy versus sick using text and audio data.

In GB experiments we didn't use any prior probabilities.

As can be seen from Figure 7.33, we divided the dataset into two parts; training and test. Then we extracted the MFCC features from the audio in both training and the test dataset audio. Finally we used SVM, k-NN and GB to classify the sounds and display the end result.

7.4.3 Experiment 3

We observed that some audio called normal and decreased after auscultation with traditional stethoscope were perceived as different pathological sounds when the same sound was listened from electronic stethoscope records. And this difference, would lead to a different diagnosis by the physician.

In this experiment, our aim was to compare the difference of diagnosis between lung sounds that was auscultated by both by traditional stethoscope and electronic stethoscope.

To this end, we used our electronic stethoscope to store lung sounds digiatally, analyze them and compare them. For the traditional stethoscope in our experiment, we used a 3M™ Littmann® Classic II S.E. stethoscope.

In this experiment, 17,930 lung sounds have been recorded from 825 sick and 805 healthy subjects from Ankara University Chest Diseases Hospital, Yıldırım Beyazıt University Chest Diseases Clinic, Yıldırım Beyazıt Education and Research Hospital Chest Diseases Clinic. Each sound clip was 10 seconds long.

While these recordings were previously diagnosed as decreased and normal lung sounds, after listening the recording that was done by our electronic stethoscope, in some cases, physicians came conclusion to different diagnosis than their previous one.

After this realization, we went over all 17,930 recordings and found that pathologic sounds could not be heard in 1,477 recordings (8.24% of total recordings) because physicians could not hear them using the traditional stethoscope. We selected 100 random recordings from these 1,477 recordings. 3 chest physicians that contributed to our research auscultated and re-diagnosed these sounds without knowing their previous diagnosis. They were asked to write their diagnosis to a table that was provided for statistic analysis.

CHAPTER 8

RESULTS

8.1 Results

8.1.1 Results of the First Experiment

For this experiment, we built 8 datasets, 4 for SVMs and 4 for CNNs. Using the information in Figure 8.1 we generated the results shown in Table 8.1.

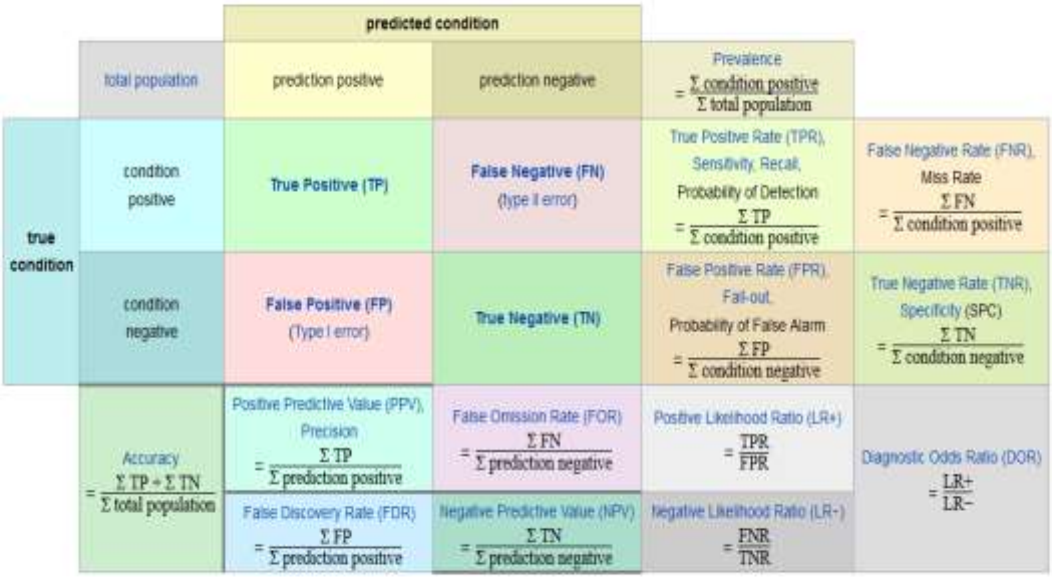

Figure 8.1 Terminology and derivations from a 2x2 confusion matrix [325]

Table 8.1 Experiment results

	Training Accuracy	**Test Accuracy**	**Training Precision**	**Test Precision**	**Training Recall**	**Test Recall**	**Training Sensitivity**	**Test Sensitivity**	**Training Specificity**	**Test Specificity**
Classification of healthy versus pathologic respiratory sounds										
CNN (600x600 Spectrogram)	98%	95%	98%	95%	98%	95%	98%	98%	98%	95%
CNN (28x28 Spectrogram)	87%	86%	90%	86%	89%	86%	89%	86%	95%	86%
SVM (MFCC)	91%	86%	94%	89%	87%	87%	87%	87%	87%	82%
k-NN (MFCC)	91%	85%	99%	90%	83%	83%	83%	83%	83%	79%
GB (MFCC)	59%	58%	82%	81%	23%	23%	23%	23%	23%	21%
Classification of respiratory sounds labeled with a singular type										
CNN (600x600 Spectrogram)	95%	85%	98%	88%	95%	85%	94%	85%	NA	NA
CNN (28x28 Spectrogram)	90%	76%	94%	79%	86%	74%	86%	74%	NA	NA
SVM (MFCC)	99%	75%	99%	75%	99%	99%	99%	99%	NA	NA
k-NN (MFCC)	99%	76%	99%	76%	99%	99%	99%	99%	NA	NA
GB (MFCC)	23%	22%	23%	22%	23%	23%	23%	23%	NA	NA

CNN: Convolutional Neural Network, MFCC: Mel Frequency Cepstral Coefficient, NA: Not available, SVM: Support Vector Machine, k-NN: k-Nearest Neighbor, GB: Gaussian Bayes

Table 8.1 (continue) Experiment results

	Training Accuracy	Test Accuracy	Training Precision	Test Precision	Training Recall	Test Recall	Training Sensitivity	Test Sensitivity	Training Specificity	Test Specificity
Classification of respiratory sounds labeled with only as type rale, rhonchus and normal										
CNN (600x600 Spectrogram)	95%	93%	94%	88%	93%	88%	97%	91%	NA	NA
CNN (28x28 Spectrogram)	87%	80%	88%	79%	85%	79%	85%	79%	NA	NA
SVM (MFCC)	89%	80%	89%	80%	89%	89%	89%	89%	NA	NA
k-NN (MFCC)	99%	79%	99%	79%	99%	99%	99%	99%	NA	NA
GB (MFCC)	42%	42%	42%	42%	42%	42%	42%	42%	NA	NA
Classification of respiratory sounds with all labels										
CNN (600x600 Spectrogram)	82%	77%	90%	80%	75%	66%	75%	66%	NA	NA
CNN (28x28 Spectrogram)	74%	62%	80%	73%	66%	56%	66%	56%	NA	NA
SVM (MFCC)	78%	62%	78%	62%	78%	78%	78%	78%	NA	NA
k-NN (MFCC)	99%	61%	99%	61%	99%	99%	99%	99%	NA	NA
GB (MFCC)	18%	15%	18%	15%	18%	18%	18%	18%	NA	NA
CNN: Convolutional Neural Network, MFCC: Mel Frequency Cepstral Coefficient, NA: Not available, SVM: Support Vector Machine, k-NN: k-Nearest Neighbor, GB: Gaussian Bayes										

8.1.2 Resultss of the Second Experiment

For this experiment, we built 6 datasets with 1,630 subjects. Using the information in Figure 8.1 we generated the results shown in Table 8.2. In calculation of the results we used binary in “classification of healthy versus sick using text data”, “classification of healthy versus sick using audio data”, “classification of healthy versus sick using text and audio data” and micro in “12 class classification of lung diseases using text data”, “12 class classification of lung diseases using audio data”, “12 class classification of lung diseases using text and audio data” as average functions.

Table 8.2 Experiment results

	Training Accuracy	Test Accuracy	Training Precision	Test Precision	Training Recall	Test Recall	Training Sensitivity	Test Sensitivity	Training Specificity	Test Specificity
12 class classification of lung diseases using text data (SVM)	91%	73%	91%	73%	91%	91%	91%	91%	NA	NA
12 class classification of lung diseases using text data (k-NN)	100%	67%	100%	67%	100%	100%	100%	100%	NA	NA
12 class classification of lung diseases using text data (GB)	64%	58%	64%	58%	64%	64%	64%	64%	NA	NA
12 class classification of lung diseases using audio data (SVM)	96%	63%	96%	63%	96%	96%	96%	96%	NA	NA
12 class classification of lung diseases using audio data (k-NN)	99%	64%	99%	64%	99%	99%	99%	99%	NA	NA
12 class classification of lung diseases using audio data (GB)	55%	48%	53%	48%	53%	53%	53%	53%	NA	NA

Table 8.2 (continue) Experiment results

	Training Accuracy	Test Accuracy	Training Precision	Test Precision	Training Recall	Test Recall	Training Sensitivity	Test Sensitivity	Training Specificity	Test Specificity
12 class classification of lung diseases using text and audio data (SVM)	99%	70%	99%	70%	99%	99%	99%	99%	NA	NA
12 class classification of lung diseases using text and audio data (k-NN)	100%	66%	100%	66%	100%	100%	100%	100%	NA	NA
12 class classification of lung diseases using text and audio data (GB)	69%	58%	69%	58%	69%	69%	69%	69%	NA	NA
Classification of healthy versus sick using text data (SVM)	78%	75%	100%	100%	55%	55%	55%	55%	55%	52%
Classification of healthy versus sick using text data (k-NN)	99%	95%	100%	94%	98%	98%	98%	98%	98%	96%
Classification of healthy versus sick using text data (GB)	98%	98%	97%	98%	99%	99%	99%	99%	99%	98%
Classification of healthy versus sick using audio data (SVM)	87%	88%	85%	89%	88%	88%	88%	88%	88%	88%

Table 8.2 (continue) Experiment results

	Training Accuracy	Test Accuracy	Training Precision	Test Precision	Training Recall	Test Recall	Training Sensitivity	Test Sensitivity	Training Specificity	Test Specificity
Classification of healthy versus sick using audio data (k-NN)	96%	92%	94%	94%	92%	94%	92%	92%	92%	88%
Classification of healthy versus sick using audio data (GB)	92%	91%	98%	98%	85%	85%	85%	85%	85%	85%
Classification of healthy versus sick using text and audio data (SVM)	72%	64%	100%	100%	43%	43%	43%	43%	43%	30%
Classification of healthy versus sick using text and audio data (k-NN)	98%	92%	100%	90%	96%	96%	96%	96%	96%	95%
Classification of healthy versus sick using text and audio data (GB)	97%	97%	98%	97%	95%	95%	95%	95%	95%	97%

8.1.3 Results of the Third Experiment

In our study, we observed that some audio called normal and decreased after auscultation with traditional stethoscope were perceived as different pathological sounds when the same sound was listened from electronic stethoscope records. This showed when recorded with an electronic stethoscope, the lung sounds that were difficult to perceive and diagnose by a traditional stethoscope such as decreased lung sounds, were heard comfortably and diagnosed easily.

We selected 100 random recordings from 1,477 recordings (8.24% of total recordings) could not be heard easily using the traditional stethoscope. Three chest physicians that contributed to our research auscultated and re-diagnosed these sounds without knowing their previous diagnosis. They were asked to write their diagnosis to a table that was provided. First diagnosis and re-diagnosed results using the records of the electronic stethoscope are given in Table 8.3.

Table 8.3 First diagnois and re-diagnosed results

Audio No	First diagnosis	1st Chest physician	2nd Chest physician	3rd Chest physician
1	Normal	Rhonchus	Rhonchus	Rhonchus
2	Normal	Rhonchus	Rhonchus	Rhonchus
3	Normal	Rhonchus	Rhonchus	Rhonchus
4	Normal	Rhonchus	Rhonchus	Rales
5	Normal	Normal	Normal	Rhonchus
6	Normal	Normal	Rales	Normal
7	Normal	Rhonchus	Rhonchus	Rhonchus
8	Normal	Normal	Rhonchus	Rhonchus
9	Normal	Rhonchus	Rhonchus	Rhonchus
10	Normal	Rhonchus	Rhonchus	Rhonchus
11	Normal	Normal	Rales	Rhonchus
12	Normal	Rhonchus	Rhonchus	Rhonchus
13	Decreased	Rhonchus	Rhonchus	Rhonchus
14	Decreased	Rhonchus	Rhonchus	Rhonchus
15	Decreased	Rhonchus	Rhonchus	Rhonchus
16	Normal	Rales	Rales	Normal
17	Normal	Rales	Rales	Normal
18	Normal	Rhonchus	Rhonchus	Rhonchus
19	Normal	Rhonchus	Rales	Rhonchus
20	Normal	Rales	Rales	Rales
21	Normal	Rales	Rales	Rales
22	Normal	Rales	Rales	Rales
23	Normal	Rhonchus	Rhonchus	Rhonchus
24	Normal	Rhonchus	Rhonchus	Rhonchus
25	Decreased	Rales	Normal	Rales
26	Decreased	Rales	Rales	Rales
27	Normal	Rales	Normal	Normal
28	Normal	Rales	Normal	Normal
29	Normal	Rales	Rhonchus	Normal
30	Normal	Rales	Rales	Rales
31	Normal	Normal	Rhonchus	Normal
32	Normal	Rales	Rales	Rales
33	Normal	Normal	Normal	Normal
34	Decreased	Rales	Normal	Normal
35	Decreased	Rales	Normal	Normal
36	Decreased	Rales	Rales	Rales
37	Decreased	Rales	Normal	Rhonchus
38	Decreased	Rhonchus	Rhonchus	Rhonchus
39	Decreased	Rales	Rales	Rales
40	Decreased	Rales	Rhonchus	Rhonchus
41	Decreased	Normal	Normal	Normal
42	Normal	Rhonchus	Rhonchus	Rales
43	Normal	Rales	Rales	Rales
44	Normal	Rhonchus	Rhonchus	Rhonchus
45	Normal	Rhonchus	Rales	Normal

Table 8.3 (continued) First diagnois and re-diagnosed results

Audio No	**First diagnosis**	**1st Chest physician**	**2nd Chest physician**	**3rd Chest physician**
46	Normal	Rales	Normal	Normal
47	Decreased	Rales	Rales	Rales
48	Decreased	Rales	Rales	Rales
49	Decreased	Rales	Rales	Rales
50	Decreased	Rales	Rales	Rales
51	Decreased	Normal	Normal	Normal
52	Decreased	Normal	Normal	Rales
53	Decreased	Normal	Normal	Normal
54	Decreased	Normal	Rales	Normal
55	Decreased	Rales	Rales	Rales
56	Normal	Normal	Rales	Rales
57	Normal	Rales	Rales	Rales
58	Normal	Rhonchus	Rhonchus	Rhonchus
59	Decreased	Rales	Rales	Rales
60	Normal	Rhonchus	Rhonchus	Rhonchus
61	Normal	Rhonchus	Rhonchus	Rhonchus
62	Normal	Rhonchus	Normal	Rhonchus
63	Decreased	Rhonchus	Rhonchus	Rhonchus
64	Normal	Rhonchus	Normal	Rhonchus
65	Normal	Rhonchus	Rhonchus	Rhonchus
66	Normal	Rhonchus	Rhonchus	Rhonchus
67	Normal	Rhonchus	Normal	Rales
68	Decreased	Rales	Rales	Rales
69	Normal	Rales	Rales	Rales
70	Normal	Rales	Rales	Rales
71	Normal	Rhonchus	Rhonchus	Rhonchus
72	Normal	Rales	Rales	Rales
73	Decreased	Rales	Rhonchus	Normal
74	Decreased	Rales	Normal	Normal
75	Normal	Rales	Rhonchus	Rhonchus
76	Decreased	Rhonchus	Rales	Rales
77	Normal	Rales	Rales	Rales
78	Normal	Rales	Normal	Normal
79	Normal	Rales	Rales	Rales
80	Normal	Rales	Normal	Rales
81	Normal	Normal	Rales	Normal
82	Normal	Rales	Normal	Normal
83	Normal	Rales	Normal	Rales
84	Normal	Rales	Rales	Rales
85	Normal	Rales	Rales	Normal
86	Normal	Normal	Rales	Normal
87	Normal	Normal	Rales	Normal
88	Normal	Normal	Normal	Normal
89	Decreased	Rales	Rales	Rales
90	Decreased	Normal	Normal	Normal

Table 8.3 (continued) First diagnois and re-diagnosed results

Audio No	First diagnosis	1st Chest physician	2nd Chest physician	3rd Chest physician
91	Normal	Rhonchus	Rhonchus	Rhonchus
92	Normal	Rhonchus	Rhonchus	Rhonchus
93	Normal	Rhonchus	Rhonchus	Rhonchus
94	Normal	Rales	Rales	Rales
95	Normal	Rales	Rhonchus	Rhonchus
96	Normal	Rales	Rhonchus	Rhonchus
97	Normal	Rales	Rhonchus	Rhonchus
98	Decreased	Rhonchus	Rhonchus	Rhonchus
99	Decreased	Rales	Rales	Rales
100	Decreased	Rales	Normal	Rales

In conclusion, we determined that:

- Only at 2 recordings (audio number 33 and 88) previously diagnosed as normal, all three chest physicians re-diagnosed these sounds as normal again.
- At other recordings, after listening the recording from the electronic stethoscope recording, they reached different conclusions, other than their previous diagnosis. The important thing here is that even the recordings that they diagnosed as decreased lung sounds, which are very hard to hear by traditional stethoscope, they reached to more distinguishing diagnosis with the recordings of the electronic stethoscope.

Three physicians participating in the study accepted the presence of other pathologic sounds except two audio clips out of randomly selected 100 audio (including normal or decreased). Since physicians could interpret the same sounds differently depending on their training and experience, the diagnosis had to be assessed with a statistical method. We interviewed two experts on statistics and reached the following conclusions:

- We decided that it would be appropriate to calculate the Kappa coefficient because we wanted to test the compatibility of the 3 different evaluators with each other over the nominal data.
- In our study, we decided that it would be better to use 2-way kappa instead of 3-way kappa for our database.

Since we used 2-way kappa, we prepared 3 tables for each comparison (physician 1 versus physician 2, physician 1 versus physician 3 and physician 2 versus physician 3):

- The first table; descriptive values (Table 8.4, Table 8.7, Table 8.10).
- The second table; probability values (Table 8.5, Table 8.8, Table 8.11).
- The third table; the symmetric measures. This is the table where Kappa is located. (Table8.6, Table 8.9, Table 8.12).

The kappa value in the third table and the significancy values in the last column of the table are important. The output of these values of 0.0 indicates that it is significant to study.

The following results were obtained (Table 8.4-Table 8.12):

Table 8.4 Case Processing Summary (1^{st} and 2^{nd}Physician)

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
1^{st}Physician * 2^{nd}Physician	100	100.0%	0	0.0%	100	100.0%

Table 8.5 FirstPhysician * SecondPhysician Crosstabulation

			2^{nd}Physician			Total
			1	2	3	
1^{st}Physician	1	Count	8	7	2	17
		% within 1^{st}Physician	47.1%	41.2%	11.8%	100.0%
		% within 2^{nd}Physician	33.3%	17.9%	5.4%	17.0%
	2	Count	13	29	7	49
		% within 1^{st}Physician	26.5%	59.2%	14.3%	100.0%
		% within 2^{nd}Physician	54.2%	74.4%	18.9%	49.0%
	3	Count	3	3	28	34
		% within 1^{st}Physician	8.8%	8.8%	82.4%	100.0%
		% within 2^{nd}Physician	12.5%	7.7%	75.7%	34.0%
Total		Count	24	39	37	100
		% within 1^{st}Physician	24.0%	39.0%	37.0%	100.0%
		% within 2^{nd}Physician	100.0%	100.0%	100.0%	100.0%

Table 8.6 Symmetric Measures (1^{st} and 2^{nd}Physician)

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Measure of Agreement	Kappa	.455	.071	6.357	.000
N of Valid Cases		100			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.

Table 8.7 Case Processing Summary (1^{st} and 3^{rd}Physician)

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
1^{st}Physician * 3^{rd}Physician	100	100.0%	0	0.0%	100	100.0%

Table 8.8 FirstPhysician * ThirdPhysician Crosstabulation

			3^{rd}Physician			Total
			1	2	3	
1^{st}Physician	1	Count	12	2	3	17
		% within 1^{st}Physician	70.6%	11.8%	17.6%	100.0%
		% within 3^{rd}Physician	46.2%	5.6%	7.9%	17.0%
	2	Count	13	30	6	49
		% within 1^{st}Physician	26.5%	61.2%	12.2%	100.0%
		% within 3^{rd}Physician	50.0%	83.3%	15.8%	49.0%
	3	Count	1	4	29	34
		% within 1^{st}Physician	2.9%	11.8%	85.3%	100.0%
		% within 3^{rd}Physician	3.8%	11.1%	76.3%	34.0%
Total		Count	26	36	38	100
		% within 1^{st}Physician	26.0%	36.0%	38.0%	100.0%
		% within 3^{rd}Physician	100.0%	100.0%	100.0%	100.0%

Table 8.9 Symmetric Measures (1^{st} and 3^{rd}Physician)

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Measure of Agreement	Kappa	.554	.068	7.857	.000
N of Valid Cases		100			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.

Table 8.10 Case Processing Summary (2nd and 3rdPhysician)

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
2ndPhysician * 3rdPhysician	100	100.0%	0	0.0%	100	100.0%

Table 8.11 SecondPhysician * ThirdPhysician Crosstabulation

			3rdPhysician			Total
			1	2	3	
2ndPhysician	1	Count	14	6	4	24
		% within 2ndPhysician	58.3%	25.0%	16.7%	100.0%
		% within 3rdPhysician	53.8%	16.7%	10.5%	24.0%
	2	Count	9	28	2	39
		% within 2ndPhysician	23.1%	71.8%	5.1%	100.0%
		% within 3rdPhysician	34.6%	77.8%	5.3%	39.0%
	3	Count	3	2	32	37
		% within 2ndPhysician	8.1%	5.4%	86.5%	100.0%
		% within 3rdPhysician	11.5%	5.6%	84.2%	37.0%
Total		Count	26	36	38	100
		% within 2ndPhysician	26.0%	36.0%	38.0%	100.0%
		% within 3rdPhysician	100.0%	100.0%	100.0%	100.0%

Table 8.12 Symmetric Measures (2nd and 3rdPhysician)

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Measure of Agreement	Kappa	.604	.065	8.468	.000
N of Valid Cases		100			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.

CHAPTER 9

CONCLUSIONS AND DISCUSSION

9.1 Conclusions

Before we started the project we aimed to tackle the question of whether lung sounds can be classified using convolutional neural networks using spectrogram images and if this technique can yield better or equal accuracy, precision and recall results compared to the traditional sound classification techniques.

As a result of our first experiment we found that lung sounds can be classified using convolutional neural networks on par with the state of the art classification techniques such as SVM, k-NN and GB.

We also wondered if lung diseases be classified via lung sounds' MFCC features and text patient data using and support vector machine, k-nearest neighbor and Gaussian Bayes algorithms.

As a result of our second experiment, we found that using text and audio data, it is possible to classify lung diseases using SVM, k-NN and GB algorithms.

Finally, we aimed to find out if the electronic stethoscope that was developed to collect lung sounds is successful in providing viable lung sound samples for the study.

For the electronic stethoscope we reached the following design goals that we set:

- Must be mobile and small, preferably pocket sized
- Must have a directional microphone
- Must be able to record low frequency audio
- Must be able to reduce noise as much as possible
- Must have low or no power consumption
- Must be able to connect to any device via an audio jack

- Must be able to record using any software on any OS on any device

Also it was successful in generating a viable dataset for the study.

9.1.1 Conclusions of the First Experiment

In classification of healthy versus pathologic respiratory sounds experiment, we found that the test set accuracy of SVM and CNN with 28x28 spectrogram images are the same [8]. SVM exceeded CNN in precision, recall and sensitivity however CNN yielded better results in specificity.

In classification of respiratory sounds labeled with singular type experiment, CNN had a better result in accuracy and precision however it SVM yielded better results in recall, sensitivity [8].

In classification of respiratory sounds labeled only as type rale, rhonchus and normal experiment, accuracy was the same in SVM and CNN however SVM yielded better results in precision, recall and sensitivity [8].

In classification of respiratory sounds with all labels experiment, CNN and SVM accuracy was the same [8]. While CNN yielded better result in precision, SVM had better results in recall and sensitivity.

However when it comes to CNN with 600x600 images it exceeds SVM in every experiment and every metric.

Overall best results were obtained in experiments; healty versus sick classification and classification of rales, rhonchus and normal lung sounds. The reason for this is, that the frequency of those classes in our dataset. They have the most number of instances in our datasets. If we had a more diverse dataset and more data, we would get better results on the other experiments as well.

9.1.2 Conclusions of the Second Experiment

In these experiments, for the number of patients we had (1,630 subjects), it was observed that the best results were found in healthy versus sick classification. The reason for that is our dataset does not have equal number of samples for each disease. Some classes are represented by just a few samples. Therefore, the classification accuracy drops as we have more classes. Also, the total number of samples affects the classification results. We have enough samples to classify 2 classes but for more accurate classification of more classes we need more samples.

In 12 class classification of lung diseases, the most accurate algorithm was SVM with text data. In classifying via audio data, k-NN was the most accurate. Using both audio and text data, SVM was the most accurate.

However when we classify healthy versus sick via text, audio and combined data, GB was always the most accurate with very high accuracy, closely followed by k-NN.

We can infer from here that when we have large number of features but limited amount of samples, SVM and k-NN are best in classifying the dataset in more than two classes. However GB is best when it comes to classifying into two classes.

Also, we can see from the results that when it comes to disease diagnosis, text and combined data produces better results than just audio data. This is also primarily true for deciding if the patient is healthy or sick. However, in deciding if the patient is healthy or sick, pure audio data can also be used as we found it to be highly accurate as well.

9.1.3 Conclusions of the Third Experiment

Kappa values were interpreted using the Table 9.1 below as proposed by Landis and Koch [326,327].

Table 9.1 Kappa values suggested by Landis and Koch

x value	Comment
< 0	No Consistency
0.01 – 0.20	Negligable Consistency
0.21 – 0.40	Weak Consistency
0.41 – 0.60	Average Consistency
0.61 – 0.80	Good Consistency
0.81 – 1.00	Strong Consistency

According to Landis and Koch:

- The kappa value between physican 1 and 2 was 0.455. This shows that there is average consistency between their diagnoses of the respiratory sounds and this consistency level is statistically significant ($p<0.05$, $p=0.00$).
- The kappa value between physican 1 and 3 was 0.554. This shows that there is average consistency between their diagnoses of the respiratory sounds and this consistency level is statistically significant ($p<0.05$, $p=0.00$).
- The kappa value between physican 2 and 3 was 0.604. This shows that there is good consistency between their diagnoses of the respiratory sounds and this consistency level is statistically significant ($p<0.05$, $p=0.00$).

We also ran a convolutional neural network to determine the accuracy of this 100 audio clips and the result was 79% accuracy, %80 sensitivity, %80 recall, %80 precision and %80 specificity.

9.2 Discussion

9.2.1 Classification of Lung Sounds

Developing a computer-based respiratory sound analysis system that can diagnose the lung disorders is an area of concern since there are a very few systems developed in the past. At present, it is difficult to compare various methods reported in the literature because of the difference in data acquisition methods or methodology. Factors that influence the results include position of the sensor. To position the sensor, it requires professionally trained physicians.

Another important issue is that very few systems have used experimental data from hospitals and many systems have used data from lung sound CDs used for training the physicians. The data from lung sound CDs used by the previous researchers are not suitable for machine learning because of insufficient data [169].

Numerous studies have demonstrated the benefits of computerized lung sound analysis [8,16,49,328]. On the other hand, few studies have been reported on the medical benefit of the computerized analysis of the classification of pulmonary sounds obtained by auscultation in pulmonary diseases [8] (Table 1.1).

It is observed that the data sets used by previous studies are very limited [8]. For example, in the studies in Table 1.1, a maximum of 2,127 voice samples were studied from a maximum of 34 subjects [8,33]. In the studies in Table 1.1, it can be seen that the results are very high when the audio data are very different, and when the audio data are similar, the results are very low [8]. These systems can be a major problem when used to make a critical decision, such as the diagnosis of the disease [8]. In our study, we collected 11 audio data from each of the 1,630 healthy and sick subjects totaling to 17,930 audio clips [8]. Because of the larger size of our dataset we managed to get consistent results in all our experiments [8].

Previous studies have shown that the audio clip size changes between 8 and 16 seconds [8]. Similarly, as a result of our work to determine the duration of the audio clips, we decided to record the audio clips for 10 seconds with the recommendation of our chest physicians [8].

In previous studies in this area, we have found that the devices and software packages on the market are being used. But as a result of our research, we formed our own custom hardware and software utilizing open source libraries to meet all our needs [8].

In other research, no explanation was given about the audio formats used [8]. Some audio formats may compromise quality over reduced disk space. This can lead to some problems [8]. For this reason, we utilized the lossless WAV format to avoid any data loss [8].

Rietveld et al. [31] they determined the audio samples they used in their study by choosing the cleanest ones from the audio they recorded [8]. In the study of Baydar et al. [35] audio clips were recorded in a completely silent room so that the audio samples were clean [8]. Though, if the system is trained cleanly, it can not be expected to routinely use it in a real environment where it is not possible to remove the system from the noise like noises in a hospital [8]. Even in the most silent hospital rooms there is noise that can affect the sound recording [8]. For this reason, we tried to isolate as much of our electronic stethoscope as possible from the sound, and we carefully identified which microphone to use [8]. At the end of the study, external noise was detected in very few of the audio data gathered from the natural surroundings [8].

As shown below, in previous studies, we have identified a classification analysis of maximal 6 types of lung sounds [8]. For example, Kandaswamy et al. [36] performed a study to classify lung sounds into one of six categories: normal, wheeze, crackle, squeak, stridor or rhonchus [8]. Forkheim et al. [29] distinguished lung sounds into isolated segments and then carried out studies to identify only wheezing in these segments [8]. Bahoura et al. [34], Riella et al. [42] and Hashemi et al. [50] classified the audio they gathered into two categories as wheezes or normal breathing sounds

[8]. Lu et al. [329] classified crackles as fine and and coarse [8]. Kahya et al. [30,39], Flietstra et al. [49] and Serbes et al. [48] classified crackles as either present or absent [8]. It has been found that the scope of these studies is very narrow due to the low amount of audio data and the focus on only a few audio types [8]. In our work we made 8 different experiments with 2, 3, 13 and 73 classes and tested our algorithm, diversifying our results highly [8].

Previous studies, so far, have not used CNNs for classification [8]. In our work, we used this new classification algorithm called CNN on the audio. We have observed that this algorithm we choose works very well and generates coherent results [8].

Since it is difficult to create a database of lung sounds, most researchers have preferred to use ready-made databases. For example, Lu et al. [329] obtained their test dataset from RALE and ASTRA databases [8]. Riella et al. [42] utilized electronically acquired lung sounds from distinct online data stores on the Internet [8]. It should be considered that the use of such ready-made data can cause major problems as recording hardware and software may differ for each audio clip [8]. In this case, the audio quality will cause classification problems because it can not be coherent in all training and test examples [8]. Our work was done using a single computer that meets all the recording conditions we wanted and the computer program we created to record audio and patient data [8].

Studies in the literature [5,29,30,39] have compared some algorithms. However, a widely accepted method of audio classification has not been used to compare their neural networks [8]. In our work, we utilized the classification results of SVMs that utilize the MFCC features to compare our CNN algorithm [8].

In the studies that were made so far, outcomes were not intended toward a practical system [8]. We improved our device and software to match the workflow of the hospital environment in our work [8]. We plan to apply this workflow to the telemedicine system, which we think will improve in the future. Thus, we think that physicians will be able to share patient audio data for remote auscultating and consultation [8].

Our electronic stethoscope however, helped physicians to diagnose these hard to diagnose lung sounds further and attain high quality medical results regardless of patient status.

9.2.2 Classification of Lung Diseases

It is a difficult job to diagnose only with auscultation. In addition, medical personnel need specialized training for diagnosing lung sounds properly [5,330]. For this reason, it is important to support physicians in decision-making by analyzing respiratory sounds with an algorithm [5,330].

Investigations that demonstrate the utility of performing a computerized analysis of lung diseases have been present in literature [8,16,49,328]. However, as shown in Table 1.2, there are few studies in the literature that utilize artificial neural network structures focusing on the diagnosis of chest diseases [3]. In these studies, using different neural network structures for the diagnosis of different lung disorders, achieved high classification accuracy utilizing assorted data sets [3]. However, since different sets of data are used in these studies, it is impossible to directly compare the results [3]. A larger data set is required to train the model with supervised learning [169,331].

Investigations in the literature have a very limited set of data, which is also shown in Table 1.2 [3,8,30,46,67,69,70,72-76,332]. Thus, their results are either very low when there is features similar or very high when there are a very different set of features [8]. Since these systems deal with a critical decision such as the diagnosis of the disease, it is clear that a possible faulty diagnosis in health would lead to irreversible vital consequences [8]. Therefore, this risk is the most important problem [8]. To avoid this problem, the data set, such as El-Solh et al. [68] and Heckerling et al. [71], must be large [8]. For this purpose, we collected 11 audio data from each of 1,630 healthy and patient subjects, resulting in a total of 17,930 audio clips [8]. Since our data set is quite large, we were able to achieve coherent outcomes in all our experiments [8].

In the previous studies, they did diagnosis classification with 2 classes, and one study with 3 classes [75]. Also, most studies, classified subjects as healthy and ill while some of them classified a subject group with two different illnesses. The problem with using low number of classes is that it does not really measure the performance and effectiveness of a given machine learning algorithm. In our study we classified 1,630 patients into 16 disease classes as can be seen from Table 7.1. However since we didn't have equal number of classes for each disease, our result was lower than expected. If we had equal number of subjects per class and more data, our accuracy of 73% can be improved.

In literature, diagnosis classification was made either by manually selected text data [3,67-71,74-76,332] or audio data [30]. In our study we ran our experiments using text, audio and text and audio combined. This provided an insight into which features are more important and if results could be improved with text and audio data combined.

In previous studies, they used traditional machine learning algorithms such as MLP, MLNN, k-NN, PNN with only text data or audio data. However, in our study, instead of traditional algoritms we used text data and MFCC features of audio data in SVM algorithm for classification.

9.2.3 Comparison of Electronic and Traditional Stethoscope

It has been reported that 30% of people around the world have abnormal lung sounds like crackles, rhonchi, and wheezes [52]. Lung sound auscultation provides useful information for diagnosing abnormalities and disorders in the respiratory system [170]. Traditional acoustic stethoscope is still generally accepted to be the most popular device that physicians use to diagnose abnormal lung sounds [52]. Lung auscultation depends on the physician's experience, ability and audio perception [16, 158]. Physicians need a long-term practice and experience to use respiratory signals to diagnose them through a traditional acoustic stethoscope [333]. Physicians' perceptions and experiences to obtain quality medical results may not always be sufficient [334,335]. It has been documented that the auscultation skills of primary care physicians are weak [333,336,337]. One drawback of the lung sound auscultation technique is that it has a high possibility of false diagnosis [16]. In short, conditions such as environmental noise and subjective diagnostic experience of the physician can lead to some undesirable faults in the auscultation [52]. In addition, the lung sounds can not be recorded or stored for follow-up or monitoring via traditional stethoscopes [52].

In addition, the human aural system does not fully meet the requirements of traditional auscultation diagnostic testing performed with a stethoscope due to its restrictions [12,13]. The ears are sensitive to deterministic audio in the time or frequency domains, but are substantially less accurate in identifying, analyzing, and classifying the noise [12]. Another reason for human deficiency in the auscultator analysis of lung sounds is their low signal-to-noise ratio [12]. Thoracic lung sounds have relatively low amplitude compared with background noise of heart and muscle sounds [12]. A physician examining a patient with a stethoscope can perceive lung sounds only at isolated locations and at separate time intervals, so evaluation of breath sound distribution relies on the physician’s memory and auscultation expertise [6]. In addition, some abnormal lung sounds may be missed even by a chest-auscultation expert in a conventional clinical setting [6]. Because of the lack of objectivity, and the qualitative nature of lung sounds, many physicians no longer rely only on auscultation as a diagnostic tool [6,12].

With the application of computer technology, new information has been obtained that has clinical importance on acoustic mechanisms and lung sounds [19,164]. The utilization of digital signal processing methods to gather data on average sounds were important footsteps that have improved the benefit of lung sounds besides the stethoscope [19,164].

In the literature, there were very small amount of research done on the subject of comparing electronic stethoscopes and traditional ones.

According to Clement Hoffmann et al., the use of an electronic stethoscope (Littmann 3200) may provide better pulmonary auscultation quality than two traditional stethoscopes (Holtex Ideal and Littmann Cardiology III) [338]. This prospective, double-blind, randomized research was evaluated using a numerical rating scale [338]. Rating scale values for Littmann Cardiology III, Holtex Ideal and electronic stethoscope were 7.4 ± 1.8, 4.6 ± 1.8 and 8.2 ± 1.6 respectively ($P < 0.0001$) for pulmonary auscultation [338].

Studies of recent date have shown that diastolic heart sounds obtained with an electronic stethoscope include markers of coronary artery disease (CAD) [339].

Mesquita et al. proved that using a digital stethoscope is a positive influence in increasing the adequacy of cardiac auditory recognition during cardiology training [340].

In a study of compared digital and standard stethoscopes on children,Kevat et al. found moderate concordance in detecting wheezing and 100% concordance in detecting crackle [341]. In addition, they have shown that digital stethoscope is more sensitive than the clinician in wheezing detection [341]. When using a standard stethoscope, it has been shown to be a poor fit in the detection of pathological breath sounds [341].

The environment noise during air transportation is very high [342]. The use of a traditional stethoscope (Littman cardiology III) and an amplified stethoscope (Littman 3100) during air transportation by Jean P. Tourtier et al. was evaluated in terms of heart and breath sounds in 32 cases [342]. This prospective, double-blind, randomized research was evaluated using a numerical rating scale and t test [342]. Rating scale values for the traditional and amplified stethoscope were 5.8 ± 1.5 and 6.4 ± 1.9 ($P = .018$) for heart auscultation and 3.3 ± 2.4 and 3.7 ± 2.9 ($P = .15$) for lung sounds respectively [342]. As a result, although the heart sounds can be heard more strongly with the amplified stethoscope, no significant difference can be detected regarding the breath sounds [342]. But the number of subjects that examined it was very small [342].

In the study of James H. Philip et al., twenty-one anesthesiologists reported that electronic stethoscopes judged better than conventional stethoscopes in the majority of the categories surveyed [343].

In a study by Szilvási, V. et al, thirty-three Beagles type dogs compared auscultations with traditional and electronic stethoscopes. As a result, electronic stethoscop in cardiac murmurs, particularly on the right hemithorax, proved to be better [344].

However, electronic stethoscope is susceptible to electronic and environmental noise as well as to rubbing noise during use [345]. The characteristics of lower frequency bands have been shown to be more resistant to noise than the characteristics of higher frequency bands [339]. There are considerable differences between an electronic stethoscopic sound and a traditional stethoscope sound [345]. These disadvantages can be minimized if the device is used carefully and with training [339].

Electronic stethoscopes also help elderly physicans and physicians with hearing impairment, because their sound output can be increased so that they can hear it better.

Our system consists only of a portable computer, simple electronic hardware, and the software. It can record, save, and replay lung sounds and analyze them in time and frequency domains. It can serve as a simple and beneficial appliance to measure and analyze lung sound.

The main features of this system are:

- The measurement is noninvasive,
- Low capital cost,
- No mechanical parts are involved, so no maintenance required,
- Flexibility,
- Usability in all kinds of hospital conditions,
- This system is modularized in software and hardware and is therefore capable of being upgraded.

If we compare our device with the other commercial electronic stethoscopes, our most important advantages are:

- Low cost (100 TL)
- Does not need a battery to operate
- Light weight and mobile
- Can be connected to any device such as desktop computers, laptops or any mobile device
- Can be used with any recording software on any platform

In our study, we observed that some audio called normal and decreased after auscultation with traditional stethoscope were perceived as different pathological sounds when the same sound was listened from electronic stethoscope records. This showed that when recorded with an electronic stethoscope, some of the pathological sounds of the human ear that were difficult to perceive with conventional stethoscopes could be comfortably heard. Three physicians participating in the study accept the presence of other pathologic sounds except two audio clips out of randomly selected 100 audio (including normal or decreased). The results obtained by physicians were assessed with kappa statistic method via SPSS to determine the diagnosis consistency because the same sounds could be subjectively assessed differently according to their training and experience. We observed; good level consistency (0.604, $p<0.05$, $p=0.00$) between physicians 2 and 3, average level consistency (0.554, $p<0.05$, $p=0.00$) between physicians 1 and 3 and average level consistency (0.455, $p<0.05$, $p=0.00$) between physicians 1 and 2.

This result shows us that if a traditional stethoscope is used in auscultation, lung sounds cannot be diagnosed as easily compared to the outputs of an electronic stethoscope. Therefore, there is chance that there can be an error in the diagnosis. As a result we believe that if electronic stethoscopes are used in auscultation, physicians would diagnose lung sounds more precisely reducing misdiagnosis.

CHAPTER 10

FUTURE WORK

10.1 Future Work

Medical imaging methods such as magnetic resonance (MR), computed tomography (CT), ultrasound imaging (US), etc. need much more complex and costly equipment and specialized personnel; in short, they are much more costly and operationally complicated [346]. While these methods are only available in well-regulated health institutions, it is not possible to use it in rural small health centers and often in primary health care facilities because of cost and operational complexity [346]. In these small-scale healthcare facilities, auscultation continues to be used as a primary tool at the first examination of patients [346]. Due to the above reasons, it would be very helpful to provide suitable decision support systems that support physicians in identifying lung sounds and diseases, particularly in remote rural areas and primary healthcare [346]. Such decision support systems can be used as diagnostic or educational tools for young and inexperienced physicians working in remote and small health centers [346].

For computer-supported auscultation, besides software, only an electronic stethoscope and a personal computer are required [346]. The use of electronic stethoscope combined with a recording software:

- Digitizes and stores lung sounds on digital mediums.
- Incorporates lung sounds into electronic health records.
- Transmits to distant systems using internet or wireless technology.
- Makes a presentation on a screen in both time and frequency domain.
- Works to eliminate noise and other unwanted components.

Even the best-performing systems are thought to perform slightly lower in terms of confidence and accuracy than medical experts in the field at present [346]. Nevertheless, it is accepted that these systems are very convenient for physicians to generate second opinions [346]. In any case, our system can be designed to be used only as an aid to the diagnosis, not to take the place of physicians.

The diagnostic value of any clinical test or examination depends upon its ability to distinguish clearly, accurately, and in a repetitive manner between the normal and abnormal.

Because auscultation is a subjective and variable method that depends on experiential and auditory training, it has visible disadvantages in interpreting diagnostic data [347]. If the audio signal digitization and processing methods are used, it is considered that the diagnostic value will be better [347]. So, new diagnostic tools are being developed that objectively monitor, store and assist physicians in practice the features of pathology [347]. If our recording software can be integrated into the hospital information system:

- The patient's own physician may be able to compare the patient's previous audio with the current situation.
- Where the patient's former physician is not available, the patient's new physician may be able to compare the audio data of the patient with the current situation.

Despite their diagnostic importance in the assessment of respiratory sounds, it is difficult to perceive some short duration sounds such as crackles [162]. Because the human ear cannot distinguish between milli-second events [162]. In addition, the localized crackles can not considerably be shown in the whole spectrum of respiratory sounds [162]. Our study aims to assist physicians in the detection, recording, storage and classification of respiratory sounds which are difficult to identify with traditional stethoscopes but are significant in the diagnosis of different lung disorders.

The diffusion of computers in medical settings over the recent years has provided a valuable tool for the study of the acoustic characteristics of lung sounds [28]. The advantage of the use of computers as supporting devices for learning has been successfully experimented with in several medical disciplines, but only recently has it been applied to respiratory sounds [28].

One drawback of the lung sound auscultation technique is that it has a high possibility of false diagnosis [173]. It requires a professionally well-trained physician to recognize the abnormalities exactly [173]. Lung auscultation is a subjective method, which depends on the experience, ability, and auditory perception of the physician [158,169]. Recently, studies have been undertaken to increase the diagnostic value of auscultation by creating a more objective base for getting parametric presentations of lung sounds [30]. To overcome this drawback, researchers started to develop computer based lung sound analysis systems [169]. At the beginning of the 1980s, computer-based lung sound analysis began to show up in the literature [169,348]. The recent advancement in the field of signal processing is yet to be applied to determine the abnormalities and disorder using computer based lung sound auscultation [169].

The only dependable and quantitative procedure for the evaluation of respiratory sound is using digital recording and its subsequent analysis [36,338]. While the emergence of electronic stethoscopes presents new opportunities, new types of electronic stethoscopes combined with additional diagnostic algorithms can change the clinical potential of the stethoscope. The most important factors that play a role in the development of electronic stethoscopes are market price, mobility, and ease of utilization. The difficulty of auscultation in patients, such as patients with decreased respiratory sound is a well-known fact [338]. Such patients are the group of patients who will benefit most with this method. It is also thought to be useful for physicians and students who experience organic hearing loss by applying a volume regulator to the electronic stethoscope.

Understanding the mechanisms of the formation of respiratory sounds is currently incomplete [349]. Recording and analysis of respiratory sounds lets to develop an objective relation between abnormal respiratory sounds and pathology [349].

Therefore, we believe, our electronic stethoscope can be used as a diagnostic tool when there is difficulty in discrimination of lung sounds with traditional stethoscope.

Additionally, mechanical improvements can be made to the stethoscope attachment to optimize sound quality and amplification.

It is thought that this study can be developed as a reliable and suitable method with telemedicine consultations in terms of evaluating the lung sounds remotely. The impact of the Internet on future developments in respiratory sounds analysis should not be underestimated. It is a vehicle for the exchange of software, databases and sound and video files. It is also a platform for remote monitoring and a powerful educational tool. Remote monitoring in medicine is an active and expanding field. Simple sound acquisition equipment and a means of transmitting data via fixed or mobile telephone, possibly via the Internet, has many possible uses in this area. An exciting prospect for the future would be the routine availability of a miniaturized portable apparatus with the ability to capture both sound and airflow, implement simple and clinically useful analysis packages and, when necessary, communicate data via mobile telephony to a specialist centre in a local hospital. This could be mass-produced as a multipurpose computerized stethoscope and may replace the current acoustic stethoscope as a basic tool for future physicians.

Through the new technologies aimed at combining smaller electronic parts, analysis programs, ability to store data and processing power with a stethoscope, physicians can be provided much more beneficial data than the simple mechanical stethoscope available.

Although such a system developed in many directions may reduce the role of the clinician, it is not possible to operate the system dependably if the physician can not obtain trustworthy data from the patient with a good medical history and careful physical examination.

The purpose of the computer system is to help the physician to increase his or her abilities and judgment, where their analysis is relatively weak, such as analysis of large quantities of data.

The sound repertoire of the lung may indeed be limited when heard through a stethoscope, but it clearly exhibits a much wider range of information content when digitally analyzed. Computer analysis is now reaching beyond the capabilities of the human ear, e.g., to resolve changes in respiratory sounds during narrowing of the intrathoracic- or extrathoracic airways. With the disappearance of auscultation as the standard to judge the clinical significance of acoustical findings, it becomes even more important to integrate lung sound analysis and traditional measurements of respiratory mechanics. Thus, one should not expect that computer based lung sound analyzers will replace the stethoscope-bearing clinician anytime soon, but they will expand the noninvasive diagnostic capabilities in respiratory medicine.

The physician usually utilizes a stethoscope to hear the audio from the body cavities. Sometimes the physician also utilizes a stethoscope to compare the pretreatment state of the patient whose clinical status has been determined with the post-treatment status. Sometimes the physician's results after auscultation may be in conflict with the patient's clinical condition, which may be difficult to interpret. In such cases, the physician can ignore the findings from the device. But sometimes, the findings of the physician may be inadequate and the new findings obtained as a result of the search for additional findings will guide to a correct diagnosis. In these types of scenarios, our device and software can be useful to the physican. But this system does not aim to take the place of a physician. Also, the physician does not need programming expertise when using this system.

The literature review found 36 articles shown in Table 1.1 and Table 1.2 that met the requirements for this review process. The research on respiratory sound analysis was divided into three categories and briefly explained. The recommendations for developing a computer based respiratory sound analysis system were presented. The future research should be focused on developing such systems with improved signal processing and artificial intelligence techniques in real time and also to commercialize it.

These decision support systems can also be utilized for educational purposes in medical faculties [346]. The present study can enhance the understanding and learning of medical students approaching the study of lung sounds for the first time. Sestini et al. [28] indicated that the exposure of inexperienced medical students to a multimedia presentation of acoustic and graphic characteristics of lung sounds signifiantly boosts their learning process compared to students receiving only conventional teaching. They suggested that the combination of acoustical, graphical and analytical representation of sounds provides a homogeneous set of information that is more easily fixed in memory and may match different learning styles. Their data confirm previous studies indicating that practising with a multimedia computer program does improve the proficiency of medical students in the recognition of recorded lung sounds [28]. The advantage of our approach is that it does not require previous computer experience by part of the students, or additional learning of program instructions and commands.

While electronic stethoscopes have advantages such as portability, low cost and user convenience, detection algorithms limit the usefulness of the method because it can be susceptible to environmental noise and physiological noise. If respiratory audio is gathered by an electronic stethoscope in a hospital environment, noise contamination is an expected question (trouble) in these records.

The use of hybrid models would also improve the classification. These artificial intelligence techniques may give improved results compared to previous methods and it is recommended to apply such algorithms in future researches.

The research on computer based respiratory sound analysis has come a long way, but the interest in commercialization is very low. The future research should be focused on developing such systems with improved signal processing and artificial intelligence techniques in real time and also to commercialize it [350].

Future researchers should concentrate on the development of computer based lung sound analysis using more advanced machine learning algorithms and also using hybrid machine learning techniques to improve the accuracy and intend to commercialize it as a product.

Computers greatly improve the efficiency of data collection and management [55]. The automated data are archived and easily retrievable, even years later, thus avoiding memory problems, potential difficulties with transcribing the data, and potential problems in deciphering handwriting [55].

Another reason for interest in lung sounds, as compared to the radiograph, is that the sounds provide more regional information [55]. The chest radiograph is a summation shadowgram [55]. Areas at the lung bases, particularly behind the heart, are not well visualized. It may be particularly applicable with children or pregnant patients, with whom radiography may have safety issues [55].

Since clinicians already obtain a qualitative assessment by using a stethoscope, the measurement of respiratory condition via transmitted sounds analysis would provide quantitative support for diagnosis and treatment. Breath sound analysis' advantage is that it can provide evidence on the status of the patient's lung on a continual basis. With additional parameters describing the patient's condition, neural networks may be an appropriate method for classification [33].

As a result, it is inevitable that there is a requirement for advanced computer-based diagnostic systems that reduce medical malpractice and adverse outcomes, improve patient security and prevent loss of lives. For this reason, the developments in machine learning techniques are now expected to be applied also to the field of medicine.

Thus, new tools for evaluating high-dimensional and complicated data sets can be supplied to physicians with machine learning.

In recent years and machine learning algorithms have been implemented with great success in many applications. Thus, it has been demonstrated that machine learning is an efficient technique. The development of computerized lung sound analysis has attracted many researchers in recent years, which has led to the implementation of machine learning algorithms for the diagnosis of lung sound.

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APPENDICES

Appendix A: The Voluntary Declaration Form

Appendix B: Questionnaire

Appendix C: Lung Function Test Results, Audio Recording, X-ray Results, Blood Test Results Form

Appendix A - The Voluntary Declaration Form

GÖNÜLLÜ BEYAN FORMU

Akciğer hastalığı olan hastalarımızın akciğer seslerini analiz ederek hastalığın tanısının koyulmasını amaçlayan çalışmada gönüllü olarak yer alıyorum. Akciğer seslerimin bu projedeki çalışmalarda kullanılmasını kabul ediyorum.

Ad:

Soyad :

Telefon no:

İmza: Tarih:

Appendix B - Questionnaire

ANKET

Araştırma projesi: Tıpta Elektronik Stetoskop Kullanarak Makine Öğrenmesi Algoritmalari Geliştirilmesi
Sorumlu Araştırmacı: Murat Aykanat
Danışman: Dr. Öğr. Üyesi Özkan Kılıç

Katılımcı ile ilgili bilgiler (kimlik bilgileri gizli tutulacaktır):
Adı Soyadı:...
Cinsiyet: ☐ Erkek ☐ Kadın
Yaş:.................

Hastanın sigara kullanma alışkanlıkları

☐ İçiyor

☐ İçmiyor

☐ Eskiden içiyordu

☐ Pasif içici

Hastanın spor alışkanlıkları

☐ Düzenli

☐ Sık sık

☐ Bazen

☐ Hiç

Nefes darlığı var mı?

☐ Evet

☐ Hayır

Öksürük var mı?

☐ Evet

☐ Hayır

Balgam var mı? Varsa rengi nedir?

☐ Evet (Rengi: ……………………..)

☐ Hayır

Kan tükürme var mı?

☐ Evet

☐ Hayır

Göğüs ağrıları var mı?

☐ Evet

☐ Hayır

Yüksek ateş var mı?

☐ Evet

☐ Hayır

Kilo kaybı var mı?

☐ Evet

☐ Hayır

Bacaklarda şişme var mı?

☐ Evet

☐ Hayır

Gece terlemesi var mı?

☐ Evet

☐ Hayır

Çarpıntı var mı?

☐ Evet

☐ Hayır

Tanı ve Düşünceler:

Doktorun

Kurum: ………………………………..

Adı ve Soyadı:………………………….

Tarih:……………………………

İmza:……………………………..

Appendix C - Lung Function Test Results, Audio Recording, X-ray Results, Blood Test Results Form

HASTA: ………………………………………………………..

AKCİĞER FONKSİYON TESTLERİ

FVC ………………….. lt ………………….%

FEV1 ………………….. lt ………………….%

FEV1/FVC ………………….%

AKCİĞER SESLERİ

ÖN		ARKA	
Sağ	Sol	Sol	Sağ
	X		

AKCİĞER GRAFİSİ

SAĞ	SOL

KAN TESTLERİ

CRP	
Lökosit	
Nötrofil	

CURRICULUM VITAE

PERSONAL INFORMATION

Name and Surname: Murat Aykanat

Title: Senior Software Developer / Electric-Electronic Engineer

E-mail: maykanat@cyangate.com

EDUCATION

High School: TED Ankara College (1998 - 2001)

1st Graduate Degree: Başkent University, Faculty of Engineering, Department of Electric and Electronics Engineering (2001 - 2010)

2nd Graduate Degree: Anadolu University, Faculty of Business Administration, Department of Business Administration (2003 - 2009)

3rd Graduate Degree: Anadolu University, Faculty of Economics, Department of International Relations (2009 - 2013)

Master's Degree: Gazi University, Institute of Informatics, Department of Informatics (2009 - 2012)

Doctorate Degree: Yıldırım Beyazıt University, Graduate School of Natural Sciences, Department of Electric and Computer Engineering (2012 - Present)

WORK EXPERIENCE

July 2016 - Present: CyanGate, Ankara [Role: Senior Software Developer/ OpenText Media Management Consultant].

During my time in CyanGate, I have provided consultancy and developed tools/web services/customizations for OpenText Media Management Systems for companies such as Kraft Heinz, Kohler, Vistaprint, Genentech, Columbia Sportswear, United Services Automobile Association and Magna International. In CyanGate, my responsibilities are:

- Installing OpenText Media Management systems and customizations.
- Configuring OpenText Media Mangement systems.
- Customizing OpenText Media Mangement UI.
- Customizing OpenText Media Management back-end systems.
- Developing tools for OpenText Media Management.
- Developing integrations between OTMM and various other products.
- Conducting technical interviews

May 2012 – May 2016: Aykanat Yazılım, ANKARA [Role: Owner/Software Developer].

Aykanat Yazılım was my private company; I mainly worked on new products, product R&D, and maintenance of current products and services.

Technologies: IIS, ASP.NET, ASP.NET MVC, WPF, C#, HTML5, CSS3, Wix Toolset

Responsibilities / Accomplishments:

- PAEON – A Decision Support System for Diagnosing and Treating Poisoning
- PAEON Veteriner – A Decision Support System for Diagnosing and Treating Animal Diseases
- Aykanat Yazılım Content Management System

- Aykanat Yazılım Standard Installer
- Aykanat Yazılım Invoice Tool
- Project PAEON was funded by the Ministry of Science and Technology. Customers were very satisfied by the Turkish localization, functionality and the price of this application compared to its competitors. PAEON was also in the top 10 selected entries to compete in Istanbul in Intel Challenge Turkey 2013.

Mar 2005 – May 2010: Proses Teknik A. Ş., ANKARA [Role: Technical Support].

While I was an electronic engineering student in Başkent University, I worked part-time in Proses Teknik A.Ş. I worked on various technical support jobs such as re-installing OS, changing various computer parts and writing basic programs to help the company.

Mar 2003 – Mar 2005: Savaş Muhasebe Bürosu, ANKARA [Role: Technical Support].

While I was an electronic engineering student in Başkent University, I worked part-time in Savaş Muhasebe. I worked on various technical support jobs such as re-installing OS, changing various computer parts and writing basic programs to help the company.

July 2008 – Aug 2008: T.Ş.F.A.Ş. Elektromekanik Aygıtlar Fabrikası (EMAF), ANKARA [Role: Intern Engineer].

During my internship, I worked in the technical support department on cleaning and building basic electronic components.

Jan 2006 – Feb 2006: Gate Elektronik A.Ş., ANKARA [Role: Intern Engineer].

During my internship I worked in general technical support department and satellite technical support department. I worked on cleaning and maintaining various electronic components.

LANGUAGE SKILLS

Turkish: Native Proficiency

English: Bilingual Proficiency [KPDS: 94 (A), TOEFL IBT: 104/120]

German: Beginner

TECHNICAL EXPERTISE

Programming/Markup/Stylesheet Languages: C#, C++, CSS3, HTML5, Java, JavaScript, Python, SQL, XML

Technologies: WPF, ASP.NET, ASP.NET MVC, Web Services, REST, Machine Learning, Artificial Intelligence, Spring Framework

IDEs: Visual Studio (2010, 2012, 2013, 2015, 2017), Eclipse, IntelliJ IDEA, PyCharm, Visual Studio Code

CMs: Jira, Trello

Version Control: GitHub, SVN, Bitbucket

Database Servers: Microsoft SQL Server, PostgreSQL Server, Microsoft SQL Server Management Studio, pgAdmin III

Web / Application Servers: Apache Tomcat, Wildfly, JBoss, IIS

Game Engines: Unity3D, Unreal Engine 4

Artificial Intelligence/Machine Learning Frameworks: Theano, Tensorflow, Keras

Graphics Tools: Photoshop CS5, Bitmap2Material, Substance Designer, Substance Painter, Maya 2013, Filter Forge, ShaderForge

Web Design Tools: Dreamweaver CS6

Miscellaneous Tools: Resharper (Visual Studio plugin), MATLAB, Maven, Microsoft Ofice (Excell, Word, Access, PowerPoint), OpenText Mediamanager (10.5, 16, 16.2, 16.3), Putty, Wix Toolset, WinSCP

OS: Windows (3.1, 95, 98, 2000, XP, Vista, 7, 8, 10), MS-DOS, Linux (Mint, Ubuntu, CentOS)

ACHIEVEMENTS

- Best Paper Award – 2016 International Conference on Advanced Technology and Sciences (Rome, Italy)
- Intel Challenge 2013 - Turkey Finalist (PAEON^{TM})
- Ministry of Science, Industry and Technology - Technoprenurship capital support (2012) for PAEON^{TM}

PROJECTS

Toybox [March 2018 – Present] [Open Source]

Technologies: Java, HTML5, CSS, JavaScript, Spring Boot, Spring Cloud, Microservices

Toybox is an open source online file storage service that can be deployed on any platform including private home servers.

Wix XML Generator [October 2017 – Present] [Open Source]

Technologies: C#, XML, Wix Toolset

Wix Toolset provides a way to harvest files with heat.exe, and you can exclude files and folders with xlst transforms. However, in my opinion, that approach is not very developer friendly.

Wix XML Generator aims ease this process by automating the process generating the file and directory structure. It is a command line tool for generating XML portion of file, directory and component structure of the Product.wxs file. To control which files are going to be in the setup file, it uses a .wixignore file similar to GitHub's .gitignore file, to ignore files and folders.

CyanGate [July 2016 – Present]

Technologies: OpenText Media Manager 10.5/16/16.2/16.3, Windows Server 2012, CentOS, Microsoft SQL Server, PostgreSQL Server, Wildfly, Java, HTML5, JavaScript, CSS3

Responsibilities / Accomplishments:

- CyanGate Asset Migrator Tool upgrade from 10.5 to 16.0 and performance upgrades
- CyanGate Asset Migrator Tool upgrade from 16.0 to 16.2 for Jboss/Wildfly.
- CyanGate Google Vision Plugin for OTMM
- CyanGate Fadel Rights Cloud Connector for OTMM v2.0.0
- CyanGate Automatic Link Generator Customization for OTMM
- CyanGate Salesforce / OTMM Integration proof of concept

Project Markdown [June 2016 – Present] [Open Source]

Technologies: C#, WPF, MVVM, HMTL5, CSS3, JavaScript, Chromium Embedded, Markdown, Wix Toolset

Project Markdown is an open source offline markdown editor.

Key features include:

- Create, print and export markdown documents.
- Export as PDF, HTML and raw markdown.
- Syntax highlighting to help users write markdown easier.
- Multi document editing via tabs.
- Split text and HTML views to see the result of the markdown that is written immediately.

Columbia Sportswear [February 2017 – May 2018]

Technologies: OpenText Media Manager 10.5, JBoss, Windows Server 2012, Java

Responsibilities / Accomplishments:

- Asset Interceptor Update
- Asset Versioning Agent Update
- Hot Folder Customization Update
- Metadata Update Tool Update.
- Nightly Sync Customization Update
- Deployment of updates into development, quality assurance and production environments.
- Restoration of quality assurance and production environments.

Merck & Co [October 2017 – May 2018]

Technologies: OpenText Media Manager 16.2, Wildfly, Azure, MS SQL Server, Windows Server 2012, Photoshop CC 2018, Java, JavaScript, HTML5, CSS3, Spring Batch, Imagemagick

Responsibilities / Accomplishments:

- Validation and deployment of customizations and metadata into development, quality assurance and production environments.
- Deployment and troubleshooting of Asset Migration Tool
- Customizing the OTMM UI for Merck branding.
- Workflows Menu Customization
- Quick Links Menu Customization
- Landing Page Customization
- Export Rights Disclaimer Customization
- Tabular Fields as Two Panel Widget Customization
- Tabular Fields as Checkbox Widget Customization
- Export Validation and Watermarking Customization

- Rights Management Customization
- Retrieving Embedded Image Metadata Customization
- Azure Web Hook Service for Asset Ingest Customization

Toyota Material Handling [May 2018]

Technologies: OpenText Media Manager 16.3, HTML5, CSS, JavaScript, ThreeJS

Responsibilities / Accomplishments:

- 3D Preview Tool proof of concept

Vistaprint (Cimpress) [November 2016 – May 2018]

Technologies: OpenText Media Manager 16, PostgreSQL Server, CentOS, Windows Server 2012, Wildfly, Java, JavaScript, HTML5, CSS3, SQL, REST, Imagemagick

Responsibilities / Accomplishments:

- Validation and deployment of customizations and metadata into development, quality assurance and production environments.
- Development of Gifsicle Integration
- Development of Spawn Creative Review Customization
- Development of Catch “Review Approved” Event Listener Customization
- Development of Review Assets Button Customization
- Development of FPO Download Customization
- Development of Language Visual Cue Customization
- Development of Expand Search Suggestion Customization
- Development of Check-out and Download Customization
- Development of Automatic MFT File Transfer Customization
- Development of Upload to Shot Folder Customization
- Migration of customizations to from 16.0 to 16.3 environment

Roche [April 2018]

Technologies: OpenText Media Manager 16.3, Centos 7, Wildfly, PostgreSQL Server, Java, HTML5, JavaScript, CSS, SQL

Responsibilities / Accomplishments:

- Customizing the OTMM UI for Roche branding
- Work Order Folder Button Customization proof of concept
- Website Generator Customization proof of concept

Georgia Pacific [May 2017 – March 2018]

Technologies: OpenText Media Manager 16.2, PostgreSQL Server, CentOS, Wildfly, Java, JavaScript, HTML5, CSS3, SQL, Servlet Filters, Imagemagick

Responsibilities / Accomplishments:

- Validation and deployment of customizations and metadata into development, quality assurance and production environments.
- Upgrade and deployment of Asset Migrator Tool v16.2
- Development of Override HTTP Methods Customization
- Development of Duplicate Asset Checker Customization
- Automated Security Policy Customization Upgrade

National Geographic Society [March 2018]

Technologies: OpenText Media Manager 16.3, Salesforce, Windows Server 2012, TomEE, Java, servlets

Responsibilities/Achievements

- Salesforce / OTMM Integration proof of concept

Monster Energy [June 2017 – February 2018]

Technologies: OpenText Media Manager 16/16.3, JavaScript

Responsibilities / Accomplishments:

- Upgraded Download Transform customization reflecting the new changes in 16.0.3.
- Deployment of Geolocation customization.
- Upgraded Download Modal customization reflecting the new changes in 16.3.

Central Arizona Project [September 2017 – January 2018]

Technologies: OpenText Media Manager 16.2/16.3, SQL, Wildfly, Oracle Server, Apache Tomcat, SSL, SSO

Responsibilities / Accomplishments:

- Consulted an engineer on the CAP side to configure existing OpenText Analytics components for a new OTDS installation without re-installation.
- Consulted an engineer on the CAP side to configure existing MFT component for a new OTDS installation without re-installation.
- Consulted an engineer on the CAP side to configure active directory sync for OTMM without re-installation.
- Consulted an engineer on the CAP side to configure SSO for OTMM.
- Consulted an engineer on the CAP side in asset migration using Asset Migration Tool for OTMM 16.2.
- Consulted an engineer on the CAP side in deployment of metadata and security configurations.
- Consulted an engineer on the CAP side to upgrade OTMM from 16.2 to 16.3.
- Consulted an engineer on the CAP side to upgrade MFT from 16.2 to 16.3.
- Consulted an engineer on the CAP side to upgrade Analytics from 16.2 to 16.3.
- Provided delta queries for security and metadata configurations.

Genentech [February 2017 – November 2017]

Technologies: OpenText Media Manager 16, PostgreSQL Server, CentOS, Java, SQL, Excelnologies: OpenText Media Manager 16, PostgreSQL Server, CentOS, Java, SQL, Excel

Responsibilities / Accomplishments:

- Validation and deployment of customizations and metadata into development, quality assurance and production environments.
- Development of Brand/Department Onboarding Tool
- Development of Folio Project Number Customization
- Genentech won the "Life Sciences Innovation Award" with our OTMM implementations in Enterprise World 2017 in Toronto, Canada.

BISK Education [October 2017]

Technologies: OpenText Media Manager 16.2, Wildfly, Java, SQL

Responsibilities / Accomplishments:

- OTMM / Kaltura Integration proof of concept

Magna International [April 2017 – October 2017]

Technologies: OpenText Media Manager 16, Java, Wildfly

- Deployment and troubleshooting of Asset Migrator Tool
- Troubleshooting SOLR localization issues

Kraft Heinz Company [August 2016 – August 2017]

Technologies: OpenText Media Manager 10.5, OpenText Media Manager 16, PostgreSQL Server, Microsoft SQL Server CentOS, Windows Server 2012, Wildfly, Java, REST, Apache POI, Apache Velocity, Apache Camelnologies: OpenText Media Manager 10.5, OpenText Media Manager 16, PostgreSQL Server, Microsoft

SQL Server CentOS, Windows Server 2012, Wildfly, Java, REST, Apache Camel, Apache Velocity

Responsibilities / Accomplishments:

- PIM Integration
- RISE Integration
- Bulk Ingest Tool for OTMM v16
- Bulk Ingest Tool for OTMM v10.15
- Customization code upgrades from version 10.5 to 16 for OTMM
- Deployment of customizations to development, quality assurance and production environments.
- Support and maintenance for customizations.

Kamehameha Schools [May 2017 – July 2017]

Technologies: OpenText Media Manager 16.2, MS SQL Server, Windows Server 2012, Java, Wildfly, SQL

Responsibilities / Accomplishments:

- Validation and deployment of customizations and metadata into quality assurance and production environments.
- Metadata and Security customization & configuration
- Asset Migration Tool deployment and troubleshooting

United Services Automobile Association (USAA) [October 2016 – June 2017]

Technologies: OpenText Media Manager 16, Microsoft SQL Server, Windows Server 2012, Wildfly, Tomcat, IIS, SSL, SQLhnologies: OpenText Media Manager 16, Microsoft SQL Server, Windows Server 2012, Wildfly, Tomcat, IIS, SSL, SQL

Responsibilities / Accomplishments:

- Consulted an engineer in OpenText Media Manager 16 installation on test and production environments.

- Consulted an engineer in OpenText Secure MFT installation and SSL Configuration on test and production environments.
- Consulted an engineer in OpenText Analytics Installation on test and production environments.
- Consulted an engineer in OpenText Creative Review Installation on test and production environments.
- Consulted an engineer in metadata and security configuration deployment on test and production environments.
- Consulted an engineer in CyanGate Asset Migrator deployment on test and production environments.
- Consulted an engineer in CyanGate FADEL Arc Connector deployment on test and production environments.
- Provided delta queries to update metadata and security configurations.

Kohler Company [October 2016 – November 2016]

Technologies: OpenText Media Manager 10.5, Microsoft SQL Server, Windows Server 2012, JBoss, Java, JavaScript, HTML5, CSS3

Responsibilities / Accomplishments:

- Update and deployment of PDF Contact Sheet Upgrade on development and production environments.

PUBLICATIONS DERIVED FROM THESIS

[1] Aykanat, M., Kılıç, Ö., Kurt, B., Saryal, S. Classifcation of lung sounds using convolutional neural networks. EURASIP Journal on Image and Video Processing, 2017:*65*, 1-9, 2017. DOI 10.1186/s13640-017-0213-2

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[1] Aykanat, M., & Bay, Ö.F. Development of an expert system based decision support system in poisonings for poison information centers, International

Conference on Advanced Technology and Sciences, 4th International Conference, ICAT'Rome. Rome, Italy, Aybil Yayınları, pp 25-26, November 23-25, 2016.

[2] Aykanat, M. *Creating File Packages in C# [online]*. Pluralsight.com, https://www.pluralsight.com/guides/creating-file-packages-in-c, May 6, 2017.

[3] Aykanat, M. *Property Copying Between Two Objects using Reflection [online]*. Pluralsight.com, https://www.pluralsight.com/guides/property-copying-between-two-objects-using-reflection, Jan 21, 2017.

[4] Aykanat, M. *Building a WPF Media Player using NAudio [online]*. Pluralsight.com, https://www.pluralsight.com/guides/building-a-wpf-media-player-using-naudio, Jun 25, 2016.

[5] Aykanat, M. *Building a Generic CSV Writer/Reader using Reflection [online]*. Pluralsight.com, https://www.pluralsight.com/guides/building-a-generic-csv-writer-reader-using-reflection, Apr 24, 2016.

[6] Aykanat, M. *Globalization with Attached properties in WPF [online]*, Pluralsight.com, https://www.pluralsight.com/guides/globalization-with-attached-properties-in-wpf, Apr 2, 2016.

[7] Aykanat, M. *Hayvan Hastalıkları için PAEON™ Veteriner Tanı ve Tedavi Programı.* "Poster". Bülent Ecevit Üniversitesi, Zonguldak, 2014.