بسم الله الرحمن الرحيم

Sudan University of Science and Technology

College of Graduates Studies

Classification of Respiratory Sounds using Wavelet Transform and Neural network.

تصنيف أصوات الجهاز التنفسي بإستخدام المويجات و الشبكة العصبية.

A Thesis Submitted in partial fulfillment of The Requirement of M.Sc Degree in Biomedical Engineering

by:

Islam Khalid El-tohami.

Supervised by:

Dr . Zeinab Adam Mustafa

September 2016

بسم الله الرحمن الرحيم

قال تعالى:

(قُلْ إِنَّ صَلاتِي وَنُسُكِي وَمَحْيَايَ

وَمَمَاتِي لِلَّهِ رَبِّ الْعَالَمِينَ

"162" لاَ شَرِيكَ لَهُ وَبِذَلِكَ أُمِرْتُ وَأَنَاْ

أَوَّلُ الْمُسْلِمِينَ "163")

سورة الأنعام الآية "162-163"

Dedication

Success is not measured by active that one up in his life .... As far as measured with difficulty overcomes.

I cannot write more than of sea water and the ground drops all.........to expensive life planets, to a beacon of love in every day of the year, to the joy of the four seasons ....to my mother.

To the candle that lit my way ....Although prides of darkness....to my father.

Acknowledgement

I would like to thank Allah first and last for being blessed by His name to complete this project until the last step.

One of the greatest pleasures, working with teacher in a project combining his experience with the passion of student. This research is a good example of such an opportunity. I would like to thank my supervisor **Dr. Zeinab Adam Mustafa.**

I also want to thank everyone helped me at this project by advice or encouragement.

Table of contents Page

List of Tables

List of Figures

Abbreviation

ATS: American Thoracic Society.

COPD: Chronic Obstructive Pulmonary Disease.

ANNs: Artificial Neural Networks.

db: Daubechies.

sym: Symlets.

ROC: The Receiver Operating Characteristic.

WT: Wavelet Transform.

WPT: Wavelet Packet Transform.

SE: Sensitivity.

SP: Specificity.

ACC: Accuracy.

TP: True positives.

FN: False negatives.

TN: True negatives.

FP: False positives.

GUI: Graphical User Interface.

ABSTRACT

Respiratory sound contains information of lung condition which helps in the diagnosis of lung diseases. Stethoscope is the traditional method used to obtain this information but it depends on the physician experience and hearing. To avoid this limitation and to make optimum benefit of the respiratory sound information a computer aided diagnosis system was built. The respiratory sound signals were divided into segments each contains one inspiratory and expiratory cycle, wavelet transform (WT) was used for analysis, features were obtained from its coefficients and finally classifying using artificial neural network (ANN) to normal sound and abnormal sound and classifying the abnormal sound to crackle and wheeze. The accuracy of classification between normal and abnormal was 95.7% and for classification between crackle and wheeze was 98.1%.

الملخص

الصوت في الجهاز التنفسي يحتوي على معلومات عن حالة الرئة مما يساعد في تشخيص أمراض الرئة. سماعة الطبيب هي الطريقة التقليدية المستخدمة للحصول على هذه المعلومات ولكن ذلك يعتمد على خبرة الطبيب وسمعه. لتجنب هذا القصور وتقديم المنفعة المثلى من المعلومات الصوتية في الجهاز التنفسي تم بناء نظام للتشخيص بمساعدة الحاسوب. تم تقسيم الإشارات الصوتية في الجهاز التنفسي إلى قطاعات كل يحتوي على دورة شهيق وزفير واحدة، و للتحليل تم استخدام تحويل المويجات ، وقد تم الحصول على ميزات من معاملاتها وصنفت أخيرا باستخدام الشبكة العصبية إلى صوت طبيعي وصوت غير طبيعي وصنف الصوت الغير طبيعي لصوت يحتوي على فرقعة وصوت يحتوي على ازيز.كانت دقة التصنيف بين الطبيعي وغير الطبيعي 95.7٪ وبين الفرقعة والأزيز 98.1٪.

Chapter One

Introduction

1.1 Introduction

Pulmonary disorders are investigated in several ways such as a medical history, physical examination, chest X-ray, respiratory auscultation etc. Respiratory auscultation (medical term of listening to sounds arising within organs such as lung.) is the most common method among them because it's an inexpensive, efficient, easy to apply and harmless for patient, it's also gives direct information about the function of lung and provides close patient-physician interaction [1].

The science of auscultation, began with the invention of the stethoscope by Laënnec in 1821, upon the discovery that respiratory sound analysis aids in the diagnosis of pulmonary infections and diseases. This instrument allowed to describe the major categories of lung sounds that form the basis of the modern classification. Since that stethoscopes have become the most common diagnostic tool by doctors in the twenty-first century [2,3].

Although stethoscope is a very useful tool it has major limitations and problems including the response of stethoscope and external noise such as ambulance, a busy emergency room etc. The proper diagnosis also requires significant training and experience of the medical personnel [1].

With the advent of computer technology and data processing methods, researchers have tried to parameterize pulmonary sounds with an aim to make auscultation a more objective and valuable diagnostic tool. During the last two decades, much research has been carried out on computer-based respiratory sound analysis. A large part of these researches include acquisition, filtering, feature extraction, spectral analyses and classification of respiratory sounds [1].

The respiratory sounds includes normal and adventitious sounds, adventitious sounds can be divided into two sub-classes: continuous or stationary sounds, like wheezes and discontinuous or non-stationary sounds like crackles. The identification of wheeze in the respiratory cycle, is of great importance in the diagnosis of obstructive airways pathologies (ex: asthma and respiratory stenosis), and the identification of crackles generally associated with pulmonary disorders (ex: pneumonia and pulmonary oedema) [14].

1.2 Problem Statement

- Using the stethoscope is a subjective methods depends on the physician experiment.
- Infection due to direct contact between physician and patients.

1.3 Objective

Designing a computer aid diagnosis system based on Wavelet transform and neural network for determining normal and abnormal lung sounds.

1.4 Methodology

A recorded and prediagnosed lung sounds will be downloaded from networks sites. Then wavelet transform is applied for denoising, decomposition and feature extraction. Finally for classification neural networks will be used.

1.5 Layout of Thesis

Chapter One: Consists of introduction, problem statement, objective and the methodology of the research.

Chapter Two: Consists of previous literature reviews.

Chapter Three: Consists of theoretical background of respiratory system, respiratory sounds, and signal processing techniques.

Chapter Four: Consists of research methodology.

Chapter Five: Consist of results and their discussions.

Chapter Six: Consists of conclusions and recommendations.

Chapter two

Literature Reviews

2.1 Literature Reviews

Respiratory sound heard over the chest using stethoscope contains information about the condition of the lung which leads to enable a noninvasis method for diagnosis the abnormalities and disorders. But it requires a professionally well trained physician to recognize the abnormalities exactly. It’s a subjective method which depends on the experience, ability, and auditory perception of the physician. Finding an objective method to overcome this drawback was needed from that researches started to develop a computerized methods for lung sounds analysis [4].

Over the last years computerized methods based on signal processing were used to analyze the lung sounds ex: Fourier transform, short time Fourier transform, wavelet transform, fuzzy logic and neural network [3].

The lung sound measurement is often disturbed by noise, e. g. heart sound, instrument and air-conditioner noises. The traditional frequency-domain filtering does not yield satisfactory result. Adaptive filter seems the best means to resolve such problem [5, 6]. However this technique requires a reference for the noise, to avoid this problem wavelet transform were used [10, 11].

Using Fourier transform in respiratory signal is capable of detecting the wheezes because it occur in a known frequency band [400 -600] Hz unlike crackles which have a wide frequency distribution [3].

Wavelet Transform (WT) and Wavelet Packet Transform (WPT) were used to decompose signals into frequency sub-bands and then extracting feature from these sub-bands (ex. energy log, mean and standard deviation). The choice and order of the wavelet to be used must depend on the dominant features of the signal being analysed. The basis functions should match the signal as closely as possible [1, 7]

Most of the classification methods used Machine learning technique because of its excellent performance and accuracy. The Most common used machine learning are neural network and support vector machine [8, 9].

Based on review paper [4] by Rajkumar Palaniappan,et all , the research on lung sounds analysis can be classified into three types: visual analysis, Statistical Analysis and machine learning. The results of their overviewed articles presented in the tables below.

Table 2.1: Visual analysis in computer-based lung sound analysis systems

Analyzed: Sound/Disorder	Sensor type	Dataset	Sensor: Position/Location	Method
Crackles	Air-coupled dynamic-type microphone	4 tuberculosis and 2 chronic bronchitis	Chest wall	Fast fourier transform
Normal, asbestosis and pulmonary edema	Electret microphone	15 subjects with lungs disorder and 5 normal subjects	Posterior basal segments of the lobes	Karhunen-loeve transformation
Normal and wheeze	Contact microphone (piezoelectric transducers)	20- Patients and 5- normal	Chest wall	Fast fourier transform
Lung sounds	Microphone	Not mentioned	Trachea	Fast fourier transform
Lung sounds	Piezo-electric transducers/microphone	493 sounds	Trachea, chest right, base right, base left	Fast fourier transform
Normal and pathological	4 Electret microphone	24 healthy and 17 pathological	Chest wall	Fast fourier transform
Lung sounds	Electret microphone	Not mentioned	Chest wall	Fast fourier transform

Table 2.2: Statistical analysis in computer-based lung sound analysis systems

Analyzed: Sound/ Disorder	Sensor type	Dataset	Sensor: Position/ Location	Method
Fine crackles, coarse crackles, and squawks	Electret microphone	6-Fine crackles, 5-Coarse crackles and 5- Squawks	Over the lungs	Wavelet-based de-noising and higher order crossing-discrimination analysis.
Respiratory sounds	EMT25C, Siemens Accelerometer	7 –trachea and 10-lungs	Trachea and lungs	ANOVA
Detecting explosive lung sound	Electrets Microphone	Patients with pulmonary Pathology	Over the lungs	FD analysis
Wheeze, Rattles, and Crackles	Acoustic analysis –sensor (Siemens EMT 25C)	102 subjects	The right upper zone (anterior chest)	Validity and reliability using k-statistics.
Wheeze and crackle	14 cannel Sony ECM-44BPT electrets microphones	Not mentioned	Posterior chest wall	Wavelet decomposition and kurtosis.
Crackles	Electret microphones	5 fine crackles, 5 coarse crackles, 4 normal and 4 wheezing.	Over the lungs	Wavelet packet transform for de-noise. FD analysis
Wheeze	5 Electret microphones (ECM-77B, Sony)	13 patients	Trachea, right and left axillae, and right and left posterior Bases	Time-frequency analysis of wheeze sound.
Normal and wheeze	Electret microphone (ECM-77B, Sony)	7 healthy and 7 asthmatic cases	Over the lungs	Time-frequency distribution, histogram, sample entropy features, discrimination analysis.
Normal, Fine, and coarse crackles	Electret microphones	Normal and simulated Data	Over the lungs	Time-variant Autoregressive (TVAR) model.
Crackles	25 channel Electret microphone	Patients with pneumonia	posterior surface of the thorax	Hilbert-Huang spectrum
Normal, crackles, and Wheezes	Contact accelerometer (EMT25C, Siemens) and Electret microphone (ECM140, Sony)	Not mentioned	Chest wall, neck and Mouth	Wavelet transform and Lipschitz regularity analysis
Wheeze and non-wheeze from patients with asthma and COPD	14 cannel Sony ECM-44BPT Electrets microphones chest piece	246 wheeze and non-wheeze	Posterior chest wall	Kurtosis, Renyi entropy, f50/ f90 ratio and mean- crossing irregularity and Fisher Discriminant Analysis (FDA)
Fine crackles, coarse crackles, and squawks	DBS database	Not mentioned	Over the lungs	Lacunarity-based discrimination analysis.
Crackles	14 cannel Sony	Patents with Cystic	Lower left lung	Kurtosis, Percentile Frequency

	ECM-44BPT Electrets microphones	Bronchitis		f90, Kullback-Liebler Distance and linear discriminant analysis
Respiratory sounds	18 piezoelectric sensors	82 patients	Posterior to the patient's back	Wilcoxon's signed-ranks test and Mann-Whitney U test

Table 2.3: Machine learning in computer-based lung sound analysis systems

Analyzed: Sound/ Disorder	**Sensor type**	**Dataset**	**Sensor: Position/ Location**	**Method**
lung sounds	Electret microphone	28 COPD, 23 restrictive lung disease patients and 18 normal	Two locations on the chest, left and right basilar	AR model ,*k*-nn classifier and quadratic classifier
Wheeze and normal	Eight microphones	Not mentioned	Anterior upper chest	Fourier transform spectrum features and ANN
Normal and pathology	Electret microphone	28 COPD, 23 restrictive lung disease and 18 Normal	Two locations on the chest, left and right basilar	AR model and *k*-nn
Normal, rhonchi, wheezes, and crackles	Electrets microphone	Not mentioned	Over the lungs	An entropy based recognition system was developed
Normal, wheeze, and crackles	Electret microphone	50 school children with asthma and 10 control	Trachea	Fourier power spectrum features and neural network
Airways obstruction in asthmatic patients	Air-coupled electret microphone	10 Asthmatic	Trachea	The Welch method of spectral estimation features and *k*-nn
Normal and pathological	2 microphones (LS-60)	6 women and 11 men	Bronchial regions of the chest	Averaged power spectral density and ANN
Normal and pathological	Microphone	Not mentioned	Chest wall	AR model and *k*-nn
Wheeze or non-wheeze	Electret microphone	12 normal and 12 wheeze	Over the lungs	MFCC features and vector quantification
Normal and pathological	Electret microphone	9 normal and 11 abnormal	Left basilar and right basilar	Signal coherence and the PCA and nearest mean classifier
Normal and wheeze	Electret microphone	12 wheeze and 12 normal	Over the lungs	Wavelet transform and GMM
Normal, wheeze, crackle, squawk, stridor, rhonchus	Electret microphone	Not mentioned	Over the lungs	Discrete wavelet transform and ANN
Lung sounds	Acoustic analysis sensor Siemens EMT 25C	8 children	Over the lungs	Statistical features and *k*-nn
Normal and wheeze	ECM, KEC-2738 Electret microphones	12 Non-smoking asthmatic wheeze and 4 normal	Thorax	Spectrogram
Normal, wheeze, and crackles	Electret microphone (EK-3024 Knowles)	129 Subjects	Chest wall	Power spectral density and ANN and GA based ANN
Normal and abnormal lung sounds	Microphone array of 5x5	19 subjects	Various positions over the lungs	Multivariate AR model features, PCA and FFNN
Normal and wheeze	ECM, KEC-2738 Electret microphones	90- wheeze and 99- normal	Thorax	Spectrogram and peak detection algorithm
Fine and coarse crackles	Electret microphone	Not mentioned	Over the lungs	Wavelet packet filter, Fractal dimension and GMM
Lung sounds	Lung sound auscultation training via CD	Not mentioned	Over the lungs	Power spectral density and *k*-means clustering algorithm
Normal and abnormal lung sounds	Electret microphone (ECM140, Sony)	21 normal and 21 abnormal	Chest wall/lower lung lobes	AR model, *k*-nn and minimum distance classifier
Normal respiratory and abnormal respiratory sounds	Piezoelectric microphone and condenser microphone	109 patients with emphysema pulmonuma and 53 normal	Chest wall and posterior chest wall	Maximum likelihood approach and HMM
Adventitious lung sounds	Electronic stethoscope	Not mentioned	Chest wall	Power spectrum features and ANN
Wheeze	R.A.L.E database	Not mentioned	Over the lungs	Processed spectrogram image features and ANN
Normal and adventitious lung sounds	R.A.L.E database	Not mentioned	Over the lungs	Discrete wavelet and Radial basis function ANN
Normal, wheeze, and crackles	Electret microphone	12- normal, 13- wheeze and 11 crackles	Over the lungs	MFCC and AR model

Normal, crackles, and wheeze	Electret microphone	Over 50 lung sounds	Over the lungs	MFCC and GMM
Normal, wheeze, and crackles	Electret microphone	279 sounds	Over the lungs	Fast Fourier transform, Power spectrum density and ANN
Asthma severity	Lab data’s	28 asthmatic patients	Over the lungs	Features were extracted and fuzzy rules

Chapter three

Theoretical background

3.1 Respiratory system

3.1.1 Part of Respiratory System

The respiratory system can be divided into upper and lower respiratory tract. The upper respiratory tract includes the organs located outside of the chest cavity (thorax) area (i.e. nose, pharynx, larynx), whereas the lower respiratory tract includes the organs located almost entirely within it (i.e. trachea, bronchi, bronchiole, alveolar duct, alveoli) [12].

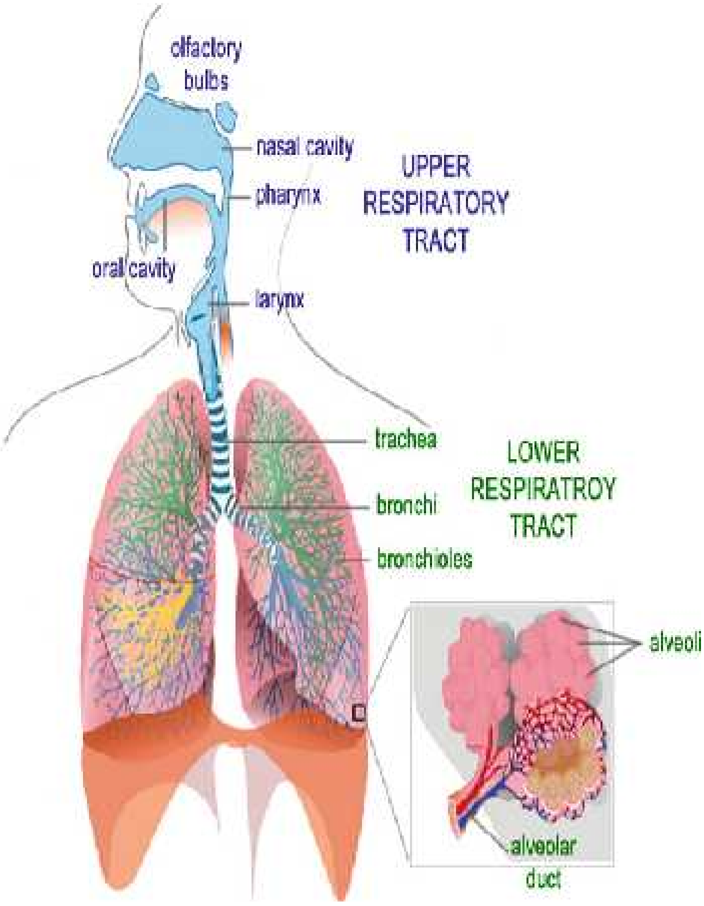

Fig. 3.1**:** Schematic of the respiratory system displayed by the upper and lower respiratory tract region [12].

3.1.2 Function of Respiratory System

The primary function of the respiratory system is to supply body with oxygen and remove carbon dioxide in which air is inspired and expired causing respiratory sound [12].

Table 3.1: Discription and function of the upper and lower respiratory track [13].

Structure	Description	Function
The Upper Respiratory Tract		
Nares	Openings into the nasal cavities	Passage of air into nasal cavities
Nasal cavities	Hollow spaces in nose	Filter, warm, and moisten air
Pharynx	Chamber posterior to oral cavity, lies between nasal cavity and larynx	Connection to surrounding regions
Glottis	Opening into larynx	Passage of air into larynx
Larynx	Cartilaginous organ that houses vocal cords (voice box); composed of the nasopharynx, oropharynx, and the laryngopharynx	Sound production
The Lower Respiratory Tract		
Trachea	Flexible tube that connects larynx with bronchi	Passage of air to bronchi
Bronchi	Paired tubes inferior to the trachea that enter the lungs	Passage of air to lungs
Bronchioles	Branched tubes that lead from bronchi to alveoli (air sacs)	Passage of air to each alveolus
Lungs	Soft, cone-shaped organs that occupy lateral portions of thoracic cavity	Contain alveoli and blood vessels

3.2 Respiratory (breath) Sounds

Respiratory sound include valuable information concerning the physiologies and pathologies of the lung and airway obstruction which help in medical diagnosis between normal respiratory sounds and abnormal respiratory sounds such as crackle, wheeze, Squawk and Stridor [14].

Breath sound: their generation is related to airflow in the respiratory tract: the chest wall, the trachea or at the mouth. It includes normal and adventitious sounds. Acoustically, this sound is characterized by broad-spectrum noise with a frequency range depending on the pick-up location [14].

3.2.1 Normal breath sounds

Respiratory sound heard or detected over the chest wall is characterised by a low noise during inspiration, and hardly audible during expiration; it peaks in frequency below

100 Hz . On trachea, normal respiratory sound is characterized by a broader spectrum of noise it covers a frequency range from less than 100 Hz to more than 1,500 Hz, with a sharp drop in power above a cut-off frequency of approximately 800 Hz audible both during inspiratory and expiratory phase[14,15].

3.2.2 Adventitious (abnormal) sounds

Adventitious sounds are additional respiratory sounds superimposed on normal breath sounds. The International Lung Sound Association classified the adventitious lung sounds into two main categories; continuous and discontinuous sounds. Continuous sounds were further classified into wheeze and rhonchi and discontinuous sound into fine and coarse crackles [16].

The American Thoracic Society (ATS) Committee on pulmonary nomenclature defines wheezes as high-pitched continuous sounds with a dominant frequency of 400 Hz or more, and rhonchi as low-pitched continuous musical sounds with a dominant frequency of about 200 Hz or less [16].

Wheezes are musical adventitious lung sounds, their duration is much longer than that of crackles. They may not necessarily extend more than 250 ms, as suggested in an ATS definition, but they will typically be longer than 80 to 100 ms [15]. Usually wheezes are heard in diseases like congestive heart failure, asthma, pneumonia, chronic bronchitis, chronic obstructive pulmonary disease (COPD) and emphysema [9].

Crackles are discontinuous, explosive, and non-musical adventitious lung sounds. They are usually classified as fine and coarse crackles based on their duration, loudness, pitch, timing in the respiratory cycle, and relationship to coughing and changing body position.Crackles being discontinuous sounds are typically less than 20 ms in duration. They are heard in inspiration and sometimes during expiration [16].

Table 3.2: Normal and abnormal breath sounds [21].

Normal Breath Sounds			
Type	**Description**	**Location**	**Characteristics**
Vesicular	Soft-intensity, low-pitched, “gentle sighing” sounds created by air moving through smaller airways (bronchioles & alveoli)	Over peripheral lung; best heard at base of lungs	Best heard on inspiration, which is about 2.5 times longer than the expiratory phase (5:2 ration)
Broncho-vesicular	Moderate-intensity and moderate-pitched “blowing” sounds created by air moving through larger airway (bronchi)	Between the scapulae and lateral to the sternum at the first and second intercostal spaces	Equal inspiratory & expiratory phases (1:1 ratio)
Bronchial (tubular)	High-pitched, loud, “harsh” sounds created by air moving through the trachea	Anteriorly over the trachea; not normally heard over lung tissue	Louder than vesicular sounds; have a short inspiratory phase and long expiratory phase (1:2 ratio)
Adventitious Breath sounds			
Name	**Description**	**Cause**	**Location**
Crackles (rales or crepitations)	Fine, short, interrupted cracking sounds; alveolar rales are high pitched. Sound can be simulated by rolling a lock of hair near the ear. Best heard on inspiration but can be heard on both inspiration and expiration. May not be cleared by coughing.	Air passing through fluid or mucus in any air passage	Most commonly heard in the bases of the lower lung lobes
Gurgles (rhonchi)	Continuous, low-pitched, coarse, gurgling, harsh, louder sounds with a moaning or snoring quality. Best heard on expiration but can be heard on both inspiration and expiration. May be altered by coughing.	Air passing through narrowed air passages as a result of secretions, swelling, tumors.	Loud sounds can be heard over most lung areas, but predominate over the trachea and bronchi
Friction rub	Superficial grating or creaking sounds heard during inspiration and expiration. Not relieved by coughing.	Rubbing together of inflamed pleural surfaces.	Heard most often in areas of greatest thoracic expansion (e.g. lower anterior and lateral chest)
Wheeze	Continuous, high-pitched, squeaky musical sounds. Best	Air passing through a constricted bronchus as	Heard over all lung fields.

	heard on expiration. Not usually altered by coughing.	a result of secretions, swelling, tumors	
Absence of breath sounds	n/a	Associated with collapsed and	Can be "heard" wherever airflow is

3.3 Signal Processing

3.3.1 Wavelet Transform

From a historical point of view, the first reference to the wavelet goes back to the early twentieth century when Alfred Haar wrote his dissertation titled "On the theory of the orthogonal function systems" in 1909. His research on orthogonal systems of functions led to the development of a set of rectangular basis functions [17].

Wavelet analysis affords a different view of data than those presented by traditional signal processing techniques due to that its capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Wavelet analysis can often compress or de-noise a signal without appreciable degradation [18].

Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted (translated along the time axis) and scaled (stretched or compressed) versions of the original (or mother) wavelet ψ (t) [17,18].

The wavelet transform of a signal x (t) can be expressed as:

$$wt(s,\tau) = \langle x, \psi_{s,\tau} \rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t)\, \psi^{*}\left(\frac{t-\tau}{s}\right) dt \qquad \text{Eq (3.1)}$$

Where the symbol $s > 0$ represents the scaling parameter, which determines the time and frequency resolutions of the scaled base wavelet ψ(t- τ). The specific values of s are inversely proportional to the frequency. The symbol τ is the shifting parameter, which translates the scaled wavelet along the time axis. The symbol ψ* denotes the complex conjugation of the base wavelet ψ (t) [17].

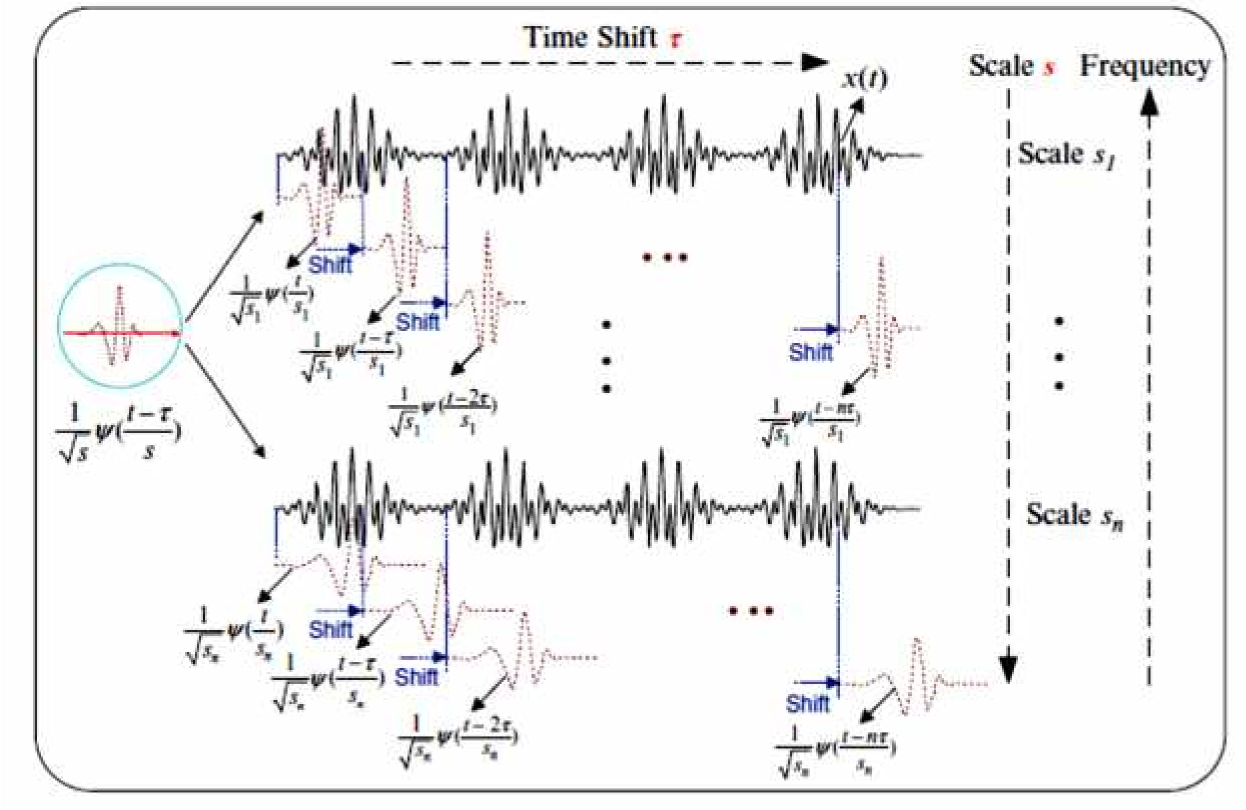

Fig 3.2: Illustration of wavelet transform [17].

In wavelet analysis, we often speak of breaking up a signal (decomposition) to approximations and details to obtain the wavelet coefficients. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components [18].

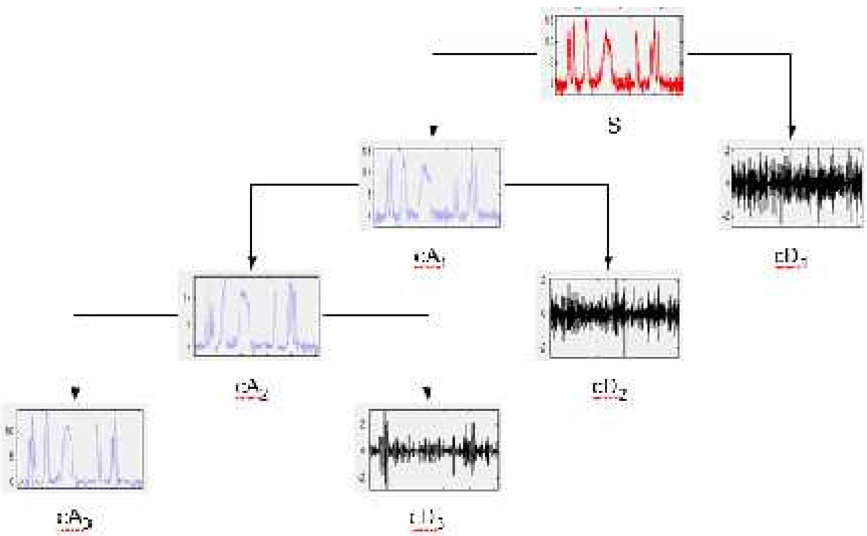

Fig 3.3: Wavelet decomposition [18].

3.3.2 Signal Features

Feature extraction is an important analysis stage. It extract a set of features from the dataset of interest to represent it. It can also be viewed as a data rate reduction procedure for voluminous data. Feature extraction is an essential processing step in pattern recognition and machine learning tasks [19].

Mean: indicated by μ is the average value of a signal. Mean measure of the central tendency and represents a probability frequency distribution of signal. The mean is found by adding up all of samples together, and divide by length of signal. Eq 3.2 represent the mean of the signal and eq 3.3 represent the mean of absolute values. Xn represents signal [1].

$$\mu = \frac{1}{N} \sum_{n=1}^{N} Xn \qquad \text{Eq (3.2)}$$

$$\mu = \frac{1}{N} \left| \sum_{n=1}^{N} Xn \right| \qquad \text{Eq (3.3)}$$

Standard deviation: is indicated by σ. Standard deviation measures the amount of variation or dispersion from the average. It represents the amount of changes in frequency distribution [1].

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (xi - \mu)^2} \qquad \text{Eq (3.4)}$$

Kurtosis: measures the "peakedness" of the probability distribution of a real-valued signal [9].

Entropy of Energy: The short-term entropy of energy can be interpreted as a measure of abrupt changes in the energy level of an audio signal [19].

3.3.3 Neural network

Artificial Neural Networks (ANNs) are conceived to mimic the behavior of biological neural networks. Some of the main abilities of an ANN are pattern recognition, decision making and extrapolation. Like the human being, ANNs learn from input (training) data.

Learning algorithms are divided into two classes: supervised learning, when an external agent tells the network the correct output corresponding to a certain input data, and unsupervised learning, where there is no such external agent. The knowledge obtained by the ANN is stored in weights of the connections among the neurons. Once the training is completed, the ANN should be able to extrapolate its recognition and decision making ability to new input data. There are three important decisions to make when constructing an ANN for a given application: (1) the network topology, (2) the learning algorithm and, (3) the activation function. These decisions have to be taken according to the available input data and the nature of the final classification [7].

The precise network topology required to solve a particular problem usually cannot be determined, it is a critical problem in the neural-network field, since a network that is too small or too large for the problem at hand may produce poor results. Although research efforts continue in this regard, in the end the only method that can be confidently used to determine the appropriate number of layers in a network for a given problem is trial and error (Gallant, 1993).

The most important and widely used learning algorithm is backpropagation. In the employment of the these algorithm, each iteration of training involves the following steps: (1) a particular case of training data is fed through the network in a forward direction, producing results at the output layer, (2) error is calculated at the output nodes based on known target information, and the necessary changes to the weights that lead into the output layer are determined based upon this error calculation, (3) the changes to the weights that lead to the preceding network layers are determined as a function of the properties of the neurons to which they directly connect (weight changes are calculated, layer by layer, as a function of the errors determined for all subsequent layers, working backward toward the input layer) until all necessary weight changes are calculated for the entire network. The calculated weight changes are then implemented throughout the network, the next iteration begins, and the entire procedure is repeated using the next training pattern [22].

Chapter four

Research Methodology

4.1 Introduction

This chapter well provide information about data acquisition and methods used for analysis, feature extraction and classification.

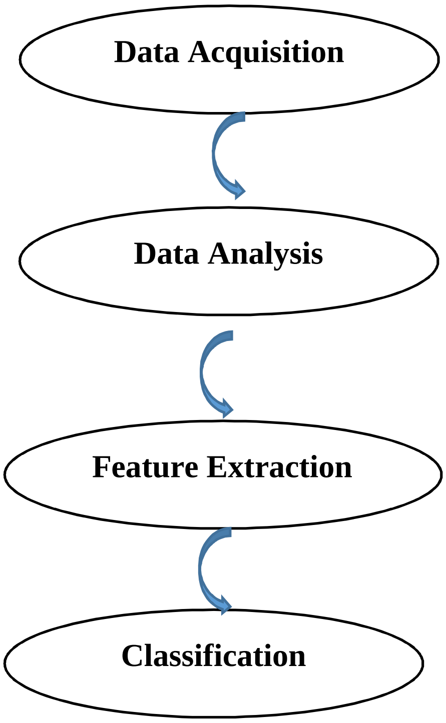

Fig 4.1: General block diagram for the proposed technique.

4.2 Data Acquisition

Most of the database was taken from Lehrer [20], it contained normal and abnormal lung sound diagnosed by doctor. The rest of it were downloaded from Internet Archive web site.

Each sound signal were divided into segments each containing one inspiratory and expiratory cycle, resulting on 17 normal sounds, 24 wheeze sounds and 28 crackle sounds. These sounds have the sampling frequency of 44.1 kHz.

4.3 Data analysis

The signals first were manually divided into segments each contain one inspiratory and expiratory.

In order to account for variability in the data collecting process the signal was normalized in amplitude. L^2- norm was used based on (M.A. Tocchetto et all) which compared the results of lung sound normalization using L^1-norm, L^2-norm and L^∞-norm , L^2-norm gave the best results. Normalization also shows that it can enhance the performance of the classification.

Wavelet transforms used to analysis the signal because of their high success ratio in previous literature studies [1, 6].

Selecting the wavelet family and a suitable number of levels is based on the nature of the signal [18]. From previous literature studies the most effective wavelet families used in lung sound analysis are Daubechies (db) and Symlets (sym).

To minimize the noise a sym4 of level 5 were applied.

4.4 Feature Extraction

After the signal being divided into segments; each was decomposed using wavelet family sym4 to level 5.The coefficients of the resulted detailed sub-band D1-D5 were used to extract suitable feature for classification.

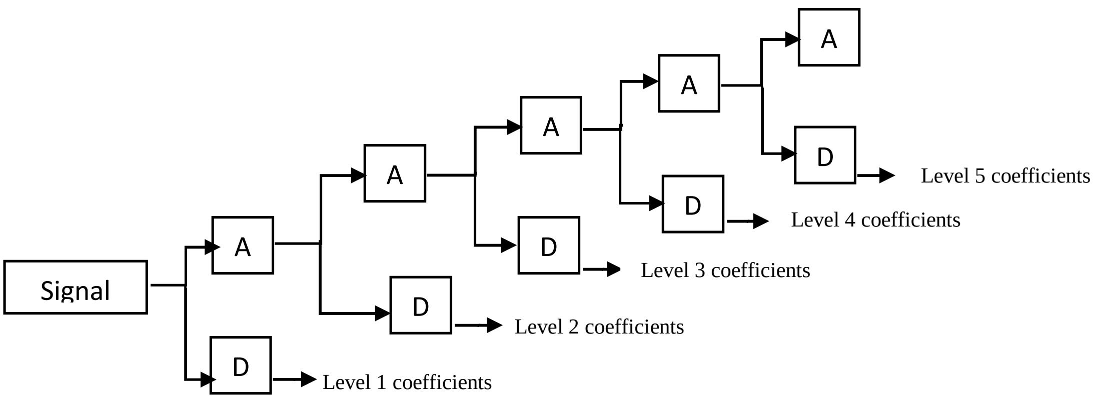

Fig 4.2: Level 5 wavelet decomposition.

In order to quantify and efficiently represent the information content in each sub-band the below functions were used:

1. Mean of the absolute values of the wavelet coefficient in each sub-band.
2. Kurtosis of the wavelet coefficients in each sub-band.

3. Standard deviation of the wavelet coefficients in each sub-band.
4. Shannon entropy of the wavelet coefficients in each sub-band.
5. Energy log of the wavelet coefficients in each sub-band.

After extracting the features a function used for selecting the most efficient features for classification called ttest2.

4.5 Classification

Neural network is one of the popular method used in classification because it's accurate and easy to apply. For learning the backpropagation algorithm were used and the activation functions we. The classification was applied in two stages: the first classification to normal and abnormal and the second classification of abnormal to Crackle and Wheeze.

A MATLAB function called ttest2 was applied for hypothesis testing of the extracted features to select the most available ones for classification

At the first stage the input of the neural network was the selected features for normal and abnormal (crackle and wheeze) samples and the desired output (target) was coded as [1 0] for normal and [0 1] for abnormal .For the second stage the input was the selected features of crackle and wheeze samples and the output was [10] for crackle and [0 1] for wheeze.

The samples were divided into: 70% training signals, 15% for testing and 15% as validation. Training signals are presented to the network during training and the network is adjusted according to its error, validation samples used to measure network generalization and to halt training when network generalization stops and testing samples have no effect on training and so provide an independent measure of network performance during and after training.

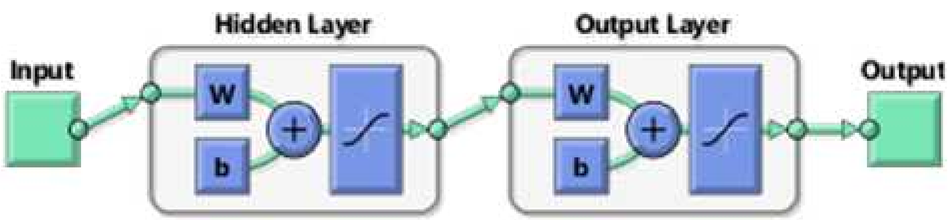

Fig 4.3: A two-layer feed-forward network

In order to evaluate the performance of the neural network classification the percentage of sensitivity (SE), specificity (SP) and accuracy (ACC) is computed. In which the sensitivity is the true normal classified cases ratio and calculated by:

$$SE = TP / (TP+FN) \qquad \text{Eq (4.1)}$$

specificity is the true abnormal classified cases ratio and calculated by:

$$SP = TN / (TN+FP) \qquad \text{Eq (4.2)}$$

and accuracy is the correct number of correctly classified cases and calculated by:

$$ACC = (TP+TN) / (TP+TN+FP+FN) \qquad \text{Eq (4.3)}$$

Where TP is the true positives, FN is the false negatives, TN is the true negatives and FP is the false positives.

Chapter five

Results and Discussions

5.1 Results and their discussions

Figures below shows an example of the downloaded signals, their segments , denoised signals and the coefficient:

- Downloaded signals:

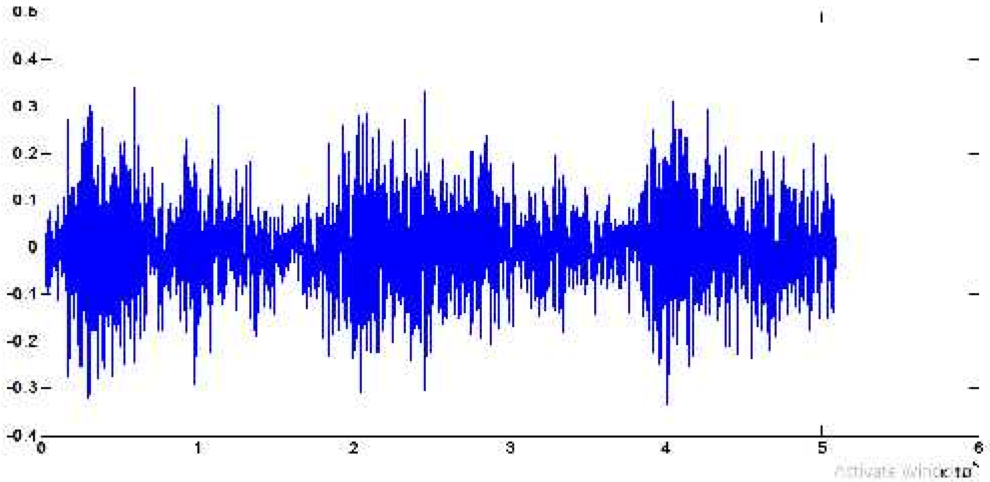

Fig 5.1: Normal signal.

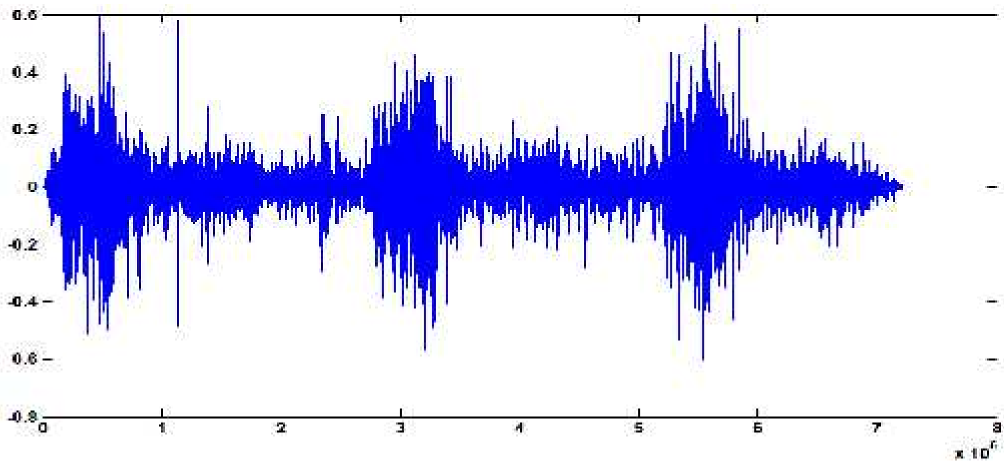

Fig 5.2 : Crackle signal.

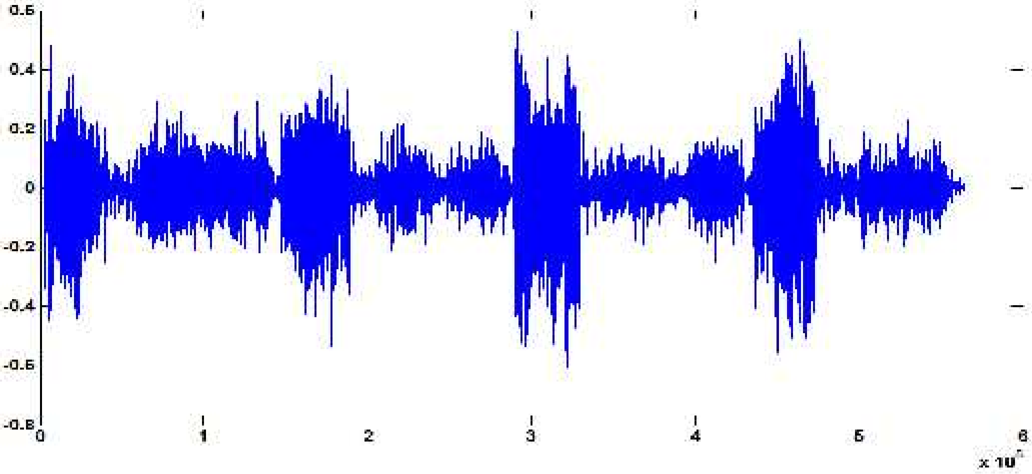

Fig 5. 3: Wheeze signal.

- Segments containing one respiratory and expiratory cycle:

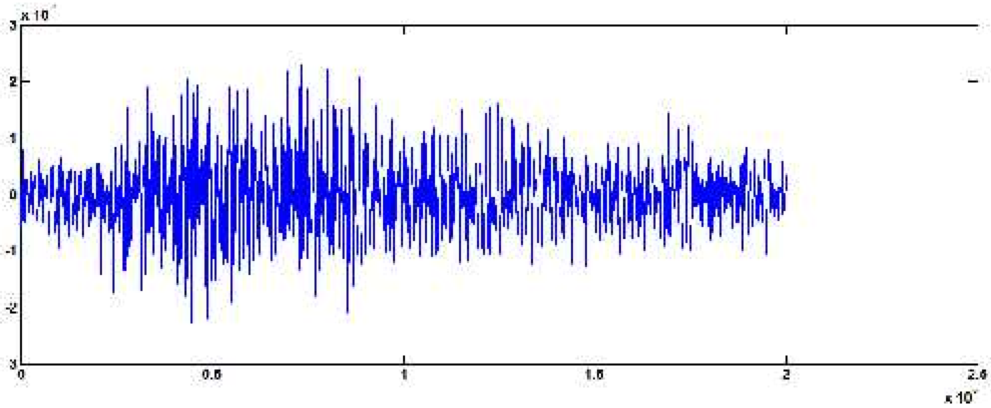

Fig 5. 4: Segment of normal signal.

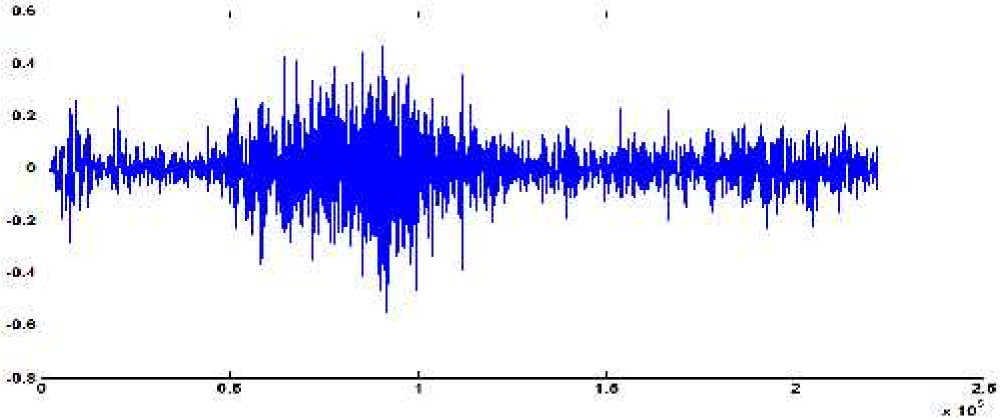

Fig 5. 5: Segment of crackle signal.

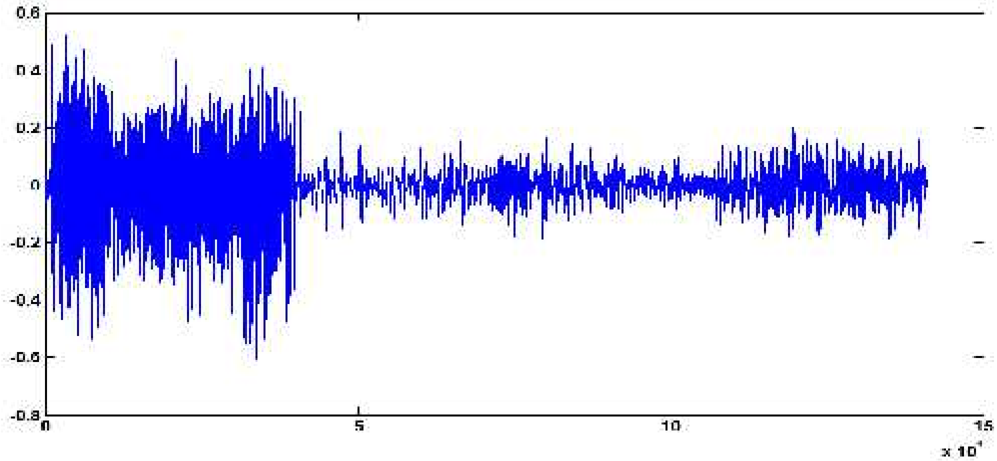

Fig 5. 6: Segment of wheeze signal.

- Normalized and denoised segments:

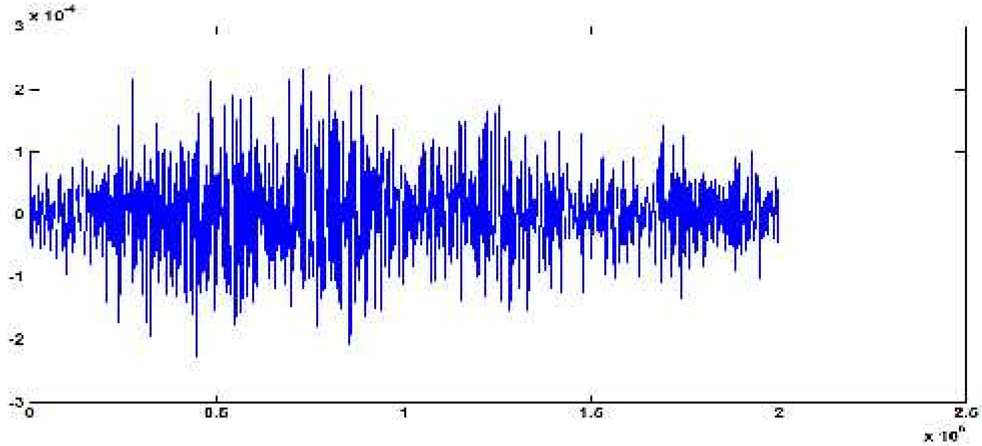

Fig 5.7 : Denoised normal signal.

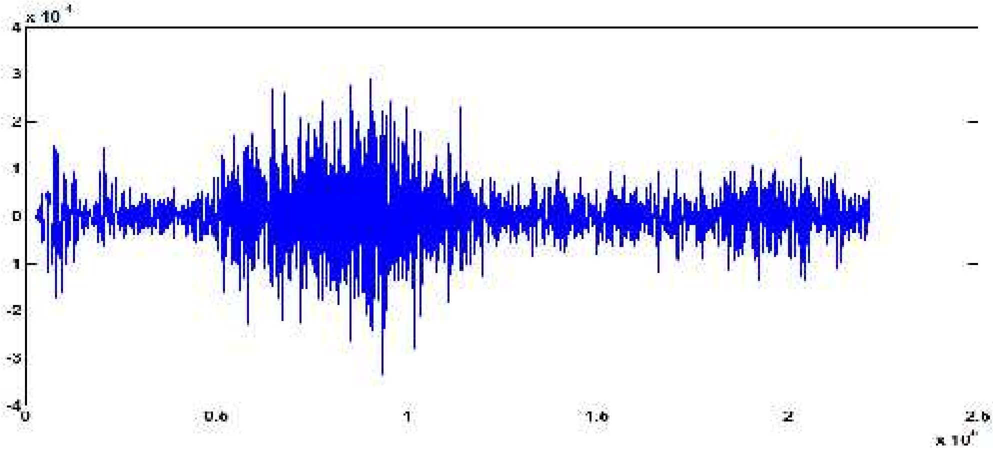

Fig 5.8 : Denoised crackle signal.

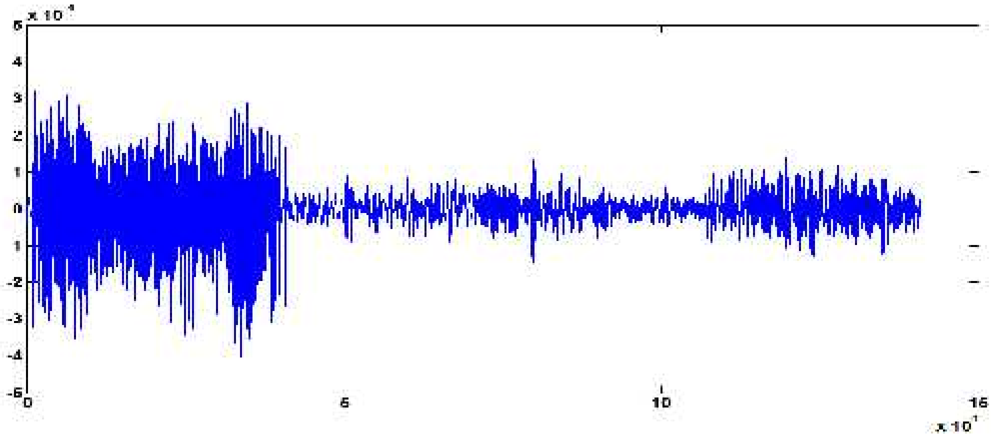

Fig 5. 9: Denoised wheeze signal.

- Coefficient of Segments:

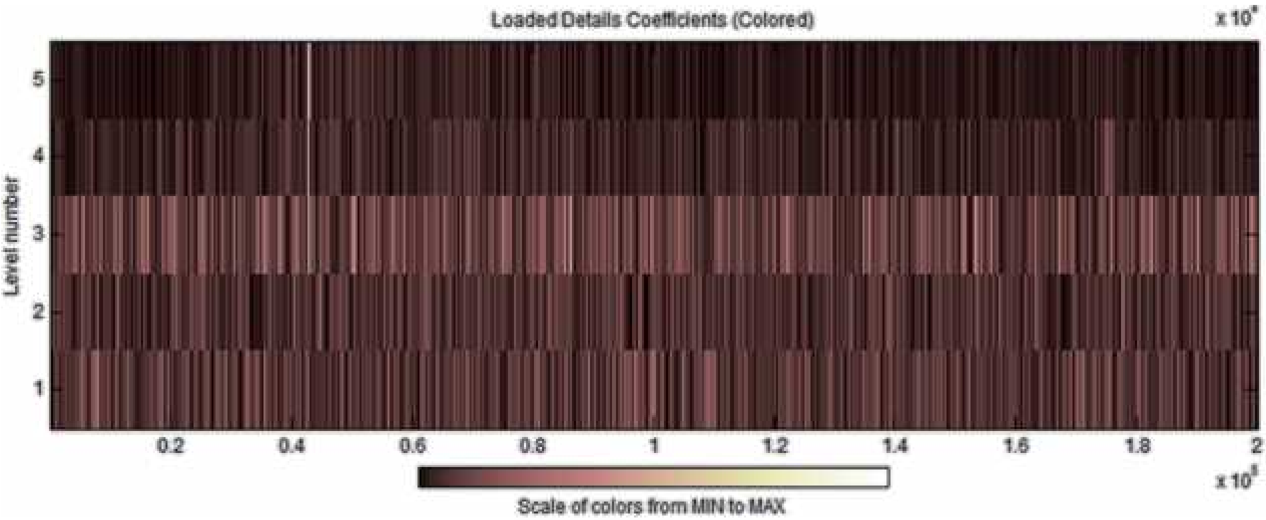

Fig 5.10 : Normal signal Coefficients.

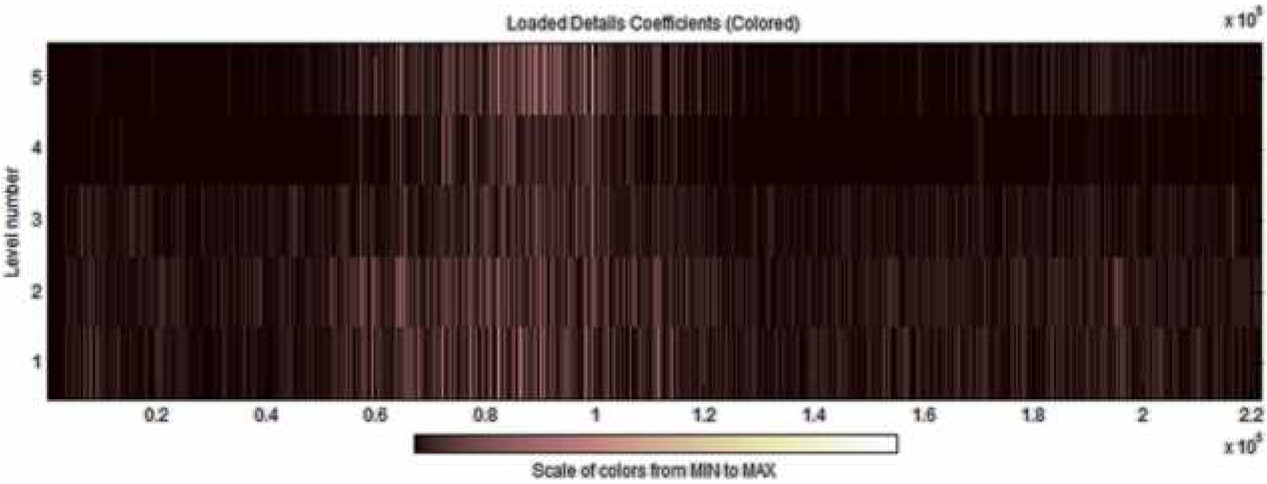

Fig 5.11 : Crackle signal Coefficients.

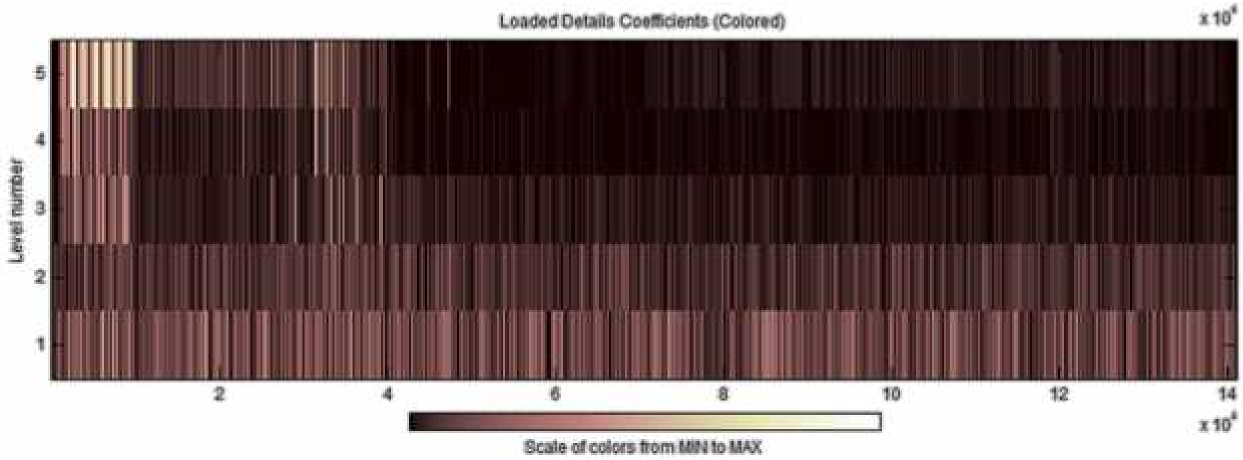

Fig 5. 12: Wheeze signal Coefficients.

At the first stage for the classification between normal and abnormal signals, number of hidden neurons were 12, the training samples 49, the validation samples 10 and the testing samples 10.

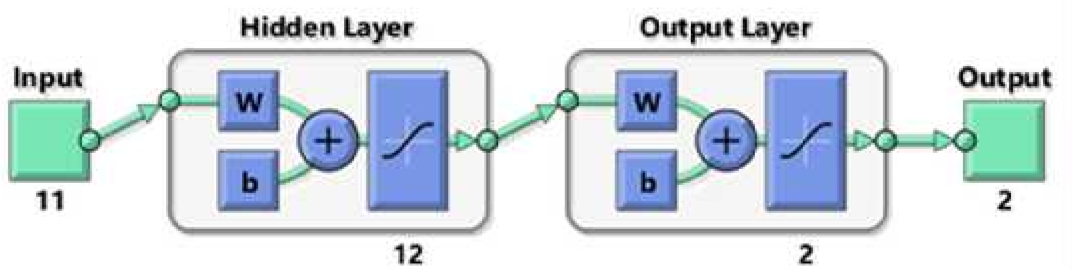

Fig 5.13 : network1: First stage classification.

The number of features extracted was 25. After applying ttest2 for selecting the most available features for classification, 11 features were selected which is the only ones used in classification. This procedure enhances the performance of the neural network.

The input of the network was the 11 features and the output (target) is a matrix of two arrays [1 0] for normal samples and [0 1] for abnormal samples.

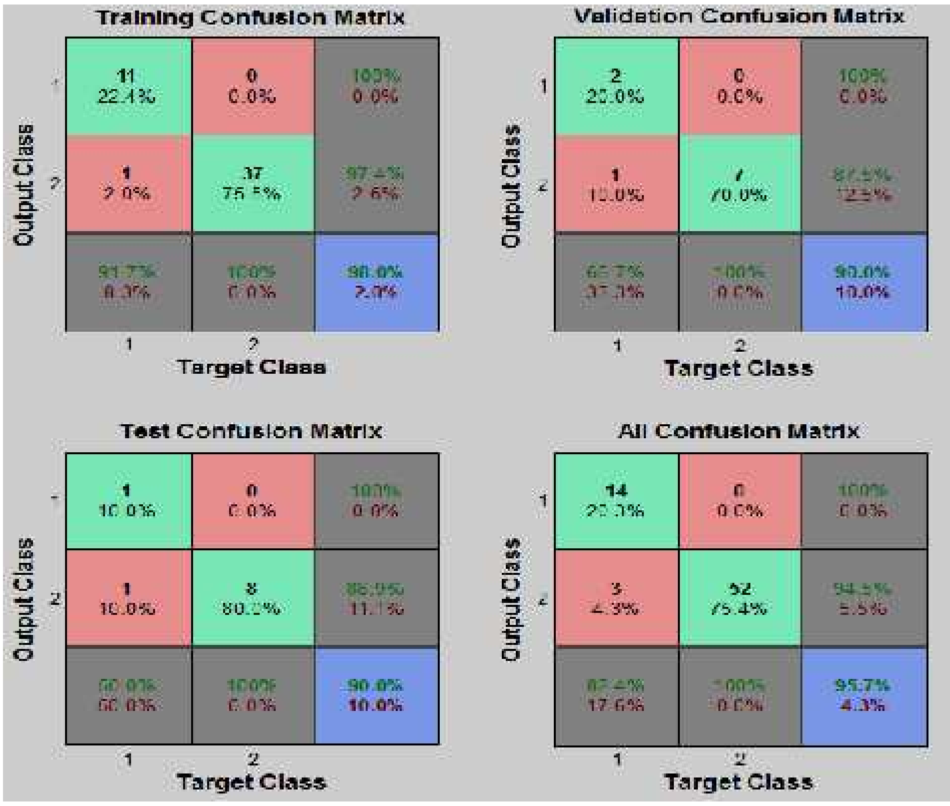

Fig 5.14 : Confusion matrixes of network1.

The confusion matrix for training, testing and validation samples and the three data combined is shown in the above Figure5.14.

The first row represented by the 1 is the normal results in which the green box is the true positive (TP), the red box is the false positive (FP). While the second row represented by 2 is the abnormal results in which the green box is the true negative (TN), the red box is the false negative (FN). The third raw represent the sensitivity, specificity, and accuracy respectively.

In All confusion matrix from the figure above the TP= 14, FP= 0, TN= 52 and FN =3.

SE =TP/ (TP+FN) =

14/ (14+3) =0.825= 82.3%

SP =TN/ (TN+FP) = 52/ (52+0) =1= 100%

ACC = (TP+TN)/ (TP+TN+FP+FN) = (14+52)/ (14+52+0+3) = 95.65%

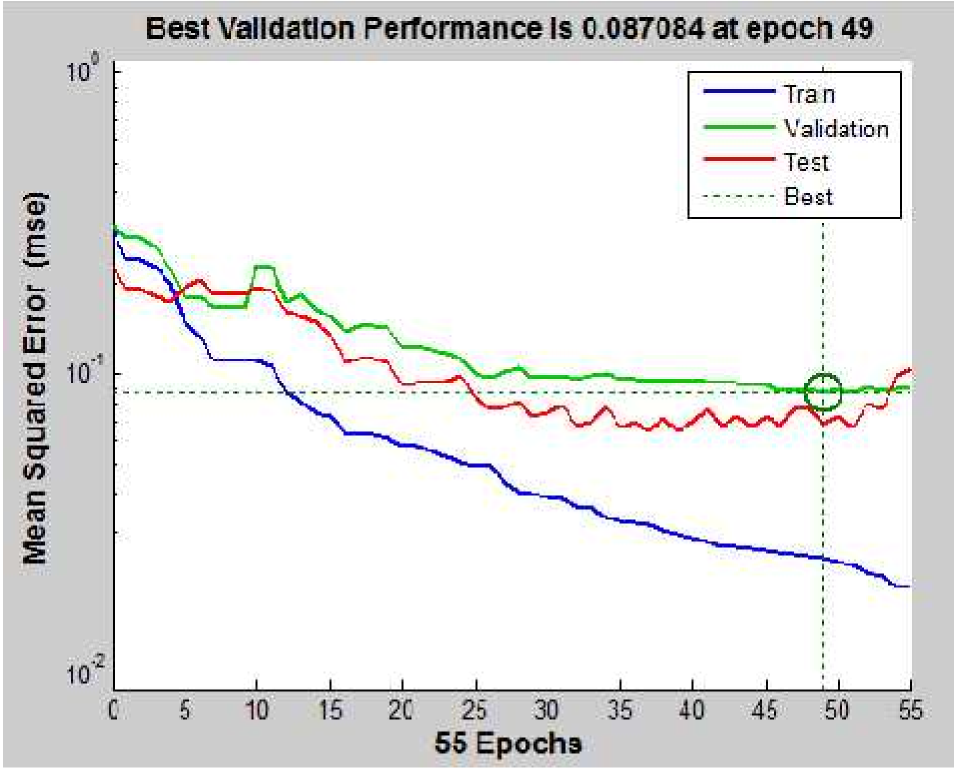

Fig 5.15 : Performance of network1.

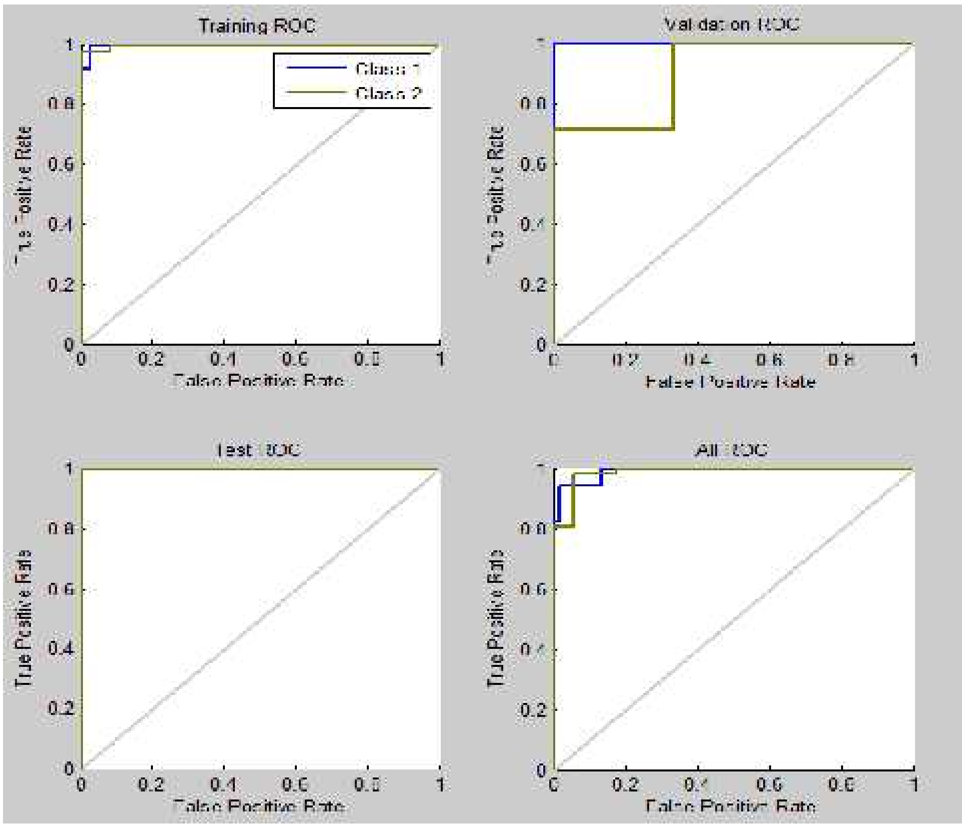

Fig 5.16 : ROC of network1.

The performance of the network is measured by calculating the mean of absolute error, the performance is 0.0688. The receiver operating characteristic (ROC) is a metric used to check the quality of classifiers. The best classifications is when the receiver operating line in the left and top sides of the plots axis. From figure 5.16 it shows that the ROC is very good.

At the second stage for classification between crackle and wheeze, number of hidden neurons were 10 , the training samples 36, the validation samples 8 and the testing samples 8. After applying the ttest2 function the used features were 11features.

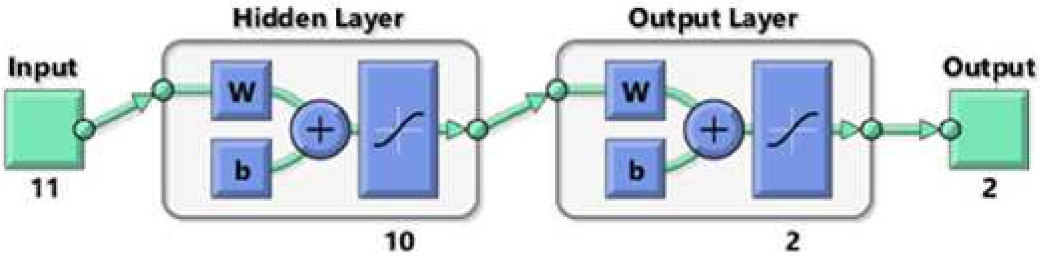

Fig 5.17 : network2: second stage classification.

The input of the network was the selected features and the output is a matrix of two arrays [1 0] for crackle samples and [0 1] for wheeze samples.

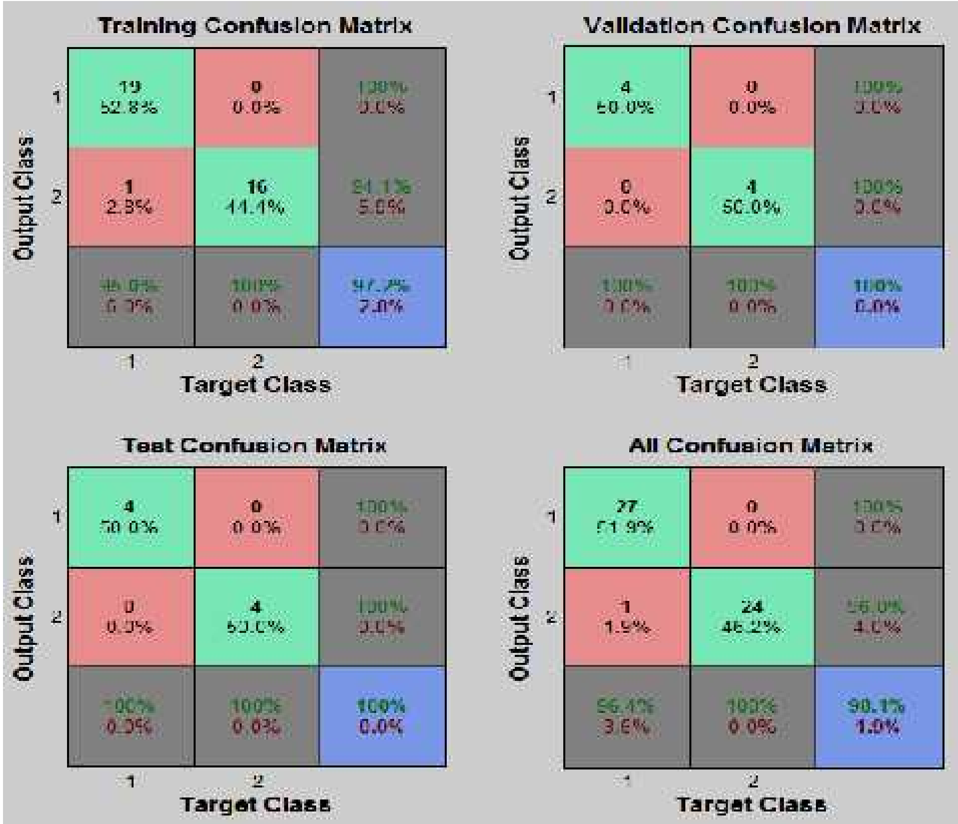

Fig 518. : Confusion matrixes of network2.

In All confusion matrix from the figure above the TP= 27, FP= 0, TN= 24 and FN =1.

SE =TP/ (TP+FN) =27/ (27+1) =96.4%

SP =TN/ (TN+FP) = 24/ (24+0) = 100%

ACC = (TP+TN)/ (TP+TN+FP+FN) = (27+24)/ (27+24+0+1) = 98.071%

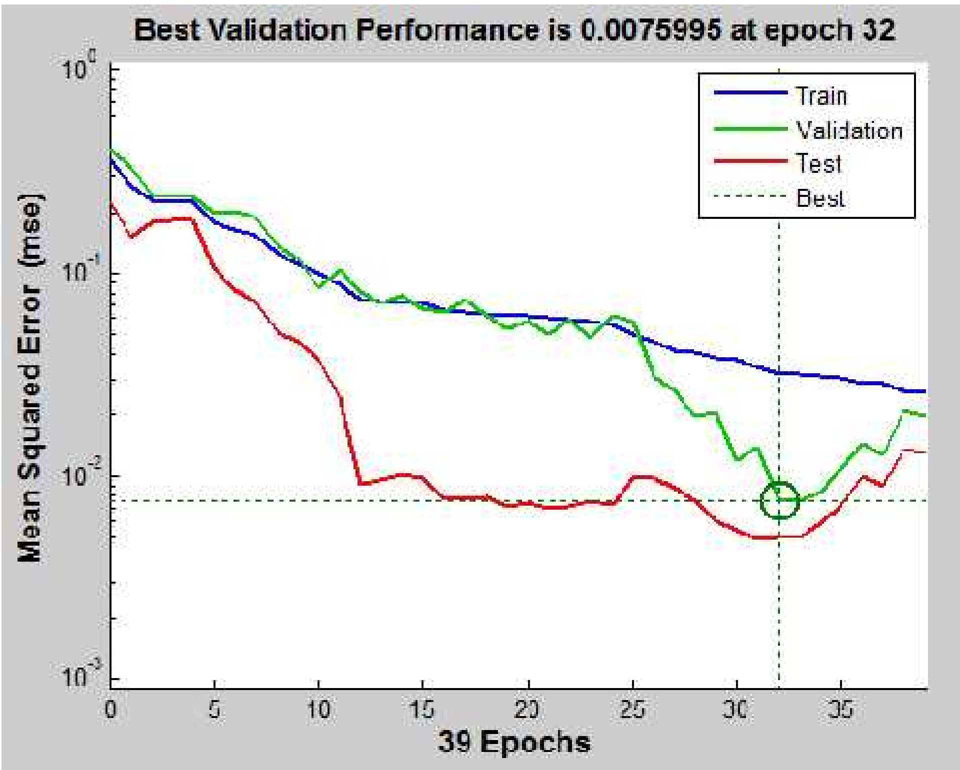

Fig 5.19 : Performance of network2.

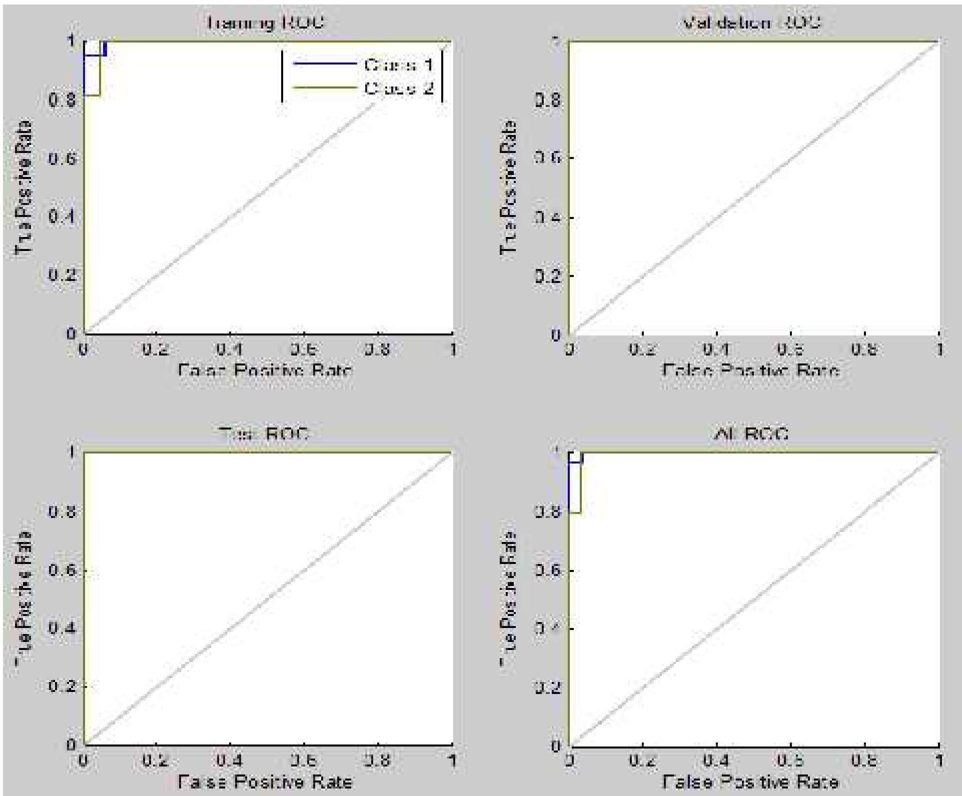

Fig 5.20 : ROC of network2.

From the above figures above the accuracy of the network is 98.1%, the performance of the network is 0.0092 and the ROC is doing best.

A graphical user interface (GUI) was built using MATLAB which contains controls called components that enable the user to perform interactive tasks to facilitate the process of clasification as shown in figure 5.21.

Fig 5.21 : GUI for respiratory sound classification .

It contains two options, the first is **Select the sound signal** which allow to select one of the imported sound signals.

The second option is **classification** which apply the process of normalization, denoising, feature extraction and finally classification to the selected signal. The result of classification appear as a message containing normal or crackle or wheeze as shown in figures below.

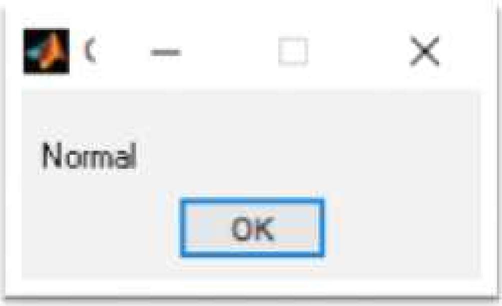

Fig 5.22 :The resulted message of classification for normal sound.

Fig 5.23 :The resulted message of classification for crackle sound.

Fig 5.24 :The resulted message of classification for wheeze sound.

Chapter six

Conclusions and Recommendations

6.1 Conclusions

A computer aided diagnosis system was built using MATLAB to classify respiratory sound to normal, crackle and wheeze in order to help in lung disease diagnosis.

The coefficient obtained from wavelet transform was fabulous features in representing the respiratory sounds segments and lead to excellent classification with accuracy 95.7% for normal and abnormal and 98.1% for crackle and wheeze.

6.2 Recommendations

- Several factors influence the analysis of the data the most important of it is the location of sound capturing (ex: vesicular , trachea or the mouth), age of the patient and the instrument used to capture the sound , these factors must be recognized and dealt with in order to minimize their influence.
- The sounds that had been able to downloaded were few so increasing the data well help getting better result and well enable to do more classification of wheeze and crackle to their types (ex: fine and course crackle and monophonic and polyphonic wheeze) .
- Classification can also be enhanced by combining the statistical methods used in features in to methods that represent the energy of the signal.

References

1. F. Z. Göğüş, B. Karlık , G. Harman, December 2015 ,“Classification of Asthmatic Breath Sounds by Using Wavelet Transforms and Neural Networks,” International Journal of Signal Processing Systems , vol. 2, pp. 106-111.
2. R. Loudon , R . L H Murhey, Jr , 1984, “Lung Sounds,” Am. Rev. Respir. Dis, pp. 663-673.
3. U. Patel, May 2011, “Computerized Respiratory SoundAnalysis: An Exploration of Methods,” CWRU School of Engineering, Department of Physics.
4. R. Palaniappan, K. Sundaraj, N. Uddin Ahamed, A. Arjunan and S. Sundaraj, 2013 “Computer-based Respiratory Sound Analysis: A Systematic Review,” IETE TECHNICAL REVIEW, vo. 30, pp. 248-256.
5. T. Tsalaile and S. Sanei, 2007, “Separation of Heart Sound Signal from Lung Sound Signal by Adaptive Line Enhancement,” 15th European Signal Processing Conference, pp. 1231-1235.
6. K.Sathesh, Dr.N.J.R. Muniraj, July. 2012, “Survey on Separation of Heart Sounds From Lung Sounds by Adaptive Filtering,”International Journal of Microsystems Technology and its Applications (IJMTA) ,Vol. 1,No. 1.
7. M.A. Tocchetto , A.S. Bazanella , L. Guimaraes ,J. L. Fragoso , A. Parraga, Aug. 2014 ,“ An Embedded Classifier of Lung Sounds based on the Wavelet Packet Transform and ANN,” The International Federation of Automatic Control, pp. 2975- 2980.
8. S. Abbasi, A. Abbasi, et all , 2013 “Classification of normal and abnormal lung sounds using neural network and support vector machines,” Proceedings of the 21st Iranian Conference on Electrical Engineering.
9. A. Hashemi , H. Arabalibiek, K. Agin, 2011, “Classification of Wheeze Sounds Using Wavelets and Neural Networks,” International Conference on Biomedical Engineering and Technology, vol.11, pp. 127- 131.
10. M. Bahoura, M. Hubin and M. Ketata , 1998, ”Respiratory Sounds Denioising using Wavelet Packets,” 2nd lntemational Conference on Bioelectromagnetism, pp. 11-12.

11. Vishnubhatla N V L N G Sharma, Sharmila A, Rajini, G.K, 2015, ”Denoising of Lung Signal Using Wavelet Transform,” Journal of Emerging Technologies and Innovative Research (JETIR), vo. 2, pp. 251-253.
12. J. Tu, K. Inthavong, G. Ahmadi, 2013, “Computational Fluid and Particle Dynamics in the Human Respiratory System,” Springer Publishing.
13. McGraw-Hill Education, 2014, “Respiratory system”.
14. S. Reichert, R. Gass, C. Brandt and E. Andrès, 2008, “Analysis of Respiratory Sounds: State of the Art,” Clinical Medicine: Circulatory, Respiratory and Pulmonary Medicine, pp. 45-58.
15. H. Pasterkamp, S. S. Kraman, and G.R. Wodicka, 1997, “Respiratory Sounds:Advances Beyond the Stethoscope,” American Journal of Respiratory and Critical Care Medicine, Vol. 156. pp. 974–987.
16. M. Sarkar, I. Madabhavi, N. Niranjan, and M. Dogra, 2015, ”Auscultation of the respiratory system,” Ann Thorac Med, v. 10(3), pp. 158–168.
17. Robert X. Gao l Ruqiang Yan , 2011, ”WaveletsTheory and Applications for Manufacturing,”, Springer Verlag.
18. M. Misiti,Y. Misiti, G. Oppenheim, J. Poggi, 1996, “Wavelet Toolbox For Use with MATLAB,” The Mathworks, Inc. Natick, Mass.
19. T. Glannakopoulos, A. Pikrakis, 2014, “Introduction to AUDIO ANALYSIS: A MATLAB Approach,” Elsevier Academic Press.
20. Lehrer,S, 2002, ”Understanding lung sounds,” Saunders, Audio CD.
21. http://shulmanusa.com/Nursingpdf/Breath%20Sounds.pdf
22. D. Leverington, 2009, “A Basic Introduction to Feedforward Backpropagation Neural Networks ”, 2009. http://www.webpages.ttu.edu/dleverin/neural_network/neural_networks.html
23. Internet Archive. https://archive.org/details/Lung_Sounds_1aim.net.
24. MATLAB, version 8.1.0.604 (R2013a), 2013, Natick, Massachusetts: The MathWorks Inc.