Diagnosis of Respiratory Diseases using Signal Processing and Machine Learning

Project report submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

By

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UNDER THE GUIDANCE OF

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May, 2019

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DECLARATION BY THE SCHOLAR

We hereby declare that work reported in the B-Tech thesis entitled **“Diagnosis of Respiratory Diseases using Signal Processing and Machine Learning”** submitted at **Jaypee University of Information Technology, Waknaghat India,** is an authentic record of our work carried out under the supervision of **Dr. Sunil Datt Sharma.** We have not submitted this work elsewhere for any other degree or diploma.

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CERTIFICATE

This is to certify that the work which is being presented in this project report titled **“Diagnosis of Respiratory Diseases using Signal Processing and Machine Learning”** for partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering and submitted to the Department of Electronics and Communication Engineering , Jaypee University of Information Technology, Waknaghat is an authentic record of work carried out by **Reetika Mittal (151016) and Sanchit Dang (151048)** during a period of July 2018 to May 2019 under the supervision of **Dr. Sunil Datt Sharma** (Assistant Professor (Senior Grade), Department of Electronics and Communication Engineering), Jaypee University of Information Technology, Waknaghat.

The above statement is made correct to the best of our knowledge.

Date: - ……………………..

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Reetika Mittal Sanchit dang

LIST OF ABBERIVIATIONS

RSV	Respiratory Syncytial Infection
MFCC	Mel-Frequency Cepstral Coefficient
MFC	Mel-Frequency Cepstrum
CIF	Cochleagram Image Feature
SVM	Support Vector Machine
LRM	Logistic Regression Model
MSLL	Maximum Side Lobe Level
HMLW	Half Main Lobe Width
SFLOR	Side Fall of Rate
PPV	Positive Predicted Value
NPV	Negative Predicted Value
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives

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ABSTRACT

There are several poor communities in this world that lack access to treatment of respiratory diseases, due to less sufficient medical expertise and less availability of diagnostic devices. Respiratory diseases like pertussis, croup, bronchitis and asthma are becoming a major problem throughout the world. Analysis of cough sound helps in detection of respiratory diseases because cough is one of the most common symptoms among all respiratory diseases. These diseases are differentiated on the basis of spectral features of cough sound. Though, in this developing era of new technologies, there are existing systems in analyzing cough signal, but still there is a need in developing tool which analyses cough signal and capable of detecting the disease at earlier stages as well as monitoring the recovery of patients suffering. In this project, we have developed a method for automatic recognition of the respiratory diseases on the basis of the cough sound. This method uses the (DSP) Digital Signal Processing techniques to extract the spectral features. In particular, we are using Short Time Fourier Transform for feature extraction, which consists of Concentration Measure and Dominant Frequency. After that we are using Neural Networks to train our machine so that it can automatically diagnose the type of respiratory disease the person is having. After that, we can easily integrate it with an expert system which provides respiratory digital health services and which provide low-cost diagnostics to base populations, to connect patients with the physicians.

CHAPTER 1
INTRODUCTION

1.1 General

With the advancement of technology in computing, storage and networking, any high speed computation on the data available across various data centers is possible today. The amount of data generated by various enterprise applications and social networking is enormous and expected to grow tremendously in the coming years. Deriving useful and intelligent information out of this data is utmost important to enhance business value and increase human centricity. Machine Learning algorithms available as a subfield of Artificial Intelligence help derive the intelligence from plethora of data available across various application domains. Artificial intelligence and Machine learning are trending technologies in industry to enable business recommendations, predict future market etc. The field of medicine is not an exception to support doctors diagnose the disease faster with high accuracy and provide personalized medication to the patrons. In this project, an in-depth discussion is carried out on diagnosing respiratory diseases accurately using machine learning algorithms.

1.2 Need of Study

Respiratory Diseases like pertussis, croup, bronchitis are most common in the first year of life. Every year, so many deaths occur because of these diseases, Infants can't even tell their symptoms to the physicians. Diagnosis of such respiratory diseases is not an easy task at all. Physicians are totally relied upon their experience, their hearing abilities, stethoscope and various laboratory tests. Moreover the automatic detection of respiratory diseases by analyzing the breathing sounds is an economical and convenient way. The existing spectral based methods for feature extraction are Mel-Frequency cepstral coefficients (MFCCs) [1], Wavelet based musical features [2], Eigen value of singular spectrum analysis (SSA) [3], Local binary patterns (LBP) [4]. Some of the widely used machine learning methods are Gaussian mixed model (GMM) [5],support vector machine (SVM) [6], k-nearest neighbors (KNN) [7], extreme learning machine (ELM) [8], Logistic regression method (LRM) [9]. Although so many methods have been developed for the classification of respiratory diseases but still there is a need of significant improvement in all the above methods to provide the medical authorities accurate and reliable methods.

1.3 Objectives

Breathing sounds has been an important indicator for diagnosing respiratory diseases.

- Interpretation of the breathing sounds by the physicians had been an essential method for diagnosing respiratory diseases.
- They were relied on their hearing abilities, stethoscope and various laboratory tests. However, these methods have always been unreliable
- With enhancing computer technologies and digital signal processing techniques, many computational methods have already been developed for such diagnosis of respiratory diseases.

In this project, we are having the following objectives :

1) Feature Extraction using Time – Frequency Analysis based methods for the respiratory disease.

2) Respiratory diseases classification using Machine – Learning Tools.

CHAPTER 2
RESPIRATORY DISEASES

2.1 Types of respiratory diseases

Croup: - Croup is one of the most deadly diseases in the first year of life. It is caused by a viral infection of the respiratory tract that causes inflammation of the windpipe and the voice box. Youngsters are most powerless to croup when they are a half year to three years old and it affects boys more than girls Its symptoms are much worse in night[10].

Bronchitis: - Bronchitis is a viral lung disease, more often than not caused by the respiratory syncytial infection (RSV). RSV contaminates over 90% of the youngsters during the first two years of life. The indications of the disease incorporate runny nose, wheezing, quick breathing, trouble in breathing, and fever. Almost 20% of children with bronchitis build up an ear disease, and 30% create asthma further in life [11].

Pneumonia: - Pneumonia is a contamination of lungs caused by bacteria, which inflames the air sacs of the lungs (one or both). The lung may create abundance liquid which can gather in the aviation routes. As a rule, pneumonia is first presumed when the youngster hints at unexplained respiratory misery [12].

Pertussis: - Pertussis, otherwise called challenging hack, is an exceptionally infectious respiratory illnesses. It is caused by the bacterium Bordetella pertussis. We also call Pertussis as Whooping cough and it is a highly contagious disease. Pertussis results in violent coughing which makes the person even hard to breathe. The person diagnosed with Pertussis often needs to take deep breathes. Pertussis can affect people of all the ages but it can be deadly for babies [13].

Asthma: - Asthma is a long-term lung inflammatory disease of the airways of the lungs that transport air to and from the lungs. In asthma, airways become narrow and swell sometimes and it produces so much mucus. This causes difficulty in breathing, coughing, wheezing and shortness of breath [14].

2.2 Flow graph for diseases diagnosis

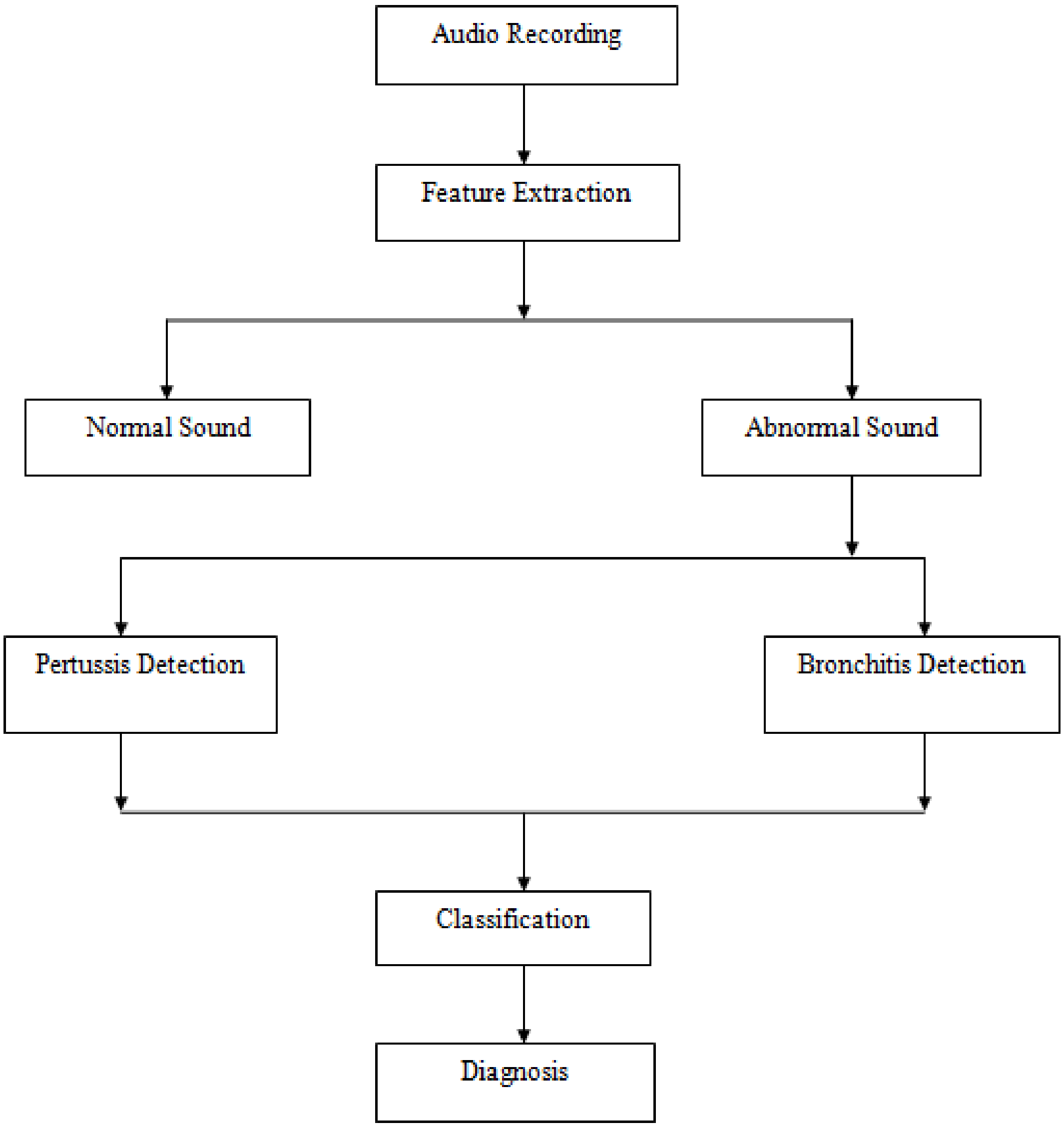


Fig 2.1 Steps for Disease Diagnosis

2.2.1 Audio Recording: - We have collected the data from the existing online sources like YouTube. From there we have taken the respiratory sounds of infants having Pertussis and Bronchitis. We have used total 42 samples while training our data. List of some of the data sources is given in the Appendix 1.

2.2.2 Feature Extraction: - Mainly three steps are required to classify the respiratory diseases: - collecting the data, extracting the features and classification [15]. This project presents a novel respiratory classification method based upon Concentration measure and Dominant Frequency. We are extracting the feature coefficients with methods of STFT (Short time Fourier Transform) which is a time-frequency based domain method. From that we are extracting the features mainly: concentration measure and dominant frequency which we have talked about later. With the help of these features, we are classifying the sound as Normal sound and abnormal sound which is further classified into respiratory diseases such as pertussis and bronchitis using Neural Networks. These classification methods are not implemented till now.

2.2.3 Disease Detection: - Detection of the respiratory diseases on the basis of feature extracted has been done.

2.2.4 Classification: - After training with the neural network, we can further classify the diseases mainly into Pertussis and Bronchitis.

2.2.5 Diagnosis: - We can diagnose any type of respiratory disease by taking its sound recording.

CHAPTER-3
LITERATURE OVERVIEW

3.1 A Cough-Based Algorithm for Automatic Diagnosis of Pertussis

Renard Xaviero Adhi Pramono, Syed Anas Imtiaz, Esther Rodriguez-Villegas develop a method for diagnosis of respiratory diseases. A typical method for time domain features, frequency domain features and Mel Frequency Cepstral Coefficients (MFCCs). This method is used for cough classification, detection and whooping sound detection. With these features extracted, an LRM classifier is used to classify the cough and whooping sound. This method achieved sensitivity 92.38% with a specificity of 90.0% and a PPV of 96.50%, NPV 79.84% [13].

3.2 Automatic Croup Diagnosis Using Cough Sound Recognition

Roneel V. Sharan, Udantha R. Abeyratne, Vinayak R and Paul Porter develop a method for diagnosis of respiratory diseases. A typical method uses a combination of linear MFCC and CIF produces best result for cough sound classification using a LRM and SVM with a sensitivity of 72.84 % and specificity of 92.16% [18].

3.3 Spectral Features

Following spectral features have been reported in the literature and these are discussed as follows-

3.3.1 Cochleagram Image Feature

We utilize the cochleagram picture of sound signs for time-recurrence investigation and highlight extraction, rather than the ordinary spectrogram picture, in a sound observation application. The flag is right off the bat gone through a gamma tone channel which models the sound-related channels in the human cochlea. The separated flag is then isolated into little windows and the vitality in every window is included and standardized which gives the power estimations of the cochleagram picture. We at that point isolate the cochleagram picture into squares and concentrate focal minutes as highlights. Utilizing two component vector portrayal strategies, the outcomes demonstrate noteworthy enhancement in generally arrangement precision when contrasted with results from writing utilizing comparative element extraction and portrayal systems yet utilizing spectrogram pictures.

3.3.2 Mel-Frequency Cepstral Coefficient

Mel-Frequency Cepstral Coefficient is a tool used for feature extraction technique mainly used for speech recognition and currently research is going on in developing the MFCC technique. MFCC is a short term power based linear cosine logarithmic spectrum on a Mel scale. This method is number –based recognition which can be recognized when spoken on telephone. Its other applications includes audio similarity methods, genre detection etc [1].

3.4 Machine Learning Tools for Classification

The machine learning tools- SVM, NN, LRM have been reported in the literature and description of these tools is given below-

3.4.1 Support vector machine

In machine learning, a support vector machine (SVMs, also support vector networks) is a supervised learning method. It is basically used as a classifier. The SVM is mainly used for analyzing the data which can be used for classification and regression analysis. An SVM model maps the points in space so that the separate categories are divided by a wide gap [6].

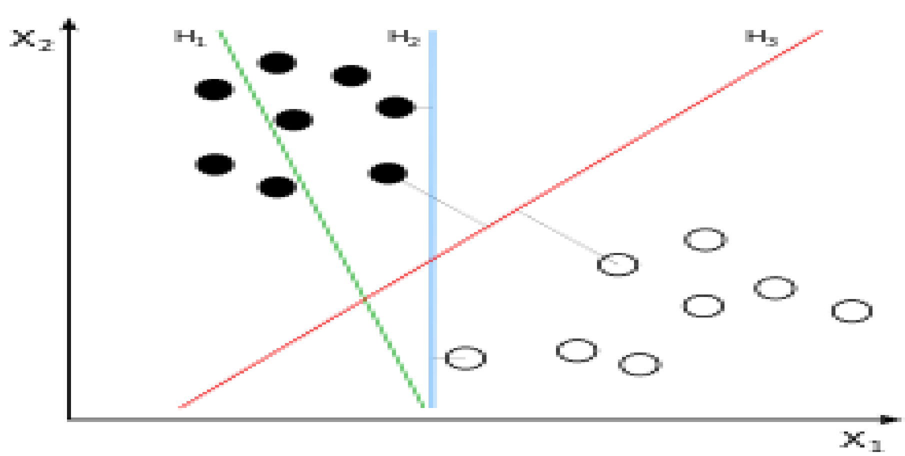


Fig. 3.1 SVM Classifier

(https://en.wikipedia.org/wiki/File:Svm_sepearating_hyperplanes_(SVG).svg)

3.4.2 Neural Network

Neural Network, also called as Artificial Neural Network is a machine learning algorithm which is inspired by the biological nervous system such as brain, process information. Neural Network consists of a large number of highly interconnected processing elements (Neurons) which work in parallel to solve the specific problems. Like our brain learns from experience, Neural Network also learn from their experience [16].

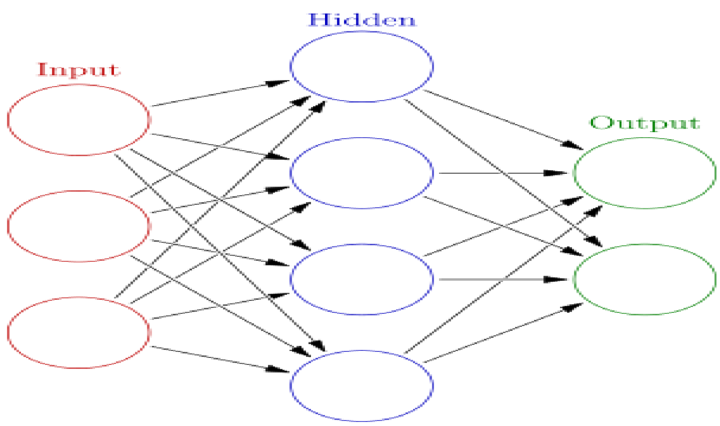


Fig 3.2 Neural Network Layers

(https://en.wikipedia.org/wiki/File:Svm_Coloured_neural_network.svg)

3.4.3 Logistic regression model

Logistic Regression Model is a statistical method used for classification of data. It is basically used for the classification of the data that is having independent variables. The logistic function is also called as sigmoidal function. It is an S-shaped curve which can take any real-value and map it to value between 0 and 1, but never exactly at those limits [9].

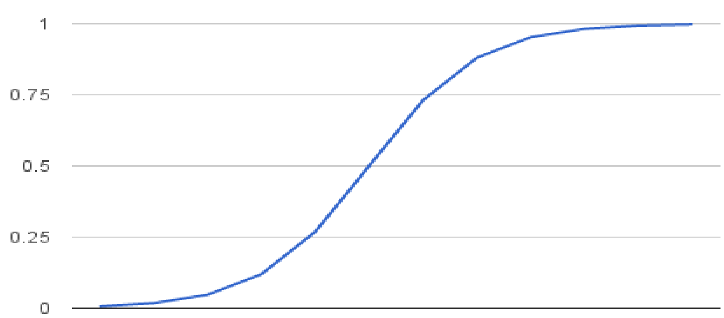


Fig 3.3 Logistic Regression Model

CHAPTER-4

MATERIAL AND METHODS

4.1 Short Time Fourier Transform

Short time Fourier Transform (STFT) is finding Fourier transform over a window. Standard Fourier transform we find provides the frequency information over the whole signal. But in STFT, we find the Fourier transform over a window and keep on moving the window further. STFT provides us the time-frequency information for signals in which frequency components vary with time. STFT of the signal $f(t)$ is defined as:

$$F\ (w,t) = \int_{-\infty}^{+\infty} f(\tau)h(\tau - t)\, e^{-j\omega\tau} d\tau$$

Where h (t) is the hamming window, w is frequency, t is time, and f (t) is input signal whose STFT has to be calculated

4.2 Calculation of STFT

1. Firstly one has to pick a window of limited length
2. Keep the window at t=0
3. Find the Fourier Transform of that segment
4. Now slide the window gradually
5. Go back to stage 3, until we reach at end of the signal

4.3 Choosing Window

We have selected hamming window because it has low ripples i.e. maximum side-lobe level (MSLL) as well as it has lower value of main lobe width (HMLW) which makes better resolution and higher rate of decay (SFLOR).

4.3.1 Window size

- Window should be narrow enough so that portion of the signal that fall inside the window is stationary.
- Most of the time, very narrow window, however, doesn't provide good localization in the frequency domain.
- If one uses wide window, it helps in providing poor time resolution and good frequency resolution.
- If one uses wide window, it helps in providing good time resolution and poor frequency resolution.

4.4 Stationary vs. Non-Stationary Signals

Stationary signals are those signals whose frequency components don't change with respect to time e.g. a sine wave is a perfect example of a stationary signal as its frequency component doesn't change with respect to time.

Non Stationary signals are those signals whose frequency components changes with respect to time e.g. a speech signal [17].

4.4.1 Stationary signal (non-varying frequency)

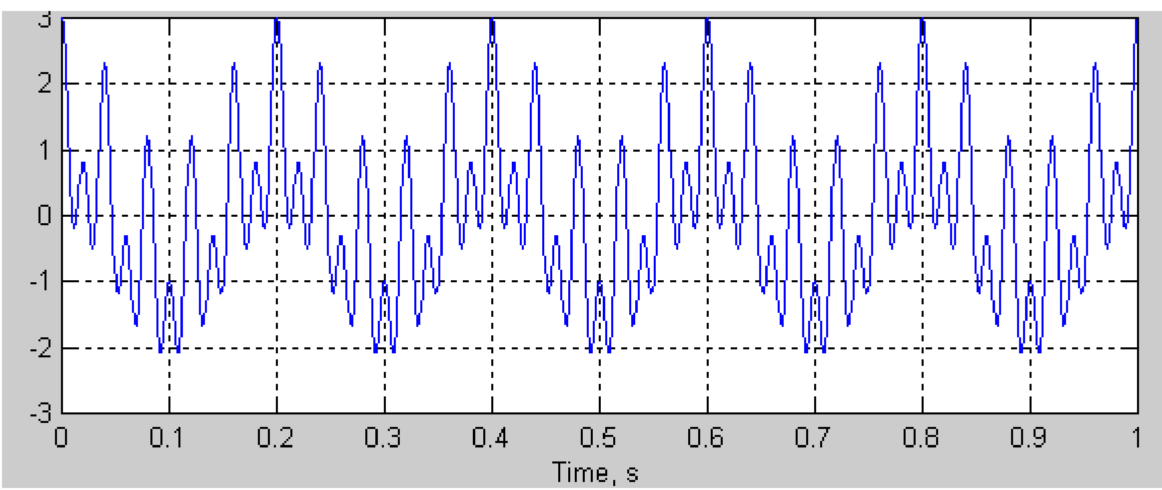


Fig 4.1 Stationary signal

In the Fourier Transform of the above signal, only three frequency components are present at all the time.

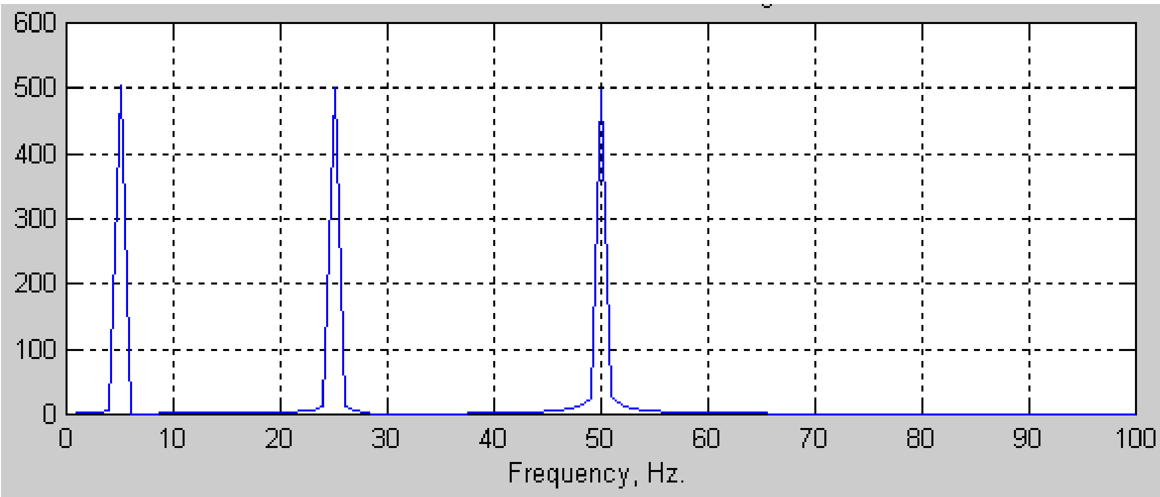


Fig 4.2 Fourier Transform of Stationary signal

4.4.2 Non-stationary signal (varying frequency)

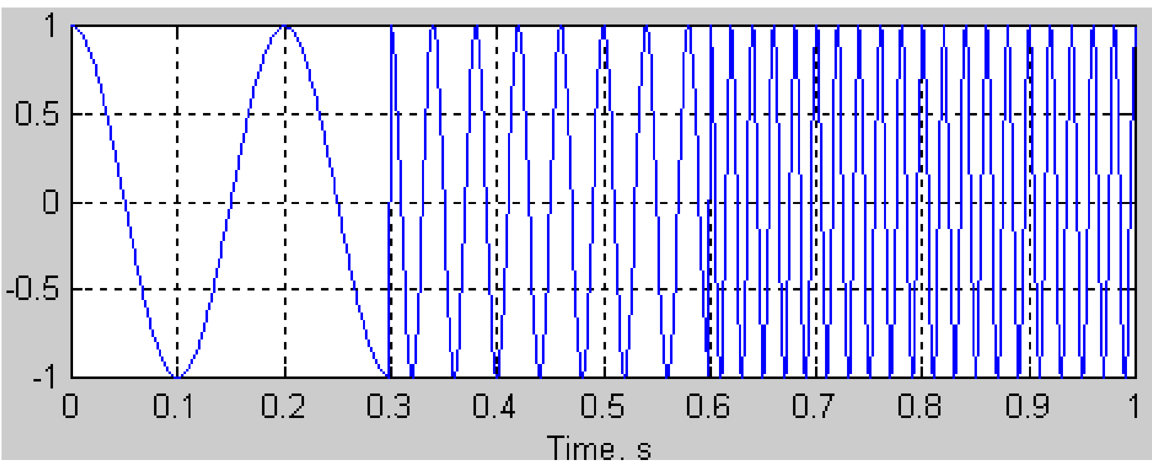


Fig 4.3 Non-Stationary signal

We are having the perfect knowledge of what frequencies exist in the above signal, but we have no information about where these frequencies are located in time!

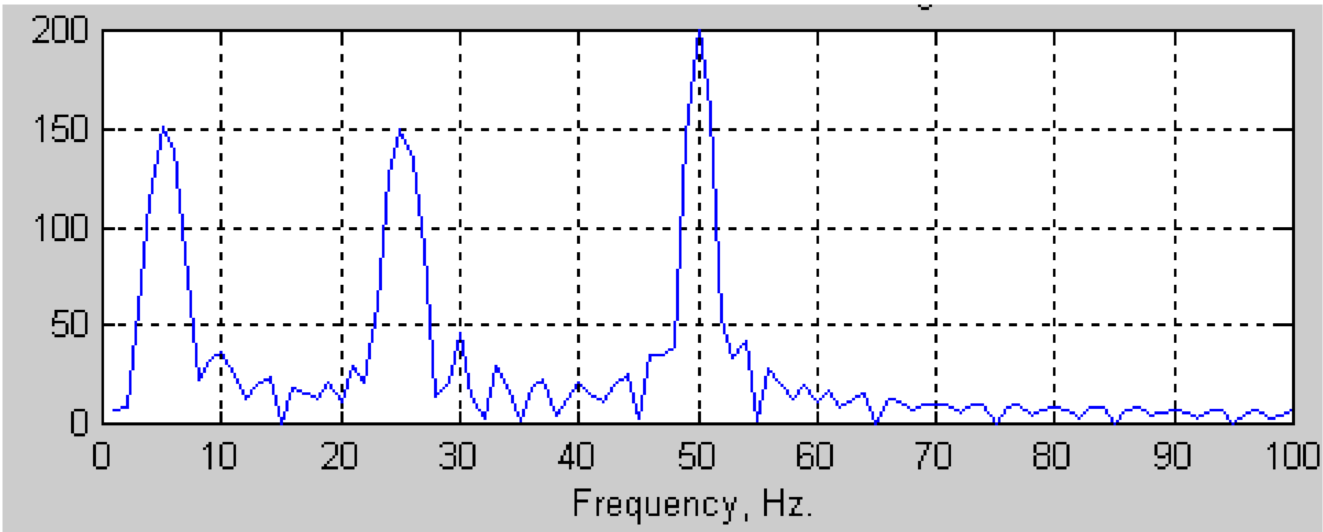


Fig 4.4 Fourier Transform of Non-stationary signal

4.5 Why to use STFT

Fourier Transform of Stationary signal clear tells us about the three frequency components present all the times but the Fourier Transform of Non-Stationary signal tells us only about the frequencies present but where these frequencies are located in time, there is no information for that. So in this paper, we have used Short time Fourier Transform as an advantage to Fourier Transform. The procedure for finding the STFT is to divide the longer time signals into shorter segments of equal length. The Fourier Transform of each short segment is then computed. Each Fourier Transform provide the spectral information of that segment, providing simultaneously time and frequency information.

4.6 Limitations of Fourier transform

- The first limitation of the Fourier transform is that it doesn't provide simultaneous time and frequency representation.
- We cannot use the Fourier transform for the non stationary signals
- Fourier Transform is not efficient for representation of discontinuities.

4.7 Feature Extraction

We are extracting the features of the respiratory diseases signals using Time – Frequency Method i.e. using Short Time Fourier Transform. The steps for feature extraction are:

- We are taking the Short Time Fourier Transform using the spectrogram function in Matlab.
- After plotting the spectrogram of a signal, we are extracting its features by summing all the power spectral densities at a particular frequency and then plotted its normalized graph.

We have find two features mainly:

- Concentration Measure
- Dominant Frequency

4.7.1 Concentration Measure

Efficient representation of time-frequency analysis provides us a quantitative criterion for evaluation of its various distributions performance. We can use it for adaptive and automatic parameter selection in time-frequency representation. Concentration measures of signal transforms were intensively studied in the area of time-frequency analysis. They are used to find an optimal, best concentrated signal representation. We have calculated the concentration measure for finding maximum concentration of energy. For this, we have taken the sum of absolute value of normalized STFT values. Then the reciprocal of that value give us concentration measure.

4.7.2 Dominant Frequency

Dominant frequency is usually meant the one that carries more energy with respect to all the other frequencies in the considered spectrum. The best way to reveal a dominant frequency is using via a spectrogram. Using Dominant frequency, we can find the hidden periodicity of the data. We are choosing the dominating frequency component only because it contains the maximum power spectral density of the signal or we can say that it contains more energy with respect to all the other frequencies in a given spectrum.

4.8 Introduction to Neural Network

Neural Networks first started as an attempt to replicate the working of the human brain so that things can be made more intelligent. Neural Networks is not as complex as it seems to be. The main idea behind the Neural Network is that it learns the relationships between cause and effect and organizes large volume of data into orderly and informative patterns. Nowadays Neural Networks is used in every field to make everything smart, perform so many incredible tasks. So many papers regarding Neural Networks have been published.

4.9 Definition of Neural Network

Neural Network, also called as Artificial Neural Network is a machine learning algorithm which is inspired by the biological nervous system such as brain, process information. Neural Network consists of a large number of highly interconnected processing elements (Neurons) which work in parallel to solve the specific problems. Like our brain learns from experience, Neural Network also learns from their experience [16].

4.10 Model of Neural Network

The most basic computational unit of the human brain is a neuron. About 86 billion neurons are present in the human nervous system and these neurons are connected with about 10^{14}—10^{15} synapses. The diagram below shows a biological neuron (left) and a mathematical model of neuron (right).

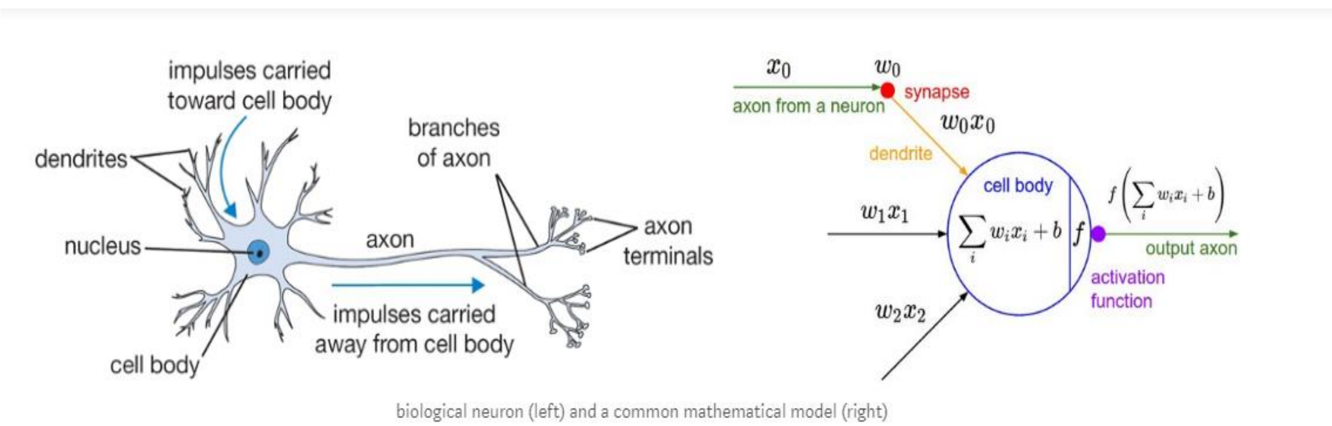


Fig 4.5 Biological Neuron and its mathematical model

4.11 Working of Neural Network

A Neural Network is basically made up of 6 components:

- **Input Nodes:** Input nodes are present in the first layer of a Neural Network. In this layer, no computation is done. This layer just passes the information given by the user to the next layer (which is hidden layer mostly).
- **Hidden nodes:** Hidden Nodes are present in between the Input layer and the output layer. In this layer, intermediate processing is done. After computing the data, it transfers the weights from the input layer to the next layer (which can be another hidden layer or output layer).
- **Output Nodes:** Output Nodes are present in the Output layer. In this layer, we use an activation function that has some kind of limits. After that the data is move to desired output format.
- **Connections and weights:** The Neural Network consists of various connections in between the neurons and the synapses, each connection just transfers the output of neuron i to the input of neuron *j*. *i* is the predecessor of *j* or we can say *j* is the successor of *i*, Each of these connections is assigned by a weight *Wij*.
- **Activation function:** The activation function is just present before the Output layer. It basically defines the output of a node according to the given inputs. A standard computer chip circuit consisting of a digital network have activation functions as "ON" (1) or "OFF" (0), depending upon the inputs. This is very much similar to the behaviour of linear perceptron. However, most of the time we use nonlinear activation function in Neural networks which allows computing non-trivial problems.
- **Learning rule:** The learnin*g* rule in a neural network is an algorithm which modifies its parameters, so that it can produce a favoured output using given set of inputs. In this learning process, modification of weights and thresholding is done.

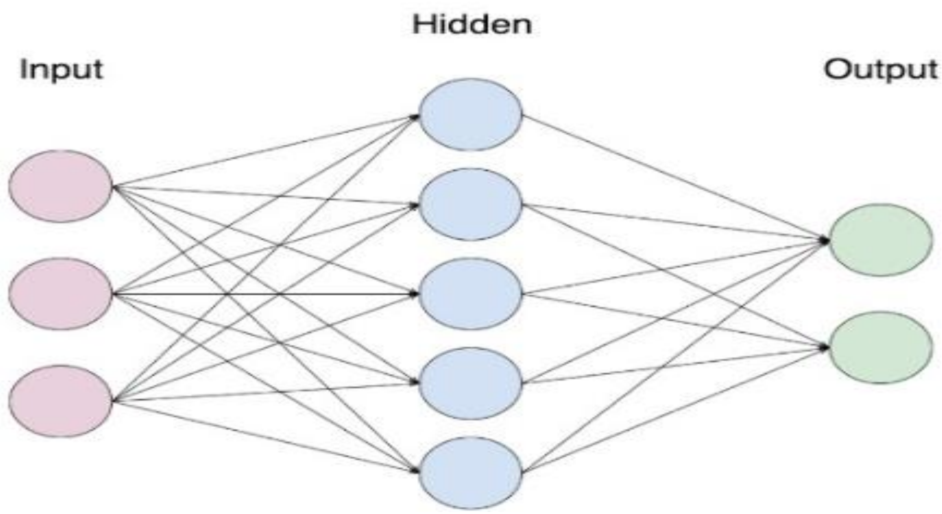


Fig 4.6 Neural Network layers

The neural network learning we have talked about happens in mainly two steps:

- Forward Propagation
- Back Propagation

4.11.1 Forward Propagation

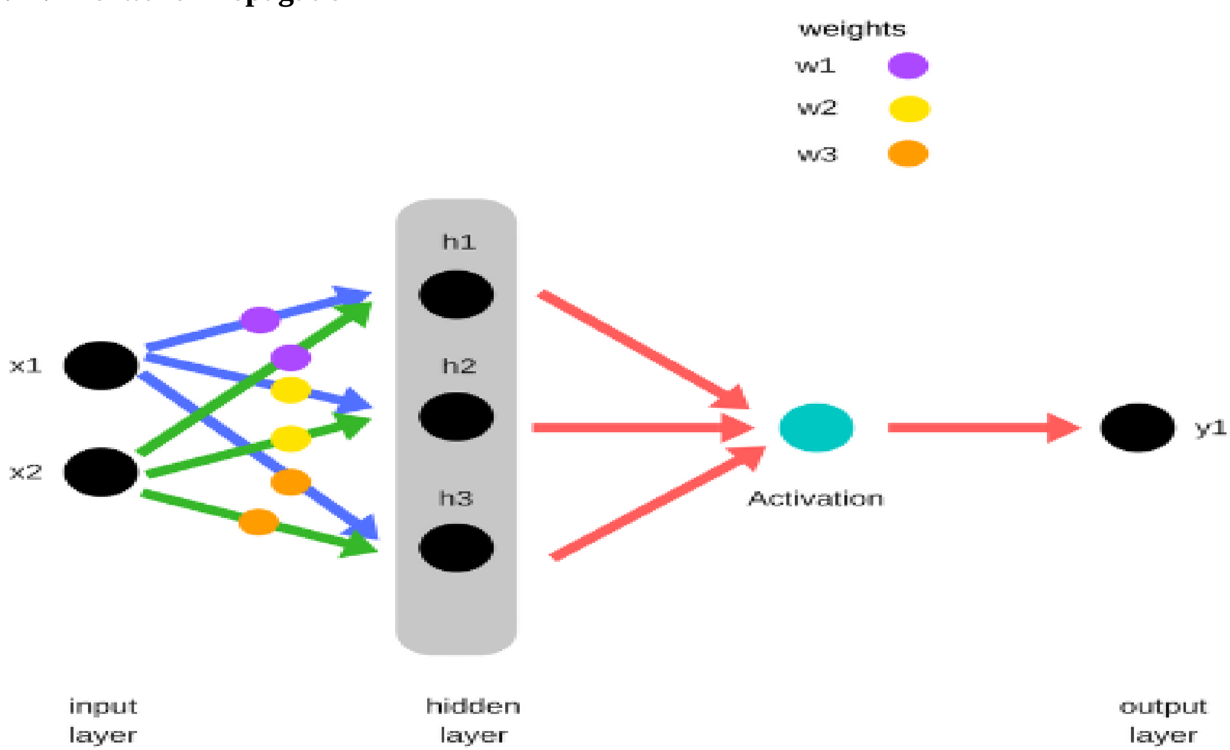


Fig 4.7 Forward Propagation model

The data is entered through input layer nodes or neurons. Each input node has some weights associated to them according to their relative importance to other inputs. These weights are randomly initialized every time we train are data. The basic idea behind this concept is that the weights *w* are learnable and they keep on modifying so as in order to minimize the error. Weights also control the strength of influence of data and the direction of data: excitatory (positive weight) or inhibitory (negative weight) from one neuron to another. The dendrites in the neuron carry the signal to the cell body where they all get summed and passed from the activation function. Data at input layer is multiplied with the corresponding weights to form next layer

- h1 = (x1 * weight1) + (x2 * weight1)
- h2 = (x1 * weight2) + (x2 * weight2)
- h3 = (x1 * weight3) + (x2 * weight3)

If the final sum of the output is above a certain threshold value, the neuron can fire the pulse else it can suppress the pulse.

- y1 = fn(h1 , h2, h3)

4.11.2 Back Propagation

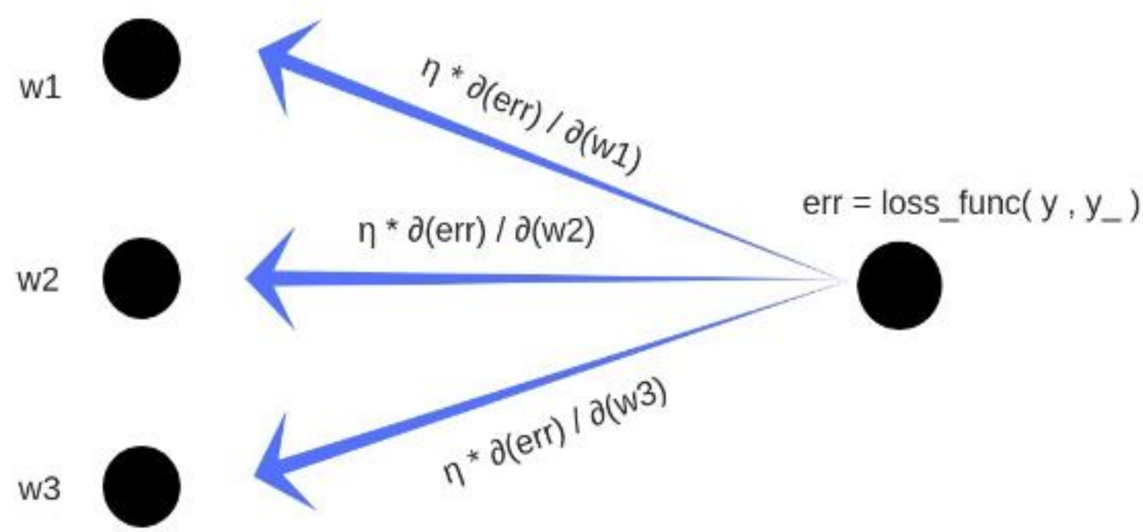


Fig 4.8 Back Propagation model

In Back Propagation model, total error is calculated by calculating the difference between the desired output and the actual output. After that, the partial derivative of error is calculated with respect to each weight. Then the differentials we calculated are multiplied by a number called learning rate (η). Its value lies in between 0 and 1. Then the resultant we get after multiplication is subtracted from the respective weights. That provides us the final results of back propagation model:

- weight1 = weight1 - (η * ∂(error) / ∂(weight1))
- weight2 = weight2 - (η * ∂(error) / ∂(weight2))
- weight3 = weight3 - (η * ∂(error) / ∂(weight3))

The Back propagation model finds the minimum value of the error using a technique called as delta rule or gradient descent method. After that, the weights that will minimize the value of error is considered to be a solution of the learning problem. We can define Gradient descent as an optimization algorithm which is used to minimize a function by iteratively moving in direction of local minima as per the calculation of the negative of Gradient [16].

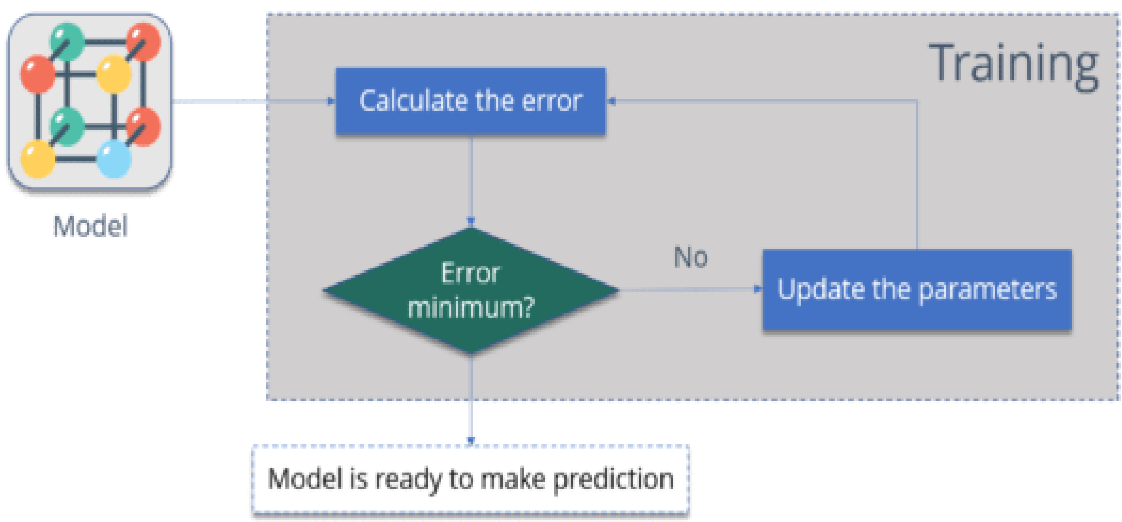


Fig 4.9 Back Propagation concept

4.12 Types of Neural Network

There are mainly two types of Neural Network which are listed below:

4.12.1 Single layer Perceptron

Simple layer Perceptron is a simplest kind of feed forward neural network. It does not consist of any hidden layer, which means it has only consists one layer. We call it a single layer because when we count the layers we don't include the input layer. The reason behind this is at the input layer no computations are done. The inputs are basically fed directly to the input layer via a user and then it transfers it to output layer via a series of weights.

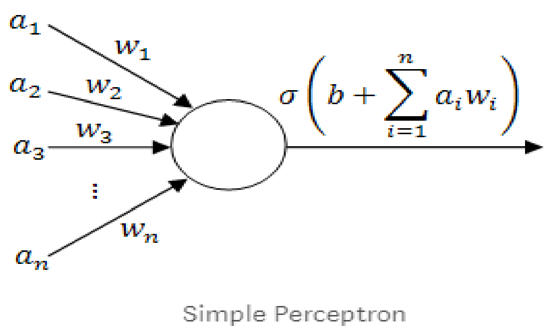


Fig 4.10 Single Layer Perceptron

4.12.2 Multi layer Perceptron

Multiple layer perceptron consists of multiple layers of computational units, which are all interconnected in a feed-forward path. Each neuron of a layer is interconnected with the neurons of the subsequent layers. Most of the time, Multi layer perceptron apply a sigmoidal function as an activation function. Multi layer perceptron are very useful in the real world as they are able to learn non-linear representations [16].

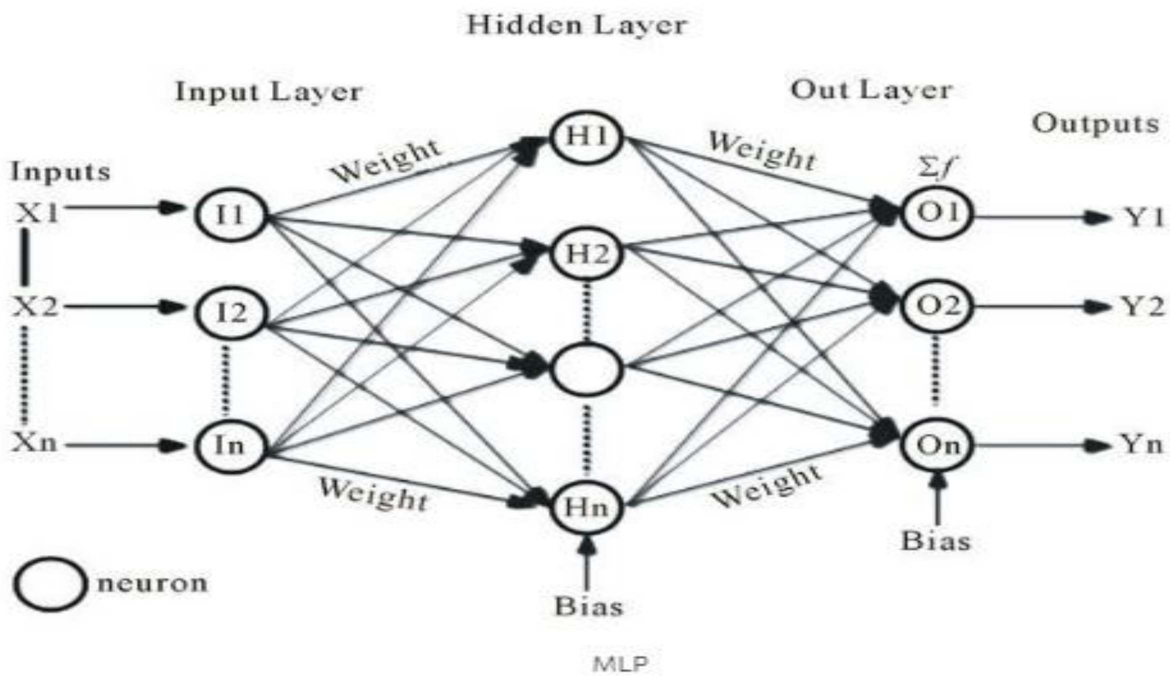


Fig 4.11 Multi Layer Perceptron

4.13 Training of Neural Network

As we have already gone through the theory of the Neural Network, now we will discuss about how we have trained our data using Neural Network.

We have prepared data of 40 samples which comprises of normal sound and abnormal sound which contains respiratory diseases Pertussis and Bronchitis

We have extracted two features:

1. Concentration measure
2. Dominant frequency

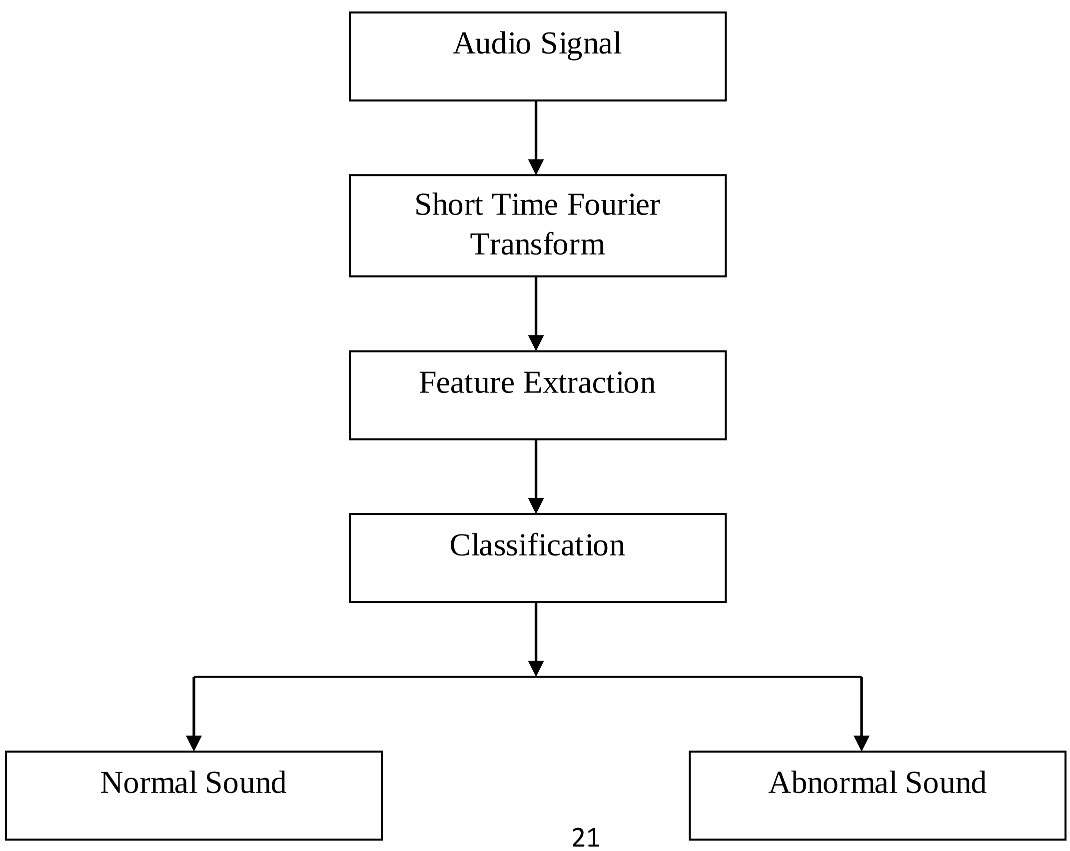
On the basis of extracted feature we will classify the samples into normal and abnormal sound. Further we are classifying the abnormal sounds into Pertusiss and Bronchitis.

4.13.1 Network Design

- Tool :- Pattern - Recognition Tool
- Input layer :-1
- Output Layer :- 1
- Hidden Layers :- 10
- Training Network – Scaled Conjugate Gradient Propagation
- Choice of Input Integration: Summed, Multiplied, Squared and Summed.
- Choice of Activation function: Sigmoid, Hyperbolic tangent, Gaussian and Linear.
- Divide the data in following format.
  - ➢ Training set- 70%
  - ➢ Validation set and Testing data- 15% & 15%
- Learning Rate: Typically 0.1 and range lies from 0.01-0.99.

4.14 Proposed algorithm

In this section, we have proposed an algorithm for the respiratory disease diagnosis using time-frequency based methods.



1. **Audio Signal:** We are plotting the time domain signals of normal sound, abnormal sound, pertussis and bronchitis. All the four time domain signals are listed below:

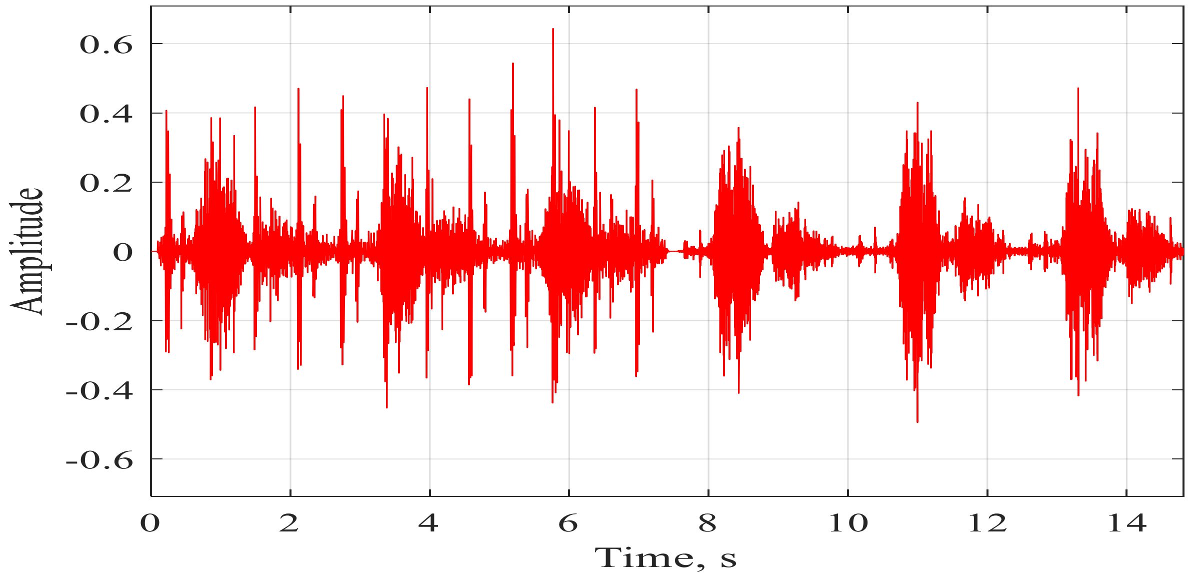


Fig 4.12 Normal Sound time domain signal

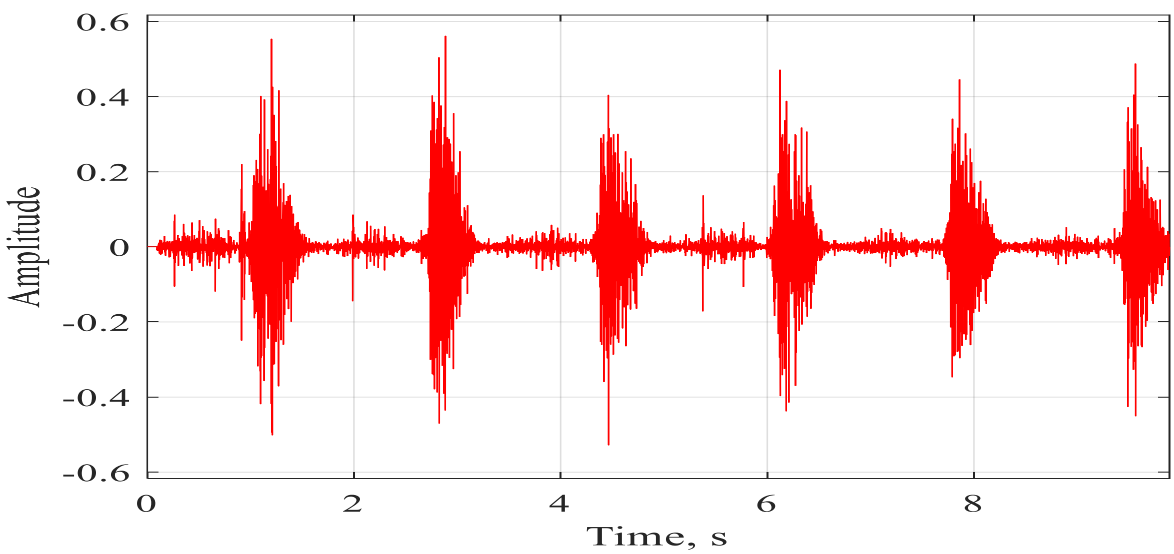


Fig 4.13 Abnormal Sound time domain signal

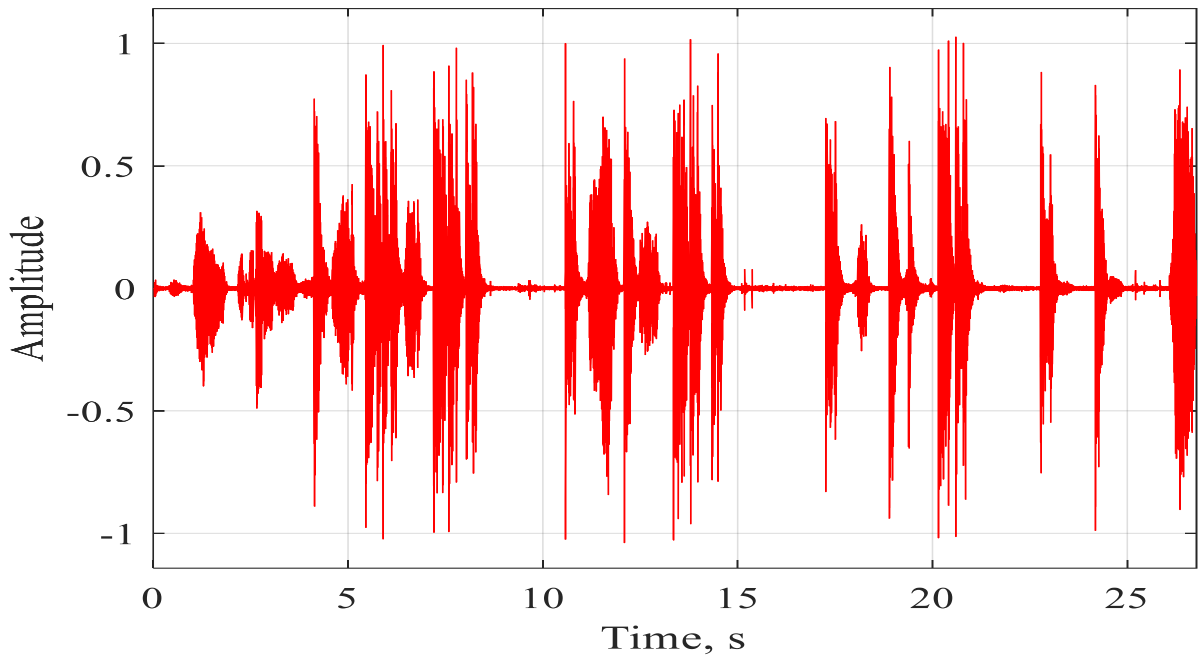


Fig 4.14 Pertussis time domain signal

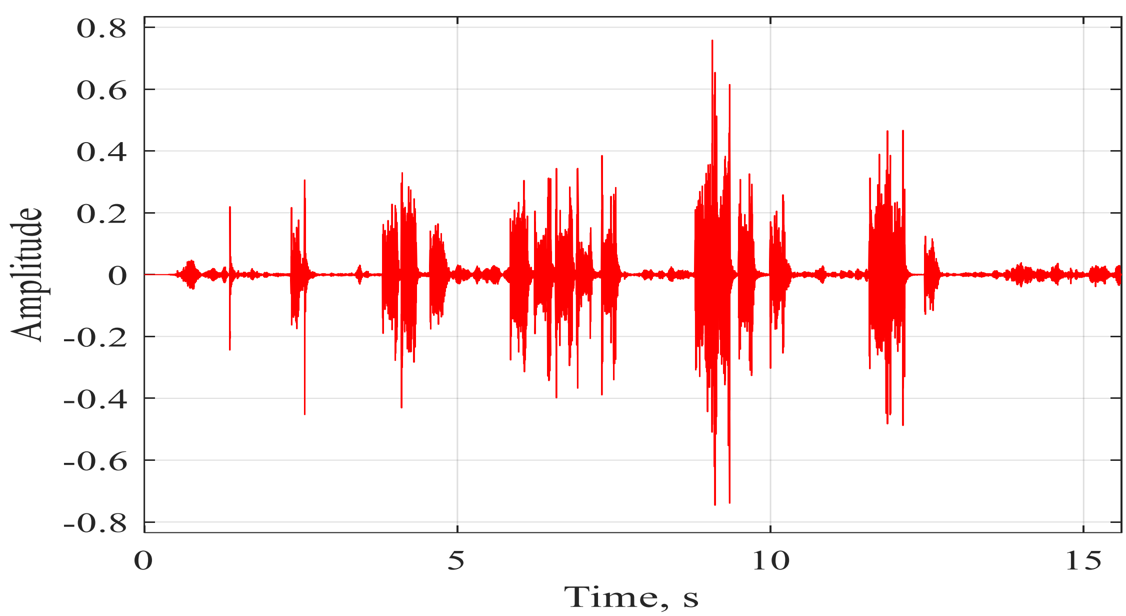


Fig 4.15 Bronchitis time domain signal

2. Short time Fourier Transform: After plotting the signals in time domain, we are plotting its Short-time Fourier Transform. All the four Spectrograms are listed below:

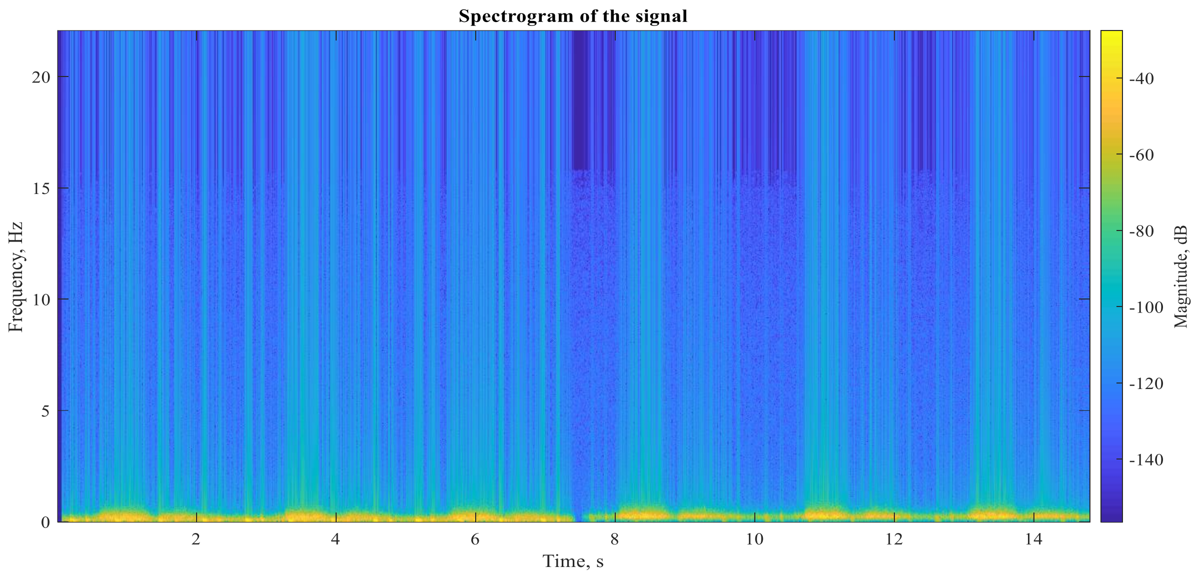


Fig 4.16 Spectrogram of Normal sound

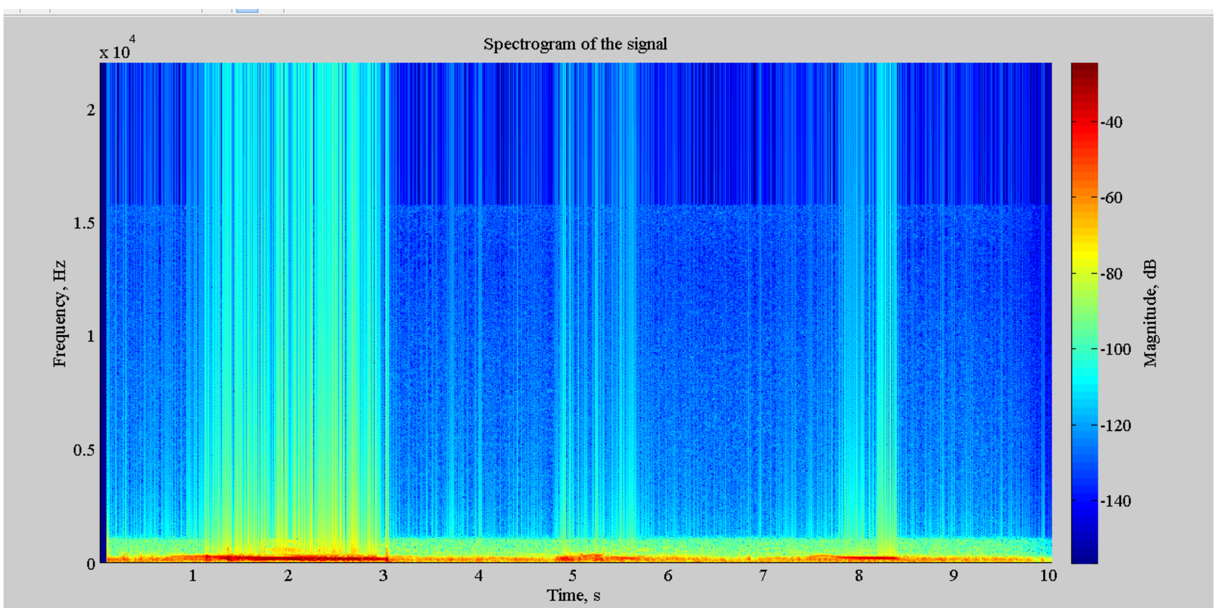


Fig 4.17 Spectrogram of Abnormal sound

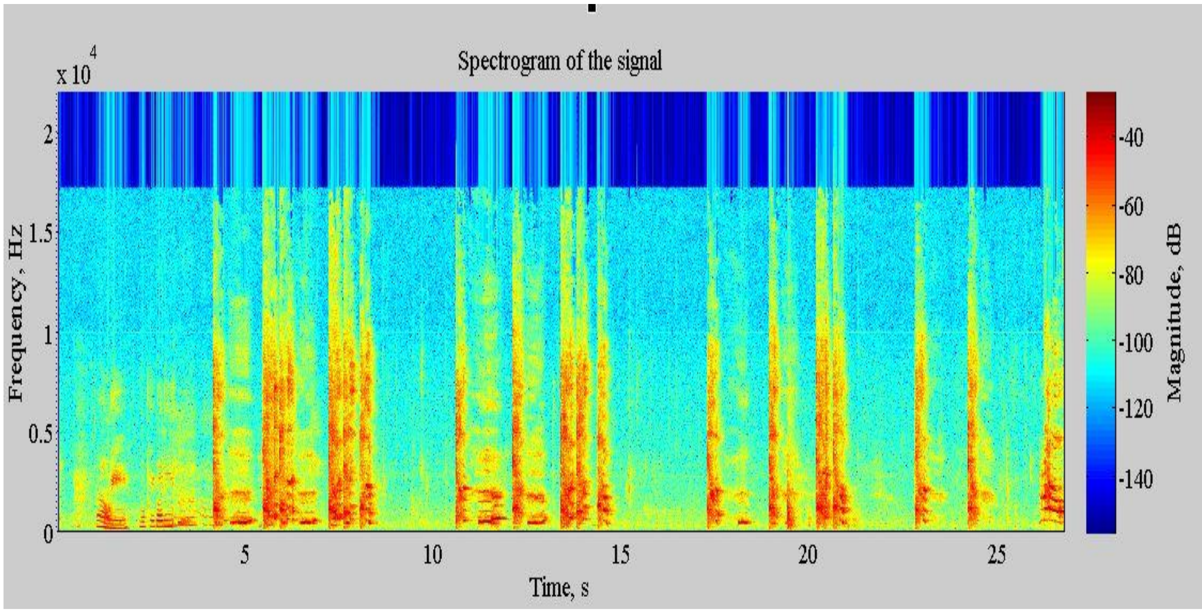


Fig 4.18 Spectrogram of Pertussis

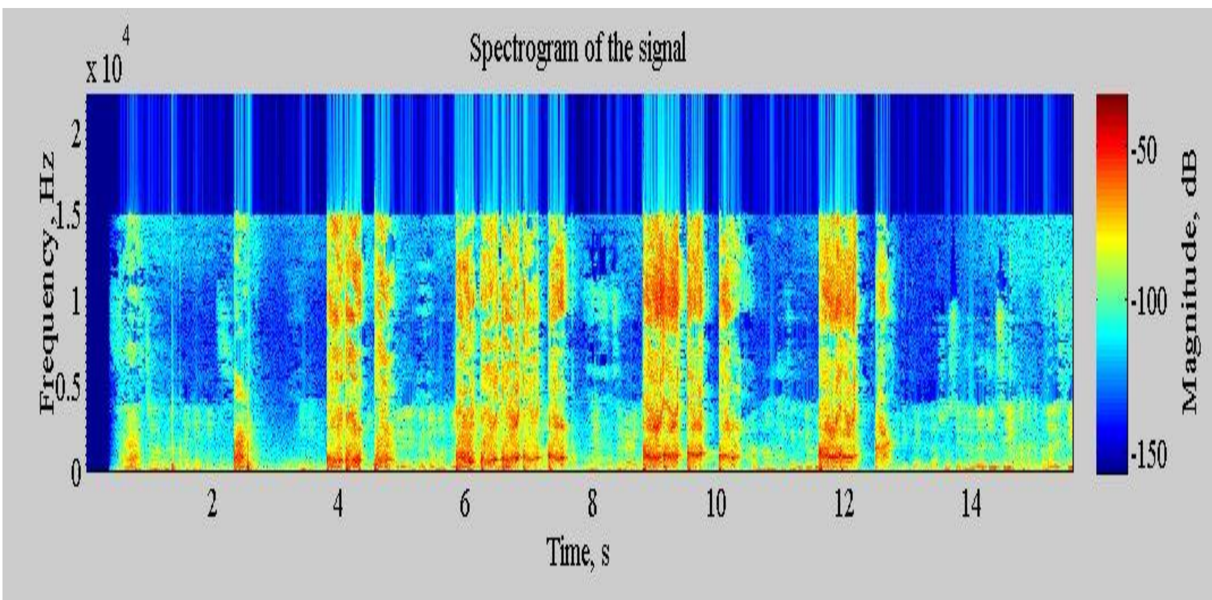


Fig 4.19 Spectrogram of Bronchitis

3. Feature Extraction: After plotting its spectrogram, we are extracting two features mainly: Concentration Measure and Dominant Frequency. All the four dominant frequency plots are listed below:

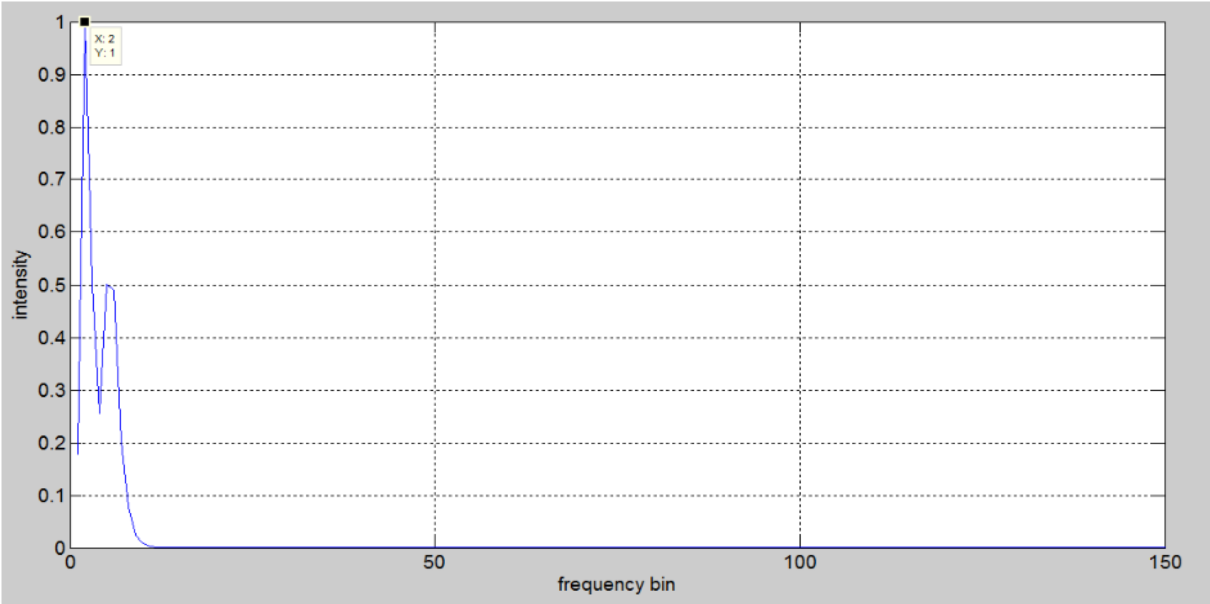


Fig 4.20 Dominant Frequency plot for Normal sound

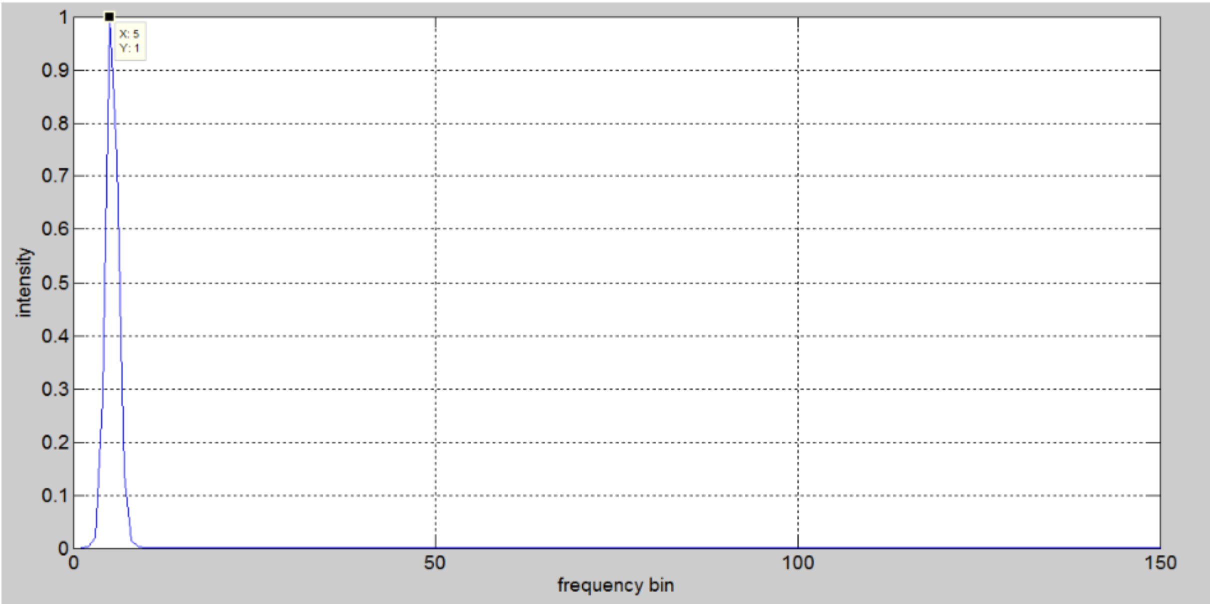


Fig 4.21 Dominant Frequency plot for abnormal sound

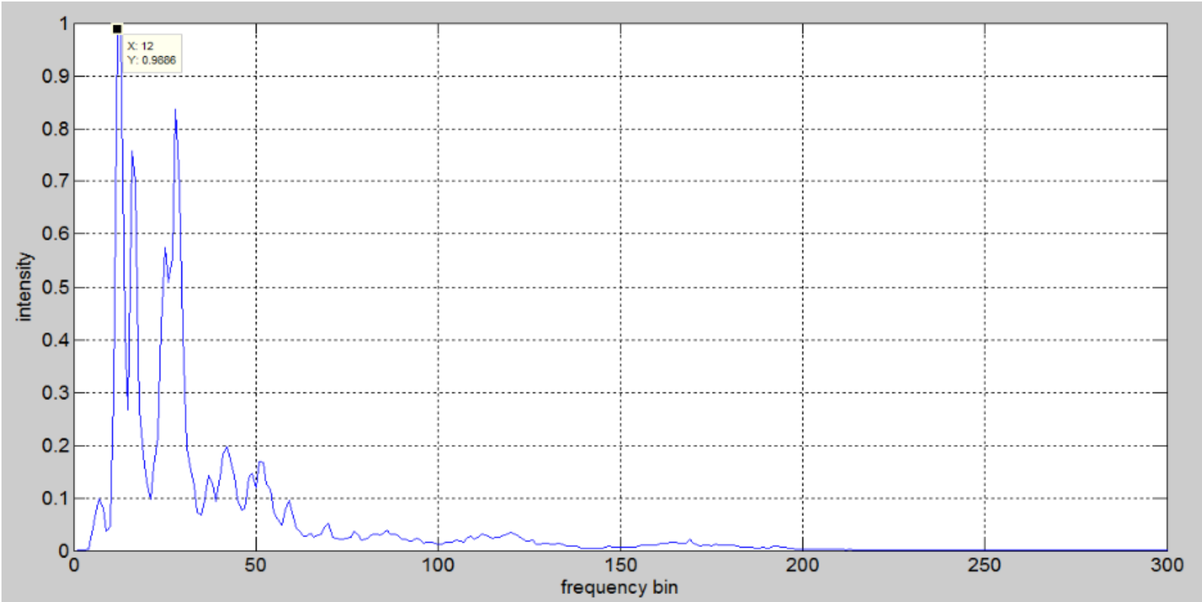


Fig 4.22 Dominant Frequency plot for Pertussis

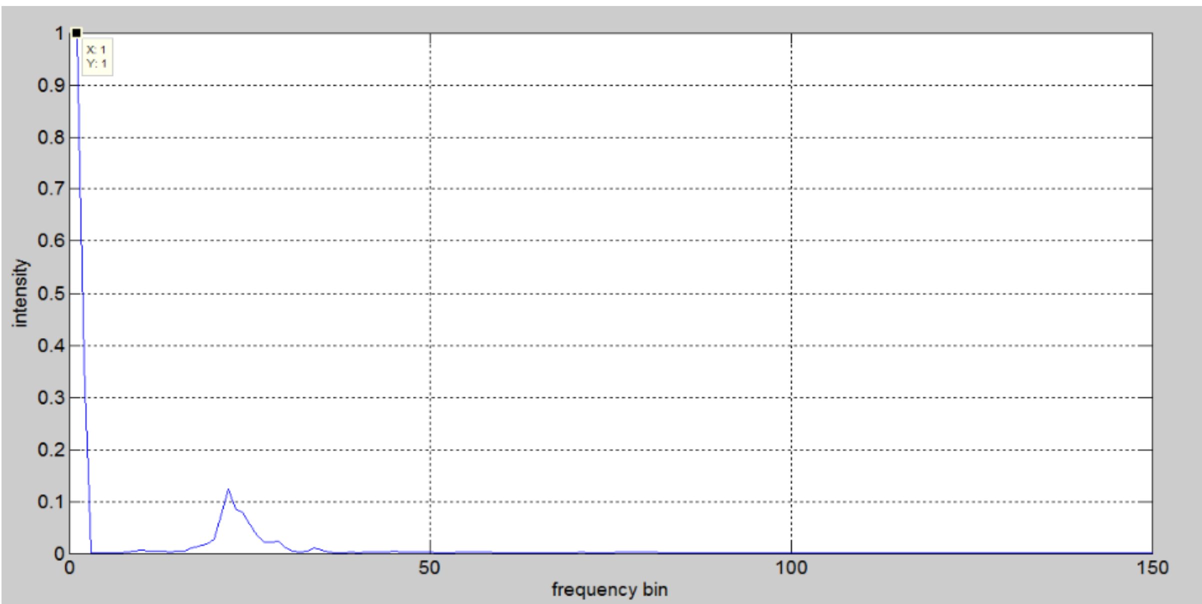


Fig 4.23 Dominant Frequency plot for Bronchitis

Table 4.1 Classification between Normal and Abnormal Sound

	Concentration measure	**Dominant Frequency (Hz)**	**Class**
Sample 1	0.0121	86.1238	1
Sample 2	0.011	81.3	1
Sample 3	0.012	89.78	1

Sample 4	0.0107	94.78	1
Sample 5	0.0117	80.245	1
Sample 6	0.0133	91.67	1
Sample 7	0.013	100.34	1
Sample 8	0.012	80.9	1
Sample 9	0.0129	103.678	1
Sample 10	0.0115	78.1238	1
Sample 11	0.0119	110.4	1
Sample 12	0.0128	88.657	1
Sample 13	0.0138	93.65	1
Sample 14	0.0109	115.67	1
Sample 15	0.0112	119.345	1
Sample 16	0.0114	99.56	1
Sample 17	0.0116	79.56	1
Sample 18	0.0138	85.123	1
Sample 19	0.0155	111.345	1
Sample 20	0.0133	93.56	1
Sample 21	0.011	87.345	1
Sample 1	0.0107	344.5313	2
Sample 2	0.011	233.45	2
Sample 3	0.0107	86.1328	2
Sample 4	0.0109	245.788	2
Sample 5	0.017	215.332	2
Sample 6	0.02	199.78	2
Sample 7	0.0137	129.112	2
Sample 8	0.028	301.34	2
Sample 9	0.0204	215.332	2
Sample 10	0.03	99.345	2
Sample 11	0.056	119.5	2
Sample 12	0.09	186.56	2
Sample 13	0.07	213.65	2
Sample 14	0.012	254.765	2
Sample 15	0.043	184.65	2
Sample 16	0.0543	158.21	2
Sample 17	0.0204	209.45	2
Sample 18	0.0135	313.654	2
Sample 19	0.045	123.55	2
Sample 20	0.034	300.98	2
Sample 21	0.0105	287.54	2
		Class 1 --- Normal Sound	
		Class 2 --- Abnormal Sound	

Table 4.2 Classification between Pertussis and Bronchitis

	Concentration measure	Dominant Frequency (Hz)	Class
Sample 1	0.0035	559.868	1
Sample 2	0.0039	560.954	1
Sample 3	0.0047	775.1953	1
Sample 4	0.004	498.54	1
Sample 5	0.0099	775.195	1
Sample 6	0.01	654.67	1
Sample 7	0.0041	645.9961	1
Sample 8	0.005	543.234	1
Sample 9	0.0053	538.33	1
Sample 10	0.0034	654.32	1
Sample 11	0.0065	698.654	1
Sample 12	0.0078	733.54	1
Sample 13	0.0023	754.345	1
Sample 14	0.0078	799.459	1
Sample 15	0.0036	589.55	1
Sample 16	0.0033	800.455	1
Sample 17	0.0087	899.54	1
Sample 18	0.0022	703.54	1
Sample 19	0.0033	1003.2	1
Sample 20	0.0041	698.432	1
Sample 21	0.0056	567.32	1
Sample 1	0.0033	775.1953	2
Sample 2	0.0039	789.432	2
Sample 3	0.0064	1076.78	2
Sample 4	0.0043	987.43	2
Sample 5	0.0039	904.3945	2
Sample 6	0.0055	987.432	2
Sample 7	0.0047	947.46	2
Sample 8	0.0087	1044.43	2
Sample 9	0.0041	990.5273	2
Sample 10	0.0068	967.54	2
Sample 11	0.0076	1100.543	2
Sample 12	0.0033	899.65	2
Sample 13	0.0087	940.524	2
Sample 14	0.0099	1205.43	2
Sample 15	0.0043	1299.543	2
Sample 16	0.0065	999.43	2
Sample 17	0.0078	1009.496	2
Sample 18	0.0089	785.74	2
Sample 19	0.0021	846.654	2
Sample 20	0.0029	879.43	2

Sample 21	0.0012	1309.54	2
		Class 1 --- Pertussis	
		Class 2 --- Bronchitis	

4.15 Classification Results

We have classified our data using Artificial Neural Network and we are attaching the confusion matrix of the classified data. A confusion matrix can be defined as a table which is used to describe the performance of a classification model running on a set of test data for which the true values of data is known i.e. Supervised Learning.

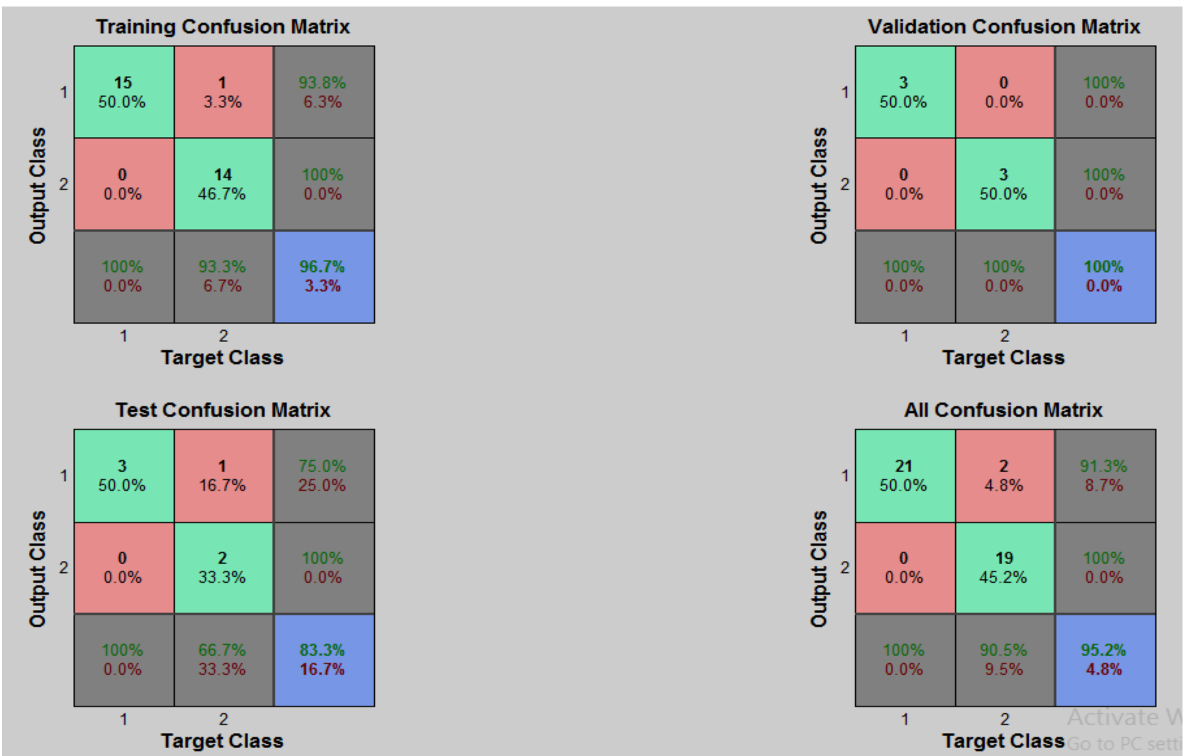


Fig 4.24 Confusion matrix for normal and abnormal sound

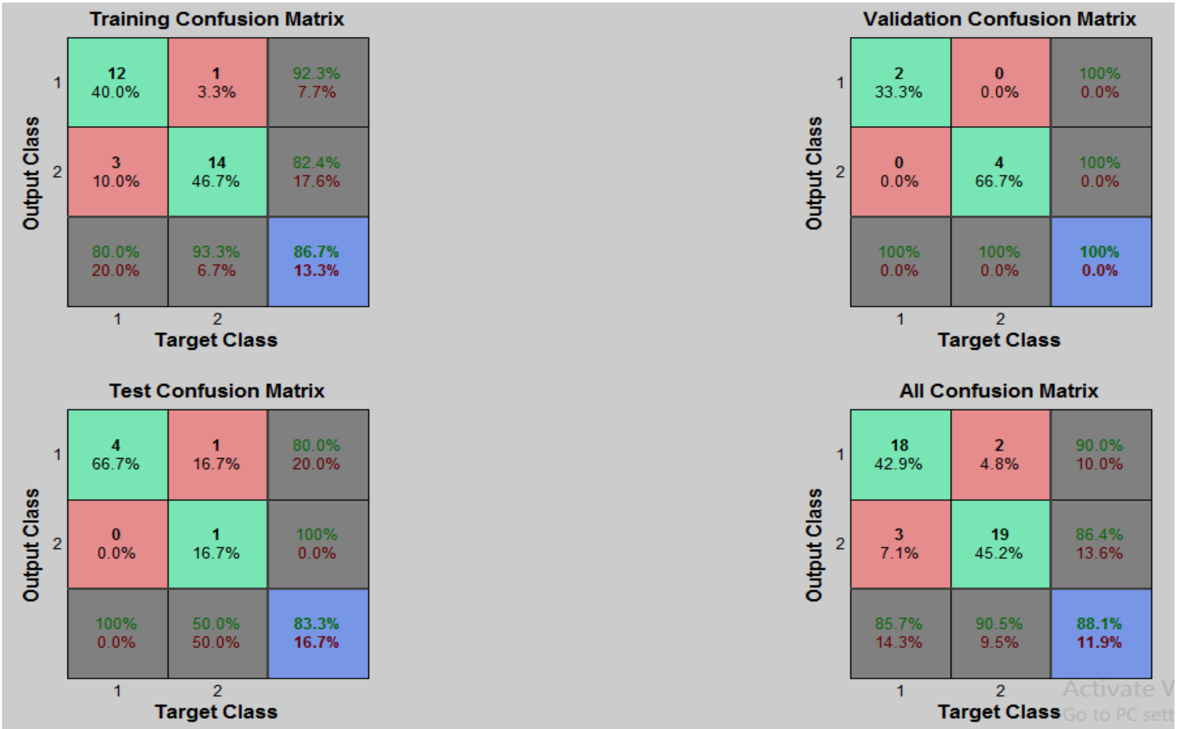


Fig 4.25 Confusion matrix for pertussis and bronchitis

4.16 Performance Evaluation

1) Sensitivity= It represents the percentage of correctly classified cases.

   Sensitivity= TP/ (TP+FN)

2) Specificity = It represents the percentage of false cases which are being correctly rejected.

   Specificity= TN/ (TN+FP)

3) Accuracy = It tells about the how often the results are being classified as correct.

   Accuracy= TP+ TN/ (TP+TN+FP+FN)

4) Positive Predicted Value (PPV) = It represents the Proportion of Positive results that are correctly detected.

   PPV= TP/ (TP+FP)

5) Negative Predicted Value (NPV) = It represents the Proportion of negative results that are correctly rejected.

NPV= TN/ (TN+FN)

Where TP=True Positives, TN= True Negatives, FP= False Positives, FN= False Negatives

Table 4.3 Results for Normal and Abnormal sound

Normal & Abnormal	Sensitivity	Specificity	Accuracy	PPV	NPV
	91.3%	8.7%	95.2%	100%	90.5%

Table 4.4 Results for Pertussis and Bronchitis

Pertussis & Bronchitis	Sensitivity	Specificity	Accuracy	PPV	NPV
	90%	10%	88.1%	85.7%	90.5%

CONCLUSION

In this project, time frequency analysis based method for the diagnosis of respiratory diseases has been developed. In this method, two features Concentration Measure and Dominant Frequency of spectrogram have been used to train the Neural Networks for the classification. The performance of the method has been tested on the normal and abnormal respiratory sounds. The accuracy of the proposed methods is 95.2%, and sensitivity is 91.3% for the classification of normal and abnormal sound where as accuracy and sensitivity for detection of pertussis and bronchitis is 88.1% and 90% respectively. In future, the performance of the proposed method may be compared with the reported respiratory disease diagnosis methods.

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APPENDIX A

Table A.1: List of data sources

No.	Source Link	Type	Age	Length(s)
1	https://www.youtube.com/watch?v = l-sNgKgAucI	Pertussis	Infant	32
2	https://workspace.imperial.ac.uk/rodriguez-villegas- ıblic/whooping-cough/TR2.mp3	Pertussis	Infant	10
3	https://www.youtube.com/watch?v=TIV460AQUWk	Pertussis	Infant	139
4	https://www.youtube.com/watch?v = wuvn-vp5InE	Pertussis	Infant	10
5	www.whoopingcough.net/cough-child-muchwhooping.wav	Pertussis	Child	26
6	www.whoopingcough.net/paroxysm.wav	Pertussis	Child	35
7	https://www.youtube.com/watch?v=Rmlo2to0ogs	Pertussis	Child	72
8	http://streaming.cdc.gov/vod.php?id=7ffe0c683b0dc2765090991b8f801	Pertussis	Child	15
9	https://www.youtube.com/watch?v=Ro7HfT8oM8k	Bronchitis	Child	13
10	https://www.youtube.com/watch?v=8HWwSi1h0pw	Bronchitis	Child	20
11	https://www.youtube.com/watch?v = pAHDqQRDPCk	Bronchitis	Infant	73
12	https://www.youtube.com/watch?v=RFwr_zbgJII	Bronchitis	Infant	61
13	https://www.youtube.com/watch?v=AIVt3e5EVtc	Pertussis	Child	86
14	https://www.youtube.com/watch?v=KZV4IAHbC48	Pertussis	Child	51
15	www.whoopingcough.net/whoop-child-slightwhoop.wav	Pertussis	Child	16
16	www.whoopingcough.net/wc-adult.wav	Pertussis	Adult	21
17	www.whoopingcough.net/images/whooping%20cough%2030%20	Pertussis	Child	30
18	www.whoopingcough.net/images/videochildwhoop3.wmv	Pertussis	Child	92
19	https://www.youtube.com/watch?v=VX98aiYpmW4	Pertussis	Infant	106
20	https://www.youtube.com/watch?v = yv4GUrI0Cw4	Pertussis	Child	37
21	https://www.youtube.com/watch?v = zuK4honWVsE	Pertussis	Infant	26
22	https://www.youtube.com/watch?v=PFNvGqw9HKY	Pertussis	Child	13
23	https://www.youtube.com/watch?v=3eJQAdkW1Aw	Bronchitis	Child	62
24	https://www.youtube.com/watch?v = iQit0aZ_Sbg	Bronchitis	Child	15
25	https://www.youtube.com/watch?v = fWUoarRzAwY	Bronchitis	Child	42
26	https://www.youtube.com/watch?v = gus1GHeS7IE	Bronchitis	Infant	16
27	https://www.youtube.com/watch?v=IYllzXfvkmY	Bronchitis	Infant	53
28	https://www.youtube.com/watch?v=IE_6K-ZfI64	Bronchitis	Infant	39
29	https://www.youtube.com/watch?v=5kAWlNZ-I_I	Bronchitis	Infant	44
30	https://www.youtube.com/watch?v=SsxsiISkLZA	Bronchitis	Infant	15