ASTHMA DISEASE DIAGNOSIS BY USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Asthma is a common chronic inflammatory disease of the airways characterized by variable and recurring symptoms, reversible airflow obstruction and bronchospasm. Such diseases have been so far predicted by pulmonologists upon performing bed examination and spirometers; analog or digital and or even conventional. This research and the proposed system in this work are based on Artificial Neural Network analysis that uses the back-propagation methodology as the justification method of the asthma presence in patients and later on to classify its severity. For this reason, seven attributes that are medically-thought related to patients with asthma are presently considered such as height, age, Forced Vital Capacity (FVC), Forced Expiratory Volume in 1 second (FEV1), ratio between FEV1 and FVC, frequency range and dose of steroids. Those parameters are then used as inputs into an artificial neural network function as said earlier that precisely conclude the stage of the disease.

Keywords—component: Asthma, Artificial Neural Network

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CHAPTER 1
INTRODUCTION

Medical research has shown that heredity and genetic facts play a vital role in the reason of being diagnosed with a specific disease. However, our daily life style has been affecting our health and increasing the negative outcome upon our body.

Respiratory diseases are spreading widely among the population due to both heredity and life style conditions. Asthma in particular is a chronic and diseases of allergic identified by using the spirometer device; this device measures the air flow of expiration, which allows us to collect sufficient data to detect respiratory diseases such as Asthma, Pneumonia and pulmonary embolism. The aim of this project is the development of an intelligent system based on the neural network algorithm in order to help pre-existing and predict Asthma, by using the data collected from different human conditions.

1.1 Contribution of The Proposed Project

This work is just detection research byusing computer aid techniques. However, this project provides different additional methods and techniques to reach the desired purpose which is to classify it into three main classes: normal, mild and severe Asthma. This is done by using classified neural network.

1.2 Aim of This Project

Asthma is a chronic disease that should be analyzed and detected in early phases. Thus, the aim of this project is to develop a new approach for the identification of the asthma through artificial neural network classifier. Thusall patients' cases must be classified aseither normal, mild or severe. The proposed system collects true and unaltered data of real asthma cases extractedfrom database consists of 76 patients for training and 74 patients for testing phase.

1.3 Project Overview

This project is divided into five chapters, which are structured as follows.

Chapter 1 is an introduction about the project definition. In this chapter the aims contributions and motivations are set. Moreover, we discuss the structure of the project methodology.

Chapter 2 introduces the disease nature and definition, in addition to the causes and the symptoms of the disease.

Chapter 3 examines the classification phase of the proposed system. This phase depends on artificial neural network classifier. In this part we define neural network and clarify its concept in addition to the back-propagation learning algorithm that is used in our system. In this chapter, the training results of the system using tables, figuresand curves such as the learning curves are provided. The system performance and theexperimental results are also discussed in this chapter through tables and figures.

Chapter 4 contains the results and the discussion of this project.

Chapter 5 includes the project management where the duration of each task is explained, in addition to the budget needed.

Chapter 6 is a conclusion of the whole work and some highlighted recommendations in addition to the difficulties faced in this project.

CHAPTER 2
SIGNS, SYMPTOMS AND CAUSES OF ASTHMA

2.1 Asthma

Asthma is a chronic disease that attacks the lungs causing an inflammation that narrows its airways. It often occurs during childhood, however it affects all ages; based on statistics done in the United States of America, more than 25 million people suffer from Asthma and 7 million of those are known to be children.

The lungs consist of airway tubes that carry the air into and out of it. These airways get inflamed once infected with Asthma, which results in swollen of these arteries and difficulty in respiration with sensitivity to any inhaled substance.

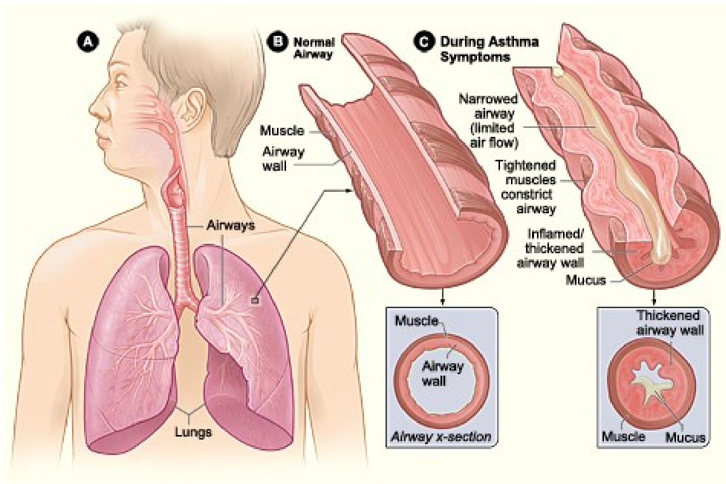


Figure 1: Lungs Anatomy (The asthma epidemic, 2006)

Figure A shows the location of the lungs and airways in the body. Figure B shows a cross-section of a normal airway. Figure C shows a cross-section of an airway during asthma symptoms.

2.2 Symptoms of Asthma

The symptoms vary between mild and severe depending on the case of each patient. However, some symptoms may persist and some may fade away using minimal treatment with Asthma medicine.

The main symptoms are the followings:

- Chest tightness, which is feeling the heaviness that squeezes on the chest.
- Shortness of breath, the airways blocks the air going into the lungs.
- Wheezing, it is the squeaky sound during breathing.
- Coughing, it gets worst at night or early morning which results in sleeping difficulties.

These symptoms do not necessarily assure that a patient has Asthma, medical procedures and tests must be made to have a certain diagnosis.

Asthma has no cure; it is a life time condition. However, with medical improvements Asthmatic patients are able to manage an almost normal lifestyle, including exercising, sleeping without breathing difficulties and maintaining an active life(Eder et al.,2006).

2.3 Causes of Asthma

There is no definite cause of Asthma and it has not been discovered yet. Research links some genetic and environmental condition factors that increase the risk of getting Asthma, especially in early life.

2.3.1 Genetic Conditions:

Genetics are major causes that develop Asthma. If one or both parents have asthma, the child might develop the condition; this is known as genetic susceptibility (Martinez et al., 1995).

2.3.2 Environmental Conditions:

Studies have shown that Asthma starts at early age. Even if it is diagnosed in the adulthood, environmental conditions emphasize the risk of being an asthmatic person. Some of the most common triggers include:

- Substances that cause allergies (allergens) such as dust mites, pollens, molds etc… The same substances that cause allergy may also trigger asthma.

- Irritants in the air including cigarettes smokes, wood fires, household sprays, perfumes etc… People nowadays are aware that smoking causes Cancer and heart disease but they still don't know that smoking is an important risk factor that causes asthma for children and a common trigger of asthma symptoms for all ages.
- Exercise and other activities especially in cold air are triggers of asthma. They are induced by physical activities that make the patient breathe harder.

Reactions to Asthma factors vary from patient to another. Some have asthma because they are exposed to more than one factor at a time. Others have severe asthma because they respond to multiple factors or triggers (Chatzimichail et al., 2010).

CHAPTER 3
NEURAL NETWORK CLASSIFICATION

3.1 Overview

This chapter discusses the theory of the artificial neural network. It introduces the history of the neural network and the different development stages of artificial neural network structure. The similarities between artificial neural network and biological brain are presented in this chapter. The structure and construction of the basic neural network is presented and its elements are discussed. The next part of this chapter discusses the back propagation learning method and presents it. Finally, different theoretical and practical functions of the artificial neural network are presented.

3.2 Introduction

Artificial neural networks are the simple simulation of the structure and the function of the biological brain. The complex and accurate structure of the brain makes it able to do hard different and simultaneous tasks using a very huge number of biological neurons connected together in grids. A first wave of interest in neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational tasks. At that time, Von Neumann and Turing discussed interesting aspects of statistical and robust nature of brain-like information processing. But it was only in 1950s that actual hardware implementations of such networks began to be produced. Artificial neural networks are used widely nowadays in different branches of science:

a- In the medical field by (Khashman, 1999 and 2000).
b- In image processing for different purposes by (Khashman et al., 2007).
c- Inpower and power quality applications such as active power filters (Valiviita, 1998) and (Sallam et al, 2002).
d- Inforecasting financial market prices, financial crises, and stock prediction by (Yuhong et al, 2010).

The above applications of neural networks imply firstly the learning of the artificial neural networks to do defined tasks. One of the most common methods of teaching artificial neural networks to perform given tasks is the back propagation algorithm. It is based on a multistage dynamic system optimization method originally proposed by Arthur E. Bryson and Yu-Chi Hoin 1969. In 1974, it was applied in the context of artificial neural networks through the works of Paul Werbos, David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams, and it became famous and led to a renaissance in the field of artificial neural networks (Yuhong et al., 2010)(Specht et al., 1991).

3.3 History of Artificial Neural Networks

The first real model of the theory of brain and artificial neural networks was suggested by the studies of McCuloch and Pitts (1943), Hebb (1949), and Rosenblatt (1958). McCulloch and Pitts wrote a research paper on how neurons might work. They tried to describe how human's brain is working and built an electrical circuit explaining their idea. Hebb presented the fact that neural connections are strengthened when they are used, that is the ways in which humans learn. If two nerves fire at the same time, the connection between them will be enhanced. The first model of neural networks was presented in these studies as a "computing machine", "the basic model of network self-organization", and "learning with a teacher" model respectively.

Widraw and Hoff developed two models called adaptive linear elements abbreviated ADALINE and multiple ADALINES or MADALINES in 1959. ADALINES were used for binary patterns while MADALINES were the first real world application of neural networks. In 1962 they proposed a learning method where the values are being tested before the weights adjustment.

Kohonen and Anderson proposed a similar system independently of one another in 1972. They used matrix mathematics to describe their ideas creating an array of analog ADALINE circuits. The neurons are supposed to activate a set of outputs instead of just one output.

After these works, it was until 1982 when the works on artificial neural networks were resumed again in the studies of Hopfield. He tried to create useful mechanisms by using bidirectional lines of connections. In 1986, three research groups proposed similar ideas to that of Hopfield. The so called back propagation algorithm using extended Widrow-Hoff rules with multiple layers. The name back propagation was used for the fact that it's propagating the error back through layers. The main drawback of the back propagation algorithm was its slow learning speed. It needs thousands of repeated iterations before learning.

Nowadays, neural networks are used in different applications in many fields of sciences. The theory behind the development of the artificial neural network is that if it is able to work in real life, it can also work on digital computers. The future of neural networks is promising and depends on the development of hardware and processing units. The next few decades are expected to see a real expansion in the use of neural networks and extension of it in many real-time applications.

Artificial neural networks are software or hardware models inspired by the structure and behavior of biological neurons and the nervous system, but after this point of inspiration all resemblance to biological systems stops. Artificial neural networks are composed of many computing units popularly called neurons. The strength of the connection or link between two neurons is called the weights. The values of the weights are true parameters and the subjects of the learning procedure. These values can be adjusted by training to perform determined tasks (Charu, 2006).

3.4 Analogy to The Human Brain

The artificial neural networksare an imitation of the function of the human biological brain. It's using the structure and the function of brain. The human brain is composed of billions of interconnected neurons. Each one of these neurons is said to be connected to more than 10000 neighbor neurons. Figure 2 shows a small snip portion of the human brain where the yellow blotches are the body of the neural cells. The connecting lines are the dendrites and axons that connect between the cells. The dendrites receive the electrochemical signals from the other cells and transmit it to the body of the cell. If the signals received are powerful enough to fire the neuron; the neuron will transmit another signal through the axon to the neighbor neurons in the same way. The signal is going also to be received by the connected dendrites and can fire next neurons.

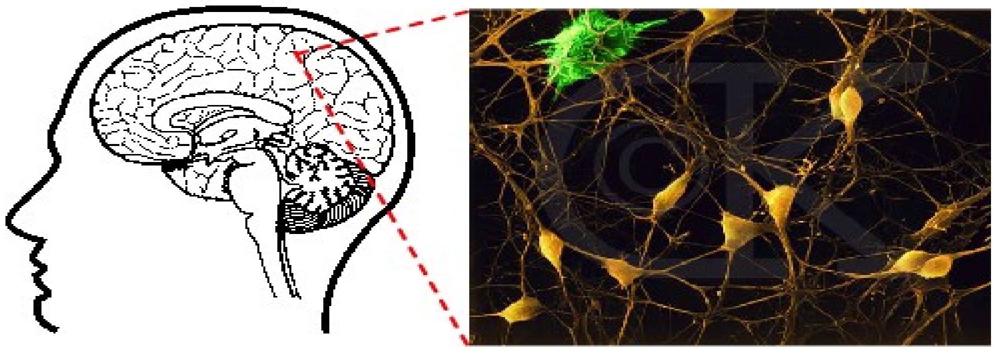


Figure 2: Inter-connections between biological neurons(Kaki, 2009)

The whole brain is composed of these billions of connections that can be activated or deactivated based on the received electrochemical signals. It is important to notice that a neuron is activated if the sum of the signals at its inputs is more than certain level. If that sum is less that the activation level, the neuron will not be able to fire and stay deactivated. Figure 2 shows the different parts of the biological neuron. As seen from the figure, each neuron is composed of five parts. These are the cell body, nucleus, dendrites, synapse, and axons. Dendrites are the parts related directly to the cell body (Soma). They receive signals from the synaptic junctions. Synapses are the connection points between two different neurons. They are responsible for transition of signal between neurons in two directions. The signals are chemically transmitted in the junction points. The potential in the synapses changes based on the chemical materials being transmitted between the neurons. The potential affects the body of the cell causing its activation if it is enough powerful (Nancy Y and Xiao, 2009).

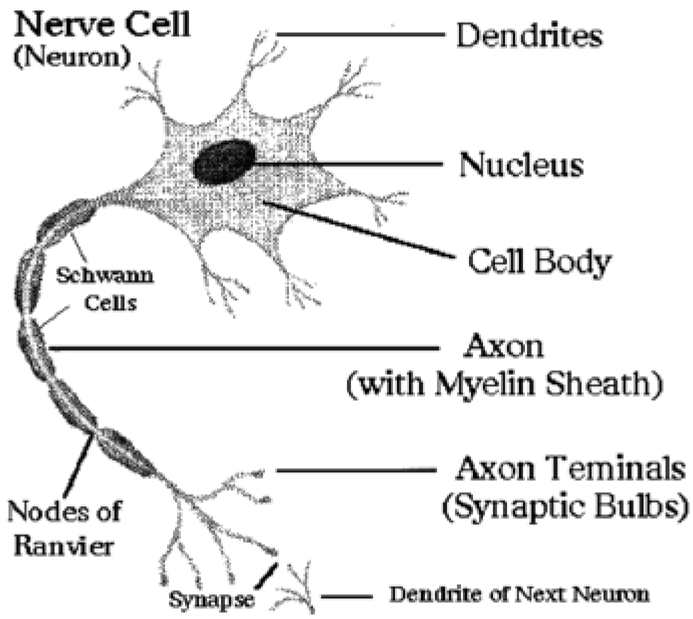
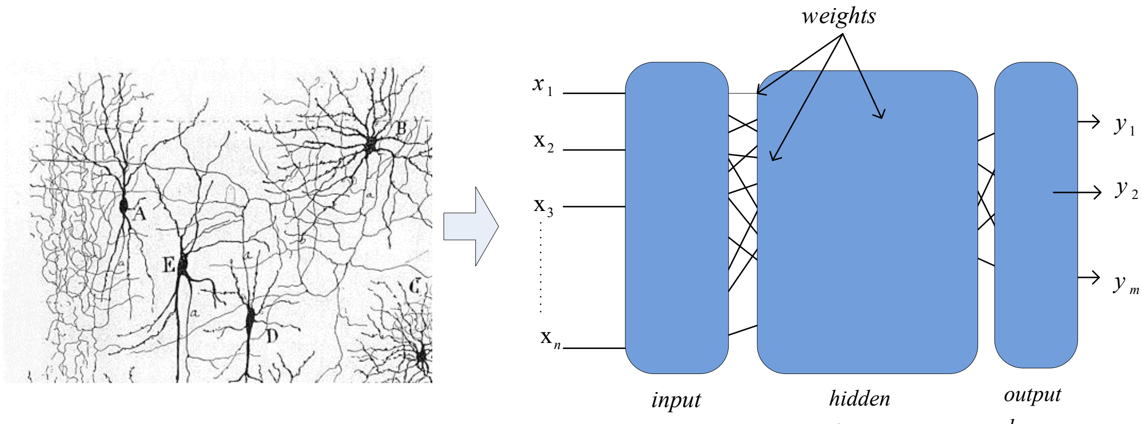


Figure 3: Structure of biological neuron (Kaki, 2009)

ANNs are based on the last described model of the biological neural networks. The ANNs still not close to modeling the complex structure of the brain, but they have proved to be efficient in problems that are done easily by humans but difficult for classical computers. An example of these applications is image recognition and prediction based on existing data. Figure-4 presents the relation and analogy between the human brain and the neural networks.



Biological neural networks.

Figure 4: Analogy between human brain and neural networks (kaki, 2009)

3.5 Artificial Neural Networks

ANNs are a structure that has inspired its origins from the human thinking center or the brain. This structure has been inspired and developed to build a mechanism that can solve difficult problems science. Most of the structures of neural networks are similar to the biological brain in the need for training before being able to do a required task. Similar to the principle of the human neuron, neural network computes the sum of all its inputs. If that sum is more than a determined level, the correspondent output can then be activated. Otherwise, the output is not passed to the activation function. Figure 5 presents the main structure of the ANN where we can see the inputs and weights in addition to the summation function and the activation function. The output function is the output of the neuron in this structure. The input of the activation function is given by:

$$TP = \sum x_n \omega_n \tag{0.1}$$

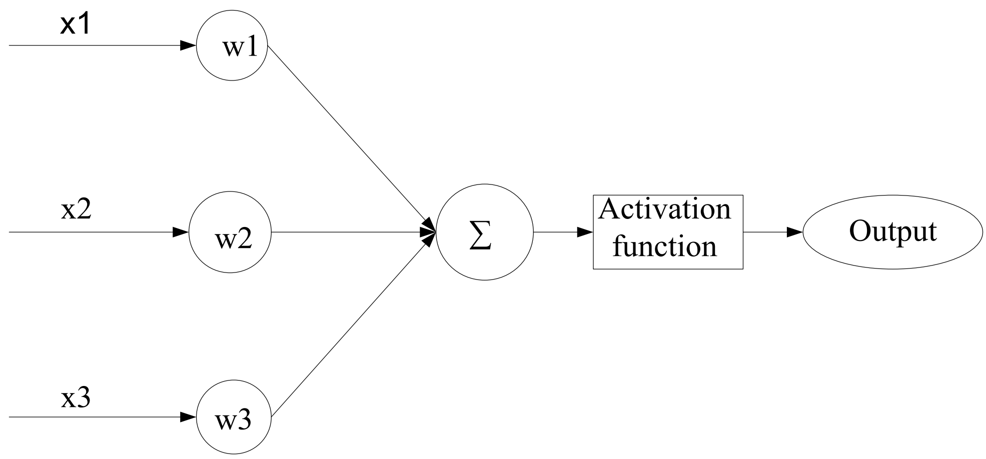


Figure 5: Basic Structure of artificial neural (Kaki, 2009)

3.5.1 Structure of ANN

The structure of artificial neural networks consists mainly of three aspects in addition to the learning method. These aspects are the layers, weights, and activation functions. Each one of these three parts plays a very important rule in the function of the artificial neural network. The learning function is the algorithm that relates these three parts together and ensures the correct function of the network.

3.5.2 Layers of ANN

Artificial neural network is constructed by creating connections between different layers to each other. Information is being passed between the layers through the synaptic weights. In a standard structure of artificial neural network there are three different types of layers:

1- Input layer: the input layer is the first one in a neural network. Its rule is the transmission of input information to the other layers. An input layer doesn't process the information; it can be considered as the sensors in biological system. It can also be called non-processing layers.
2- Output layer: The last layer in the neural network whose output is the output of the whole network. In contrary to the input layer, the output layer is a processing layer.
3- Hidden layers: this is the main part of the network. It consists of one or more of processing layers. They are connecting the input layers to the output layers. Hidden layers are the main processing layers where the weights are being updated

continuously. Each one of the hidden layers connects between two hidden layers or one hidden and input or output layer.

Figure 6 presents the layers of the neural network and the connections between the layers. As shown in the figure, the inputs are fed to the input layer. The output of the input layer is fed to the hidden layers. The output obtained from the hidden layers is fed to the output layer that generates the output of the network.

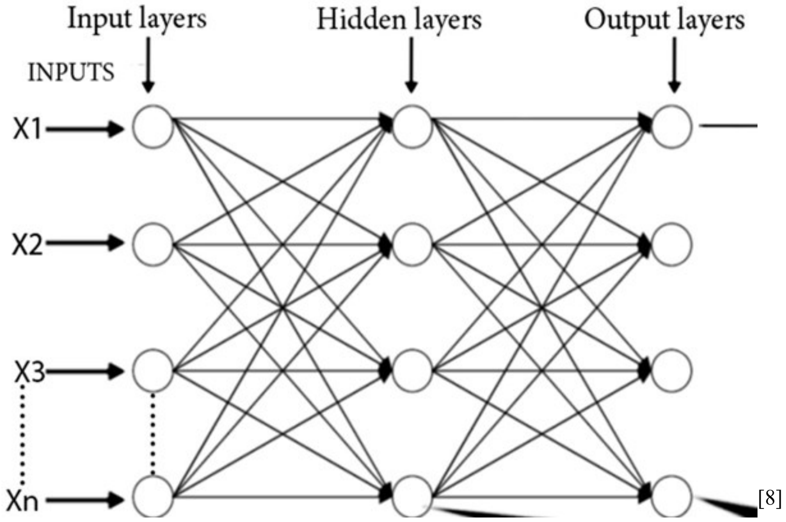


Figure 6: Layers structure in ANNs (Kaki, 2009)

3.5.3 Weights of ANN

The weights in an ANN represent the memory of that network in which all information is stocked. The values of the weights are updated continuously during the training of the network until the desired output is reached. The memory or weights are then stored to be used in future (Kiran. K, 2009).

3.5.4 Activation Functions or Transfer Functions

When the inputs are fed to the layers through the associated weights and finding the sum of them, an activation or transfer function is used to determine whether the output is to be activated or not. Or in some activation functions, the function is used to determine how much the processed input will share in constructing the total output of the network. Activation functions are very important in neural networks because they can decide whether the input to the neuron is enough to be passed to the next layer or not. There are many types of activation functions in artificial neural networks:

- Linear Activation Functions or Ramp:

The output is varied linearly when the input is small. If the input is large, the absolute output is limited by 1 as shown in figure 7. The function of this transfer function is defined by:

$$o(TP) = \begin{cases} -1 & TP \le -1 \\ TP & -1 \le TP \le 1 \\ 1 & 1 \le TP \end{cases} \tag{0.2}$$

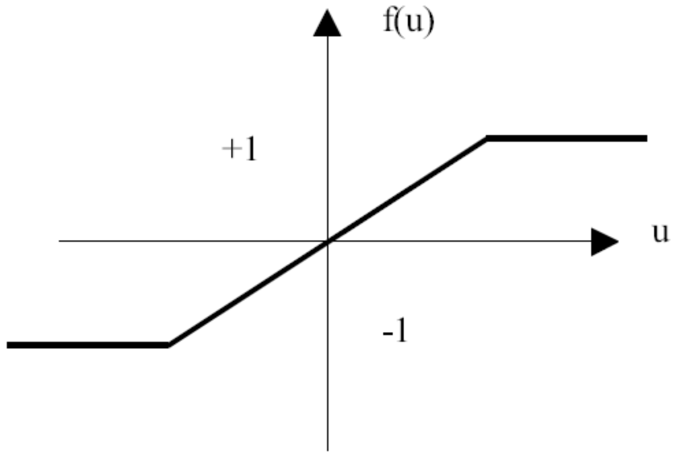


Figure 7: Ramp activation function (Collin Fyfe, 1996)

- Threshold Function (Hard Activation Function):

In the threshold function the output is zero if the summed input is less than certain value of threshold, and 1 if the summed input is greater than threshold. This way the output is oscillating between two values. It can be either activated or deactivated like in figure 8. The function of the hard function is defined by:

$$o(TP) = \begin{cases} 0, & TP < \theta \\ 1, & TP > \theta \end{cases} \tag{0.3}$$

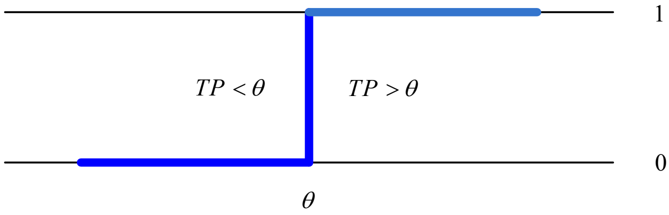


Figure 8: Hard activation function (Collin Fyfe, 1996)

- Sigmoid Function:

This function can range between 0 and 1, but in some cases it can be useful to range it between -1 and 1. The logarithmic sigmoid and hyperbolic tangent is of the most common sigmoid functions. These two functions are the most used in the back propagation because they are differentiable. The formulas of these two functions in addition to the curves are presented in figure 9. The slope of the curves can be varied based on the application for which it is used.

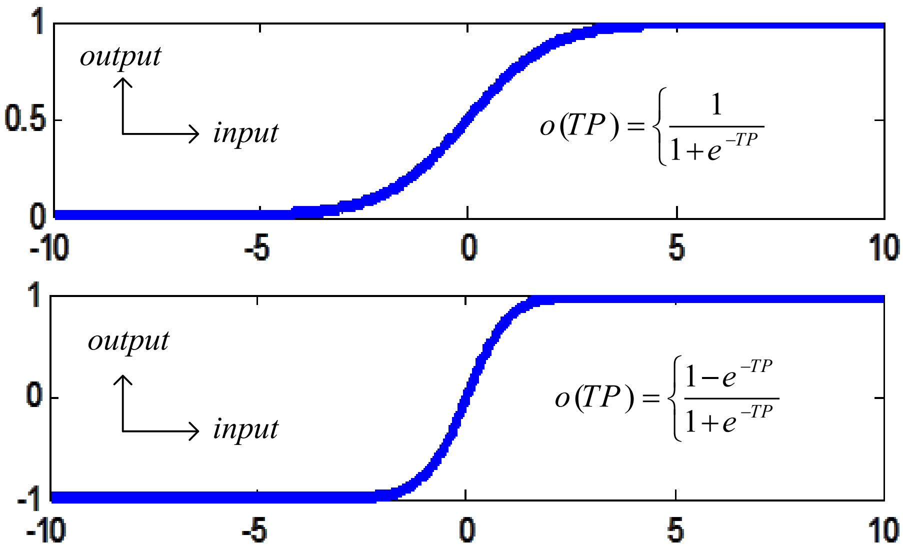


Figure 9: Logarithmic and hyper tangential sigmoid activation functions. (Collin Fyfe, 1996)

In the back propagation algorithms, the log-sig and tan-sig functions are the most used. The main advantage of these two functions is the fact that they can be easily differentiated. The derivative of the logarithmic sigmoid is given by:

$$\frac{d}{dt}o(\theta) = o(\theta) * (1 - o(\theta)) \tag{0.4}$$

3.5.5 Classification of ANNs

Artificial neural networks can be classified based on different aspects; these are the flow of information, function or task, and the training method. The flow of information can be either from input layer toward hidden and output layers. It can also flow from next layer to the previous layer. According the function, neural networks are used to accomplish many different tasks. These tasks can be categorized into four main categories:

- Classification: where an object is assigned to a group of known categories.
- Association: linking objects to more precised categories.
- Optimization: where the task is to find the best solution for a case or problem.
- Organization: The classification of ANNs can be done based also the training method.

3.5.6 Training Methods of ANNs

Generally, the training of a network is an attempt to lead the network to converge toward desired output or outputs. Two main learning methods are used in teaching the networks. These are the supervised and the unsupervised learning method.

- Supervised learning:

The artificial neural network is provided by input data and desired target for this data. The network then updates its weights according to a defined algorithm rule until it converges to a minimum error or reaches a maximum number of iterations. A very important example of the supervised learning method is the error back propagation method.

- Unsupervised learning:

In this method, the input data is provided to the network which in turn modifies its weights according to defined conditions. (Fyfe C, 1996).

3.5.7 Back Propagation Algorithm

The back propagation training algorithm uses a feed forward process, a back propagation updating method, and supervised learning topology. This algorithm was the reason of neural networks development in the 80s of the last century. Back propagation is a general-purpose learning algorithm. Although it is very efficient, it is costly in terms of processing requirements for learning. A back propagation network with a given hidden layer of elements can simulate any function to any degree of accuracy.

The back propagation algorithm is still as simple as it was in its first days. That is due to its simple principle and efficient algorithm. The input set of training data is presented at the first layer of the network, the input layer passes this data to the next layer where the processing of data happens. The results after being passed through the activation functions are then passed to the output layers. The result of the whole network is being then compared with a desired output. The error is used to make a one update of the weights preparing for a next iteration. After the adjustment of the weights, the inputs are passed again to the input, hidden, and output layers and a new error is calculated in a second iteration and vice versa.

The mentioned process continues until achieving an acceptable level of the error so that the network can be considered has learned. Figure 10 presents the structure of the network with layers and back propagation process.

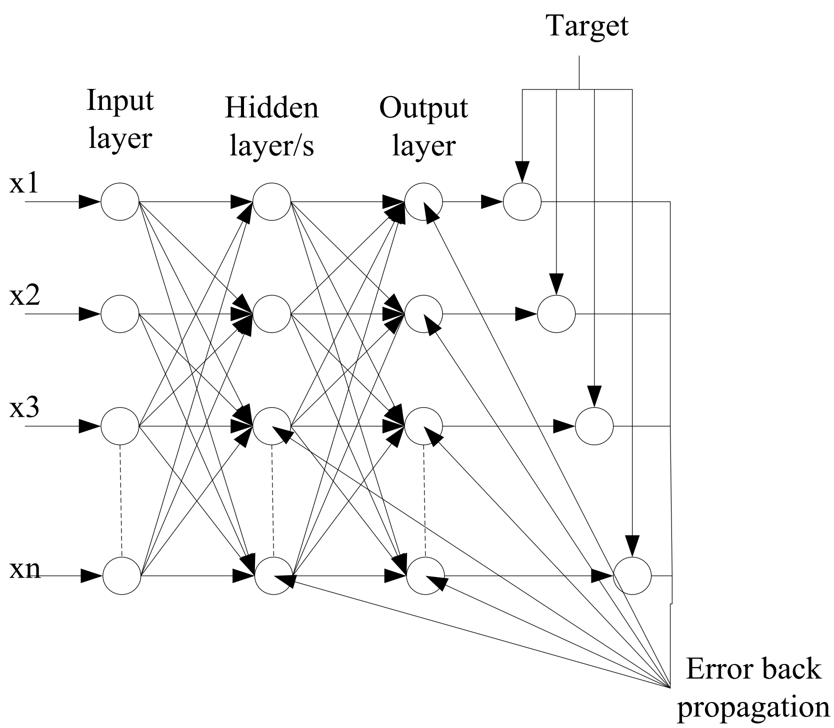


Figure 10: Structure of ANN and error back propagation (Gupta, 2006).

There are two essential parameters controlling the training of a back propagation network. The learning rate is used to control the speed of learning. It decides whether a great adjustment of weights will be done at each iteration or just small adjustments. It is important to mention here that a high learning rate is not advised because it can cause the network to memorize things instead of learning. A reasonable value of learning rate can do the job perfectly. Another parameter is the momentum factor which is used to control the oscillation of error in some local minimums. It is very important to avoid some kinds of falling into fake minimums and ensure the continuity of training (Charu G, 2006).

Modeling of Back Propagation Algorithm is an algorithm that uses the theory of error minimization and gradient descent to find the least squared error. Finding the least squared error imposes the calculation of gradient of the error for each iteration. As a result, the error function must be continuous derivable function. These conditions lead to the use of continuous derivable activation functions as they are the precedents of error calculation. In most of cases, the tangent or logarithmic sigmoid functions are used. The sigmoid function is defined by:

$$o(x) = \frac{1}{1+e^{-ax}} \tag{0.5}$$

Where the variable "a" is a constant controlling the slope of function. Where the derivative of the sigmoid function is given by:

$$o^{\backslash}(x) = f(x)(1-f(x)) \tag{0.6}$$

The equations describing the training of the network can be divided into two categories:

1- Feed forward calculations: used in both training and test of the network.
2- Error back propagation: used in training only.

In the feed forward process, the output or total potential can be given by:

$$TP = \sum x_n \omega_n + b_n \tag{0.7}$$

Where, x_n is the input vector, w_n is the weight matrix, and b_n is the bias values vector. The total potential obtained in each layer must be passed by an activation function. The activation function can be either linear or non-linear function. An example of a linear function that is mostly used in neural networks is the sigmoid function given in the following equation. Another example is the tangent sigmoid given by:

$$o(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{0.8}$$

It is important to notice that this function is also continuous and derivable. The derivative of this function is given by:

$$o^{\backslash}(x) = 1 - \frac{(e^{x} - e^{-x})^{2}}{(e^{x} + e^{-x})^{2}} \quad (0.9)$$

The output of the last activation function is the actual output of the neural network. This output is then compared with the goal of training to generate the error signal. The error signal is actually defined by the following equation. The goal of the training of neural network is always to minimize that error.

$$E = \sum (T - o)^{2} \quad (0.10)$$

Where, T signifies the target output. An error function is then defined based on the value of E such that:

$$\Delta_{j} = (T_{j} - o_{j}) o_{j} (1 - o_{j}) \quad (0.11)$$

This value is propagated back to the network using the next equations to update the weights and biases of the different layers. The weights are then updated using the next equation:

$$\omega_{jhnew} = \omega_{jhold} + \eta \Delta_{j} o_{h} + \alpha(\delta \omega_{jhold}) \quad (0.12)$$

Concerning the hidden layers, their weights are updated using the error update defined by:

$$\Delta_{h} = o_{h}(1 - o_{h}) \sum \omega_{jh} \Delta_{j} \quad (0.13)$$

The new weights values are then given by:

$$\omega_{hinew} = \omega_{hiold} + \mu \Delta_{h} o_{i} + \alpha(\delta \omega_{hiold}) \quad (0.14)$$

The values of α and η are the well-known momentum factor and learning rate. At the end of weights update, a new feed forward iteration is done again. The error is being calculated, at each iteration, until it arrives to an accepted error value.

3.5.8 Applications of Artificial Neural Networks

Artificial neural networks are used in different fields of science in many applications these days. In some applications they are still in the research mode. The neural network technology is a promising field for the near future. In this part of our work, different fields of application of artificial neural network will be discussed. The neural networks are used mainly in pattern recognition, pattern association, function approximation, control systems, beam forming, and memory.

- Pattern Association:

It is a brain like distributed memory that learns by association. Auto association is a process where the neural network is supposed to store a set of vectors by presenting them to the network. In a hetero association structure, a set of inputs is being associated with an arbitrary set of outputs. The hetero association is supervised learning process.

- Pattern Recognition:

Pattern recognition is a simple task done by humans in their everyday life with merely no effort. Simply, we can recognize the smell of some food that we have tasted before easily. Familiar persons can be recognized even if they are aged or their expressions have been changed since last time we saw. Pattern recognition is known as a process by which a received signal can be assigned to a prescribed number of categories. Although pattern recognition tasks are very easy for humans, they are very difficult to be carried out using traditional computers. The neural networks have presented an excellent approach for carrying out pattern recognition tasks using computing machines.

A well trained network can easily recognize and classify a pattern or group of patterns to classes. Face recognition, fingerprint recognition, voice recognition, iris recognition and many other applications are examples of pattern recognition.

- Function Approximation:

Interpolation and function approximation has been a very important field of numerical mathematics. It is very to determine the function describing the relation between discrete variables. Related set of input output numerical association can be modeled using linear or nonlinear functions. Neural networks can be used to describe the relation between input and output variables of the set. Neural networks can approximate function in two different ways:

1- System identification: figure 11 shows the scheme of system identification task. If we have an unknown system that we need to model, a neural network can be associated with the system. The input output relationship of the system can then be modeled by the neural network during the training. The weights of the neural networks are updated until it will produce the same output of the system if subjected to the same input.

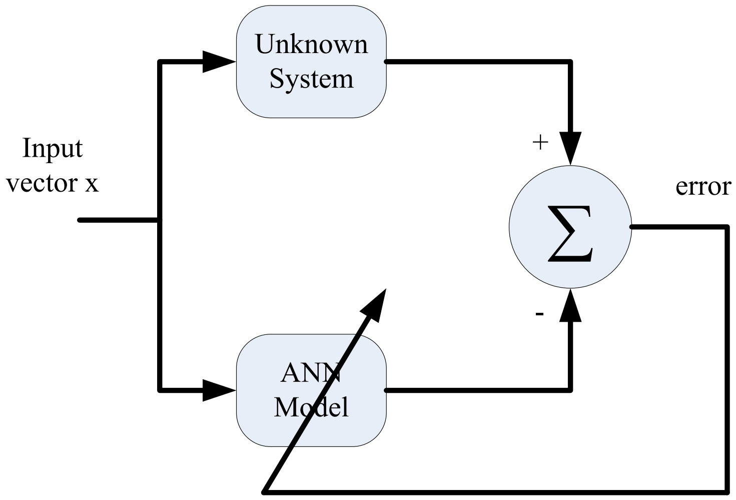


Figure 11: System identification using neural networks (Hykin, 1999)

2- Inverse system modeling: as shown in figure 12 the inverse of the system to the left can be modeled using artificial neural network. After training the input of the whole system should be equal to its output.

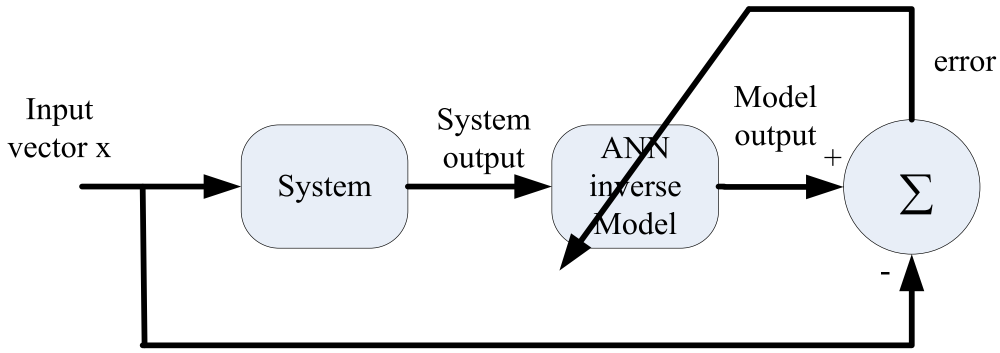


Figure 12: Inverse System Modeling Using ANN (Hykin, 1999).

- Control:

The control of processes is another learning task neural networks can do. The brain is evidence that a distributed neural network can be used in the systems control. If we consider a feed-back process like the one shown in figure 1, the system is using a unity feed-back to control the process. The plant output is fed back to the control that compares output with the desired output. A neural network controller can be used to generate the appropriate control of the plant.

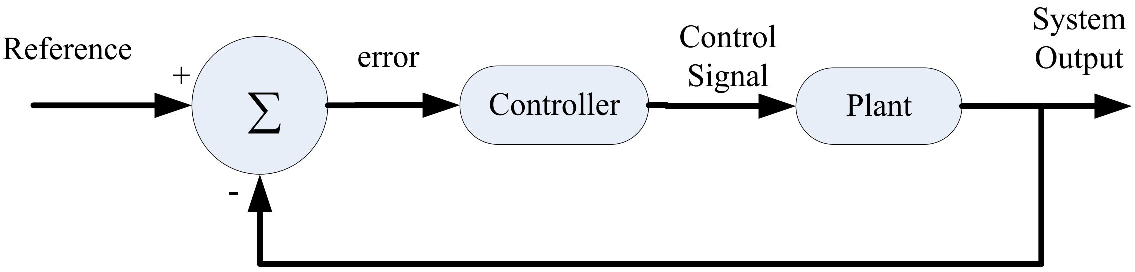


Figure 13: The use of ANN for control processes (Hykin, 1999).

- Filtering:

The term filtering is referred to the process or algorithm by which prescribed data is been extracted from noisy data. The noise is being then rejected. Filtering is a very important task. Noise rejection in microphones and speakers, in telephones, stereos, digital communication devices and many other communication means is done using filtering. A simple description of the filtering task using artificial neural networks is shown in the figure 14.

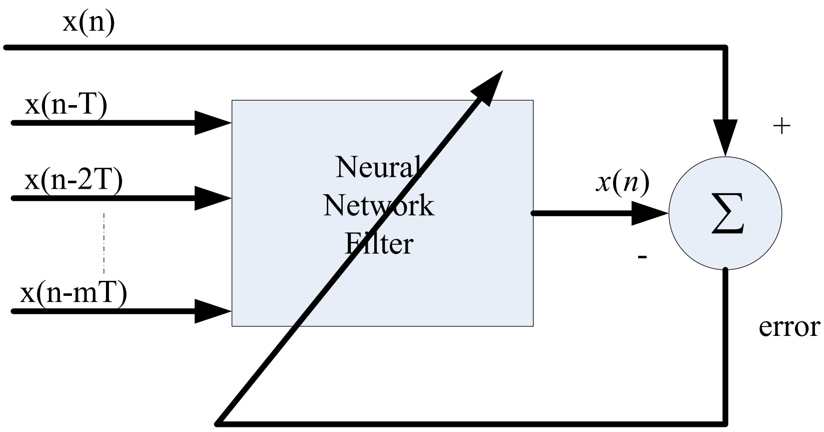


Figure 14: Filtering using artificial neural networks (Hykin, 1999).

CHAPTER 4
MATERIALS AND METHODS

4.1 Intelligent Asthma Prediction System: Training Phase

In this phase, all asthma cases are classified as normal, mild and severe. Back propagation neural network analysis methodology is employed at this stage and on. Random data is collected of 150 cases including 75 females and 75 males of different ages in which 75 cases are classified as having no asthma; normal, 31 and 44 other cases are classified as having mild and severe asthma respectively. *See Appendix 2 for further details of the data.*

Our intelligent system has used 76 patients' data for artificial neural network system training; 38 of which is considered normal, 16 mild, and 22 severe. This step is crucial to start up the recognition of case severity being under testing. Therefore, any output value of any case under testing is measured against the whole three recognized cases that the system has been trained on. The input layer consists of 7 neurons reflecting the input parameters of our data *(see tables 9 and 10 in Appendix 2);* the hidden layer consists of 15 neurons while the output layer has 3 neurons depicting the asthma classifications. Figure-15 illustrates the proposed artificial neural network system architecture.

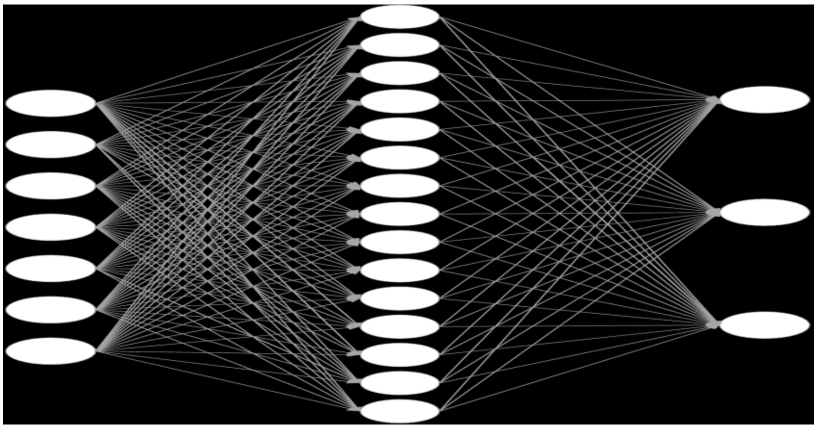


Figure 15: Architecture of the proposed system.

4.2 Data Representation

This report selects seven attributes, inputs; age, height, Forced Vital Capacity (FVC), Forced Expiratory Volume in one second (FEV1), ratio FEV1/FVC, frequency range and dose of steroids. However, two main parameters (FEV1 & FVC) show high credibility for the asthma prediction. Table-1 shows the listings of the medical data that are used as inputs for the artificial neural network, networks. Moreover Table-2 shows the output classes or Asthma classifications according to our proposed system.

Parameters	Description	Range
Age	Age in years	Continuous
Height	Height in cm	Continuous
FVC	Liters	Continuous
FEV1	Liters in 1 second	Continuous
FEV1/FVC	Normal	>= 0.7
	Mild	0.5<ratio<0.7
	Severe	<0.5
Frequency range	Normal	450L-500L
	Mild	400L-449L
	Severe	350L-399L
Dose of Steroids	Normal	0 ug
	Mild	172.1<dose<342.7
	Severe	1, 221.6<dose<1,464

Table 1: Input Parameters

Asthma Classes	Asthma Presence/ Severity
Class 1	Normal
Class 2	Mild
Class 3	Severe

Table 2: Output Classes/ Classifications

Table 2 explains the three classifications as set up into our system:

1- Normal: No asthma being detected; ratio ≥ 0.7

2- Mild: Mild asthma being detected; ratio is between 0.5 and 0.7

3- Severe: Severe asthma being detected; ratio is ≤ 0.5.

4.3 System Training

Weuses MATLAB programming as its main software tools that utilize the back-propagation algorithm. The initial step was to create a system and then train it for basic operation, for example, 'AND" "OR" so as to minimize the mean square error value down to 0.01.All training sessions utilize back-propagation methodology with both adaptive learning rate and momentum; with the function "traingdx" and with the transfer function "logsig". The network is then fed with the normalized datasets for the three sets and their output targets respectively. Table 3 represents 4 recorded data of the 7 attributes before normalization. Table 4 represents the same data after being normalized.

Refer to Appendix 2 for the whole Asthma database used in this project.

Table 3: Attribute values for 4 patients before normalization

Attributes	Patient 1	Patient 2	Patient 3	Patient 4
Age	35	49	18	80
Height	175	181	175	175
FVC	4.2	2	2.5	3.85
FEV1	0.9	0.5	1.5	2.73
FVC/FEV1	0.21	0.25	0.6	0.7
Freq. range	350	351	410	450
Steroid dose	1000	997	172.1	0

Table 4: Attributes for the same 4 patients after normalization

Parameters	Patient 1	Patient 2	Patient 3	Patient 4
Age	0.035	0.049147	0.043902	0.177778
Height	0.175	0.181545	0.426829	0.388889
FVC	0.0042	0.002006	0.006098	0.008556
FEV1	0.0009	0.000502	0.003659	0.006067
FVC/FEV1	0.21	0.25	0.6	0.7
Freq. range	0.35	0.352056	1	1
Steroid dose	1	1	0.419756	0

Training the system and making it adhere to the wanted results is not an easy task. Indeed several trainings may be required to achieve that and end up with good acceptable results. Therefore, several trials have been done in this project to reduce and reach the minimum mean square error, *MSE;* percentage. The degree of difficulties in such systems can sometimes be misleading since the best training results, minimum MSE, may not always indicate the best performance (testing) of the neural network system.

To start the training, variable parametersare selected as listed below. This is done as such toindicate whether or not the training results could show up within desired limits. Otherwise, they can be modified by the programmer and have their values changed until reaching acceptable limits. Then an acceptable performance of the neural network is checked for the largest percentage of accuracy rate up to100%.

- Number of hidden neurons
- Momentum rate
- Learning rate
- Number of iterations (epochs)

4.3.1 First Training Result

The network was set to run 5000 maximum iterations with a learning rate of 0.4, a momentum rate of 0.006, 10 hidden neurons and a minimum mean error of 0.018. This high number of iterations is done on purpose since our application is medical and has to show high degree of reliability. Figure-16 shows the first training result (learning curve) of the system.

In short, figure-16 has indicated that the system has kept training itself without any interference on the input data provided by the user until it has reached the lowest value of MSE.

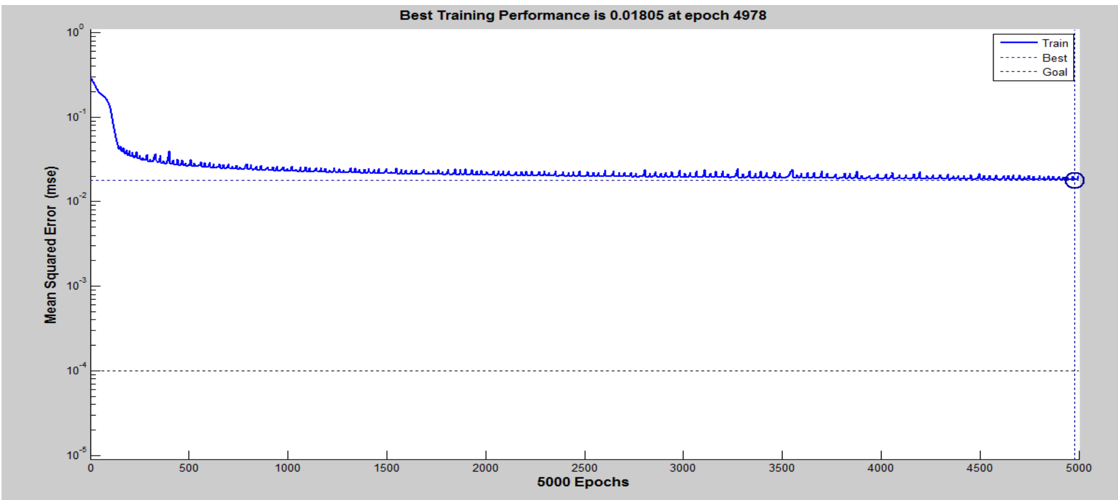


Figure 16: Variation of MSE with iteration numbers

To further ensure system stability and accuracy, Regression was computed by the software and drawn as illustrated in Figure-17. In statistical modeling, *regression* analysis is a statistical process for estimating the relationships among variables. It includes many techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables (or 'predictors'). The regression plot as seen is simply the curve plot of the desired output (dotted line) versus the actual output. In figure-17, it is remarked that the target and the actual output are very close which means that the error is minimized and the network is well trained by showing the training ratio at 95%.

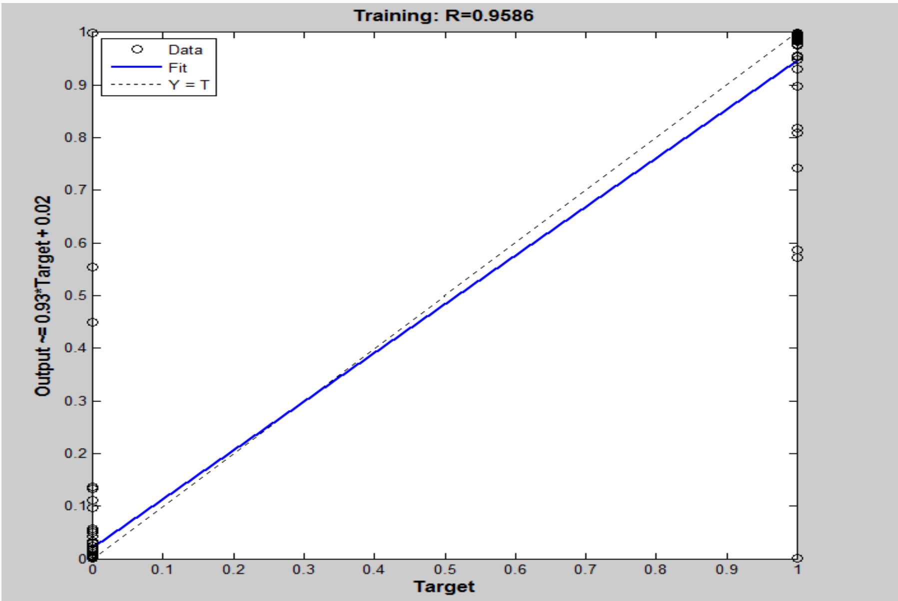


Figure 17: Actual Vs. Target Output

Having achieved the first training does not mean the conclusion of a satisfying outcome yet. Therefore, additional trials are required in search of better results. So, we changed the parameters, already mentioned, again as stipulated next.

4.3.2 Second Training Result

To enhance the results, a second training has been initiated with thefollowing values:

- Number of hidden neurons = 15
- Learning Rate = 0.1
- Momentum rate = 0.080
- Number of iterations = 9000

Figure-18 shows the result obtained by using the parameters as set above.

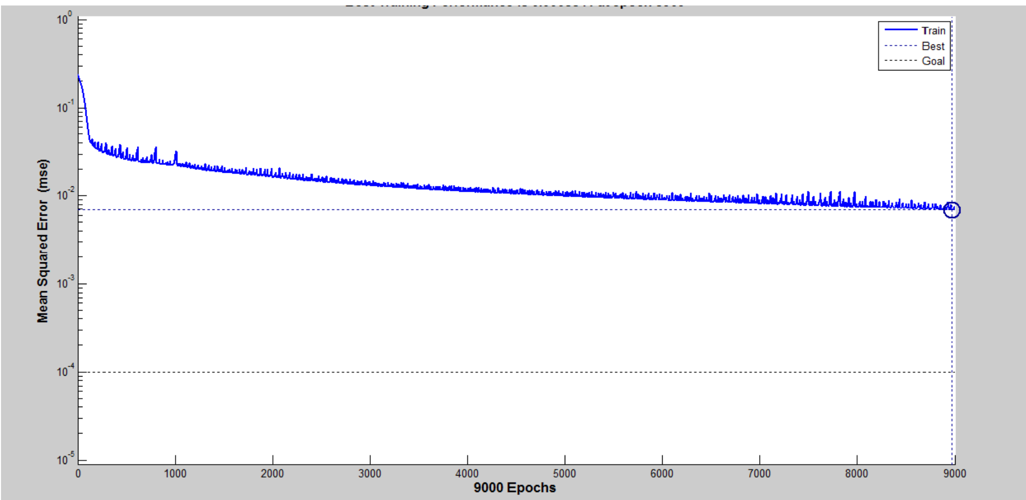


Figure 18: Variation of MSE with number of iterations

Figures 18 and 19 shows that the training result is becoming more satisfying with 98% learning ratio, which means that our neural network is capable of recognizing the testing performance.

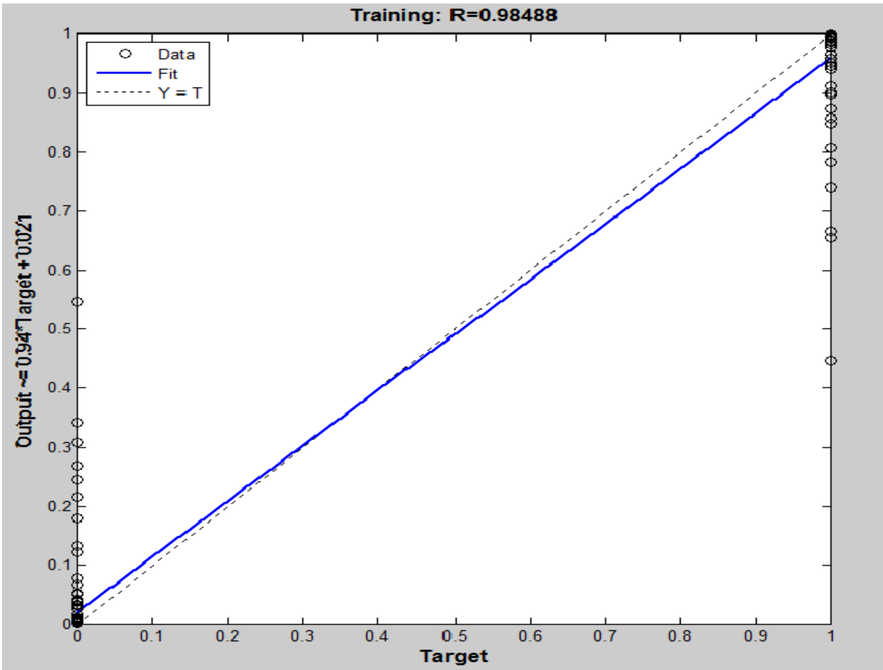


Figure 19: Actual Vs. Target Output

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4.3.3 Third Training Result

As noted before, a third training cycle was initiated with different variable settings to get the most recognized testing performance.

The network has run for 5000 maximum iterations with a learning rate of 0.04, a momentum rate of 0.008 and a minimum error of 0.014. The following is the training result (learning curve) of the system.

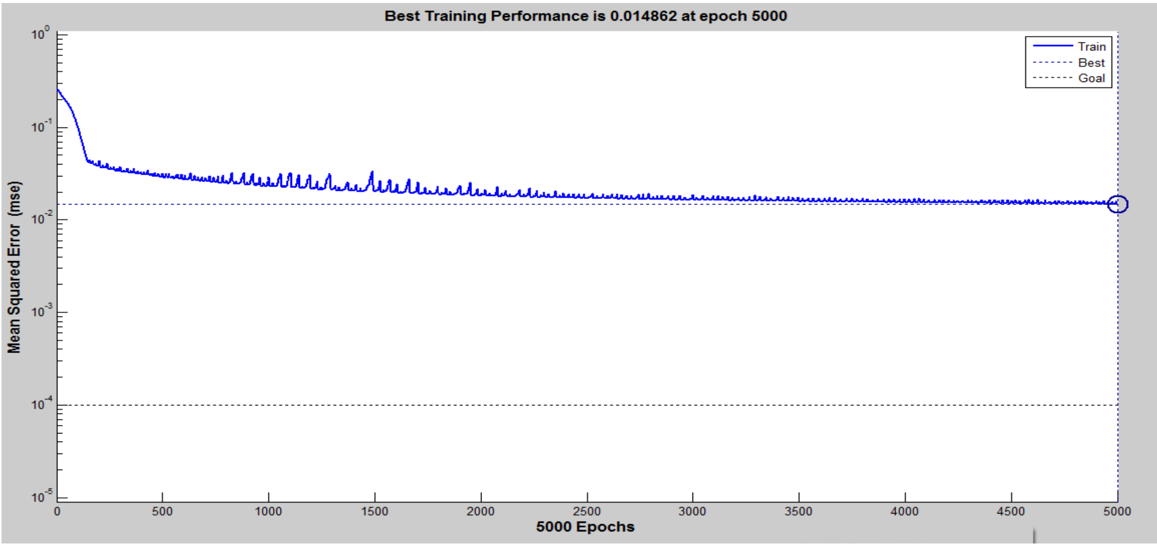

Figure 20: Variation of MSE with iteration numbers

This figure below represents the regression plot of the desired output (dotted line) and the actual output. As theactual output is far from the target as the error is increased. In this figure, it is remarked that the target and the actual output are very close which means that the error is minimized and the network is well trained (training ratio = 96%).

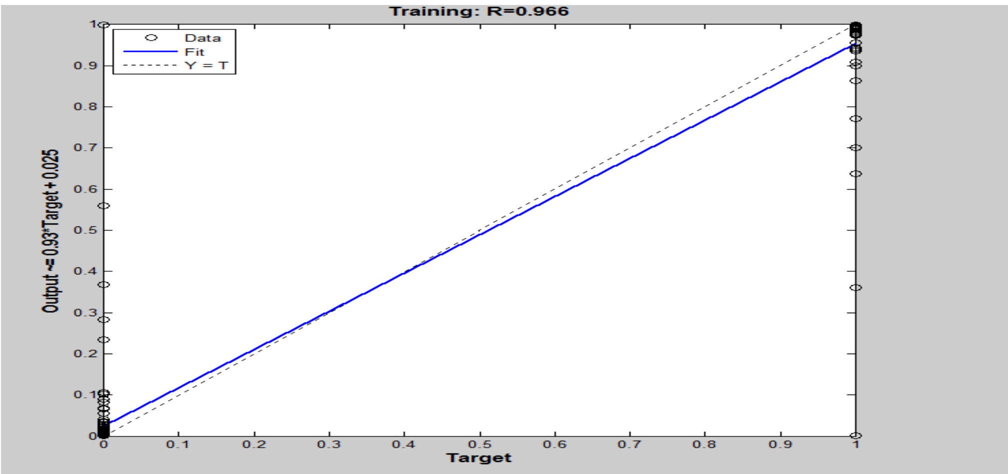

Figure 21: Actual Vs. Target Output

This training is considered the best training result because it has given the highest recognized testing result with minimum errors. The next section will explain the testing recognized results.

4.4 Intelligent Asthma Prediction System: System Performance (Testing)

4.4.1 Testing With 96% Training Ratio for Higher Performance

The network was tested on a dataset of 74 records; 37 for normal, 15 for mild and 22 for severe cases.

The next series of figures (a), (b), (c), (d), and (e) show the recognition rate of the training phase. They show the results of the three output classes according to the training system performed. The threshold for this project is 0.8; meaning that each value greater than 0.8 is similar to 1 while each value that is less than 0.8 is similar to 0.The recognized results are values similar to either (1 0 0), (0 1 0) or (0 0 1).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0.9973	0.9973	0.9972	0.9972	0.9972	0.9970	0.9972	0.9971	0.9971	0.9971	0.9971	0.9970	0.9969	0.9970	0.9968	0.9962	0.9961
2	0.0111	0.0098	0.0108	0.0110	0.0098	0.0063	0.0078	0.0099	0.0088	0.0082	0.0085	0.0074	0.0068	0.0072	0.0063	0.0047	0.0033
3	4.9023e-06	5.4846e-06	5.0884e-06	5.0227e-06	5.7030e-06	1.1094e-05	7.2122e-06	5.7757e-06	6.4753e-06	6.8960e-06	6.7571e-06	7.9185e-06	8.7499e-06	8.1185e-06	9.9015e-06	1.4428e-05	2.0971e-05
4																	
5																	
6																	
7																	
8																	
9																	
10																	
11																	
12																	

(a)

	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1	0.9966	0.9958	0.9960	0.9958	0.9941	0.9952	0.9944	0.9889	0.9942	0.9913	0.9926	0.9862	0.9925	0.9931	0.9908	0.9882	0.9905
2	0.0045	0.0026	0.0031	0.0025	9.9465e-04	0.0082	0.0107	7.8378e-04	0.0097	0.0897	0.0248	0.0048	0.0012	0.0021	0.0014	7.3045e-04	6.1752e-05
3	1.4781e-05	2.7368e-05	2.3478e-05	3.0877e-05	8.7968e-05	3.4779e-05	2.1314e-05	8.5604e-04	2.6729e-05	4.4258e-06	1.2250e-05	8.9863e-05	5.2466e-04	2.3947e-04	3.5553e-04	7.1925e-04	0.0187
4																	
5																	
6																	
7																	
8																	

(b)

	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51
1	0.9892	0.9789	0.9904	0.9895	0.0095	0.0119	0.0353	0.0087	0.0129	0.0151	0.0098	0.0165	0.0090	0.0087	0.0066	0.0068	0.0043
2	0.0043	0.0285	1.1305e-04	4.7730e-04	0.9997	0.9995	0.8951	0.9998	0.9991	0.9661	0.9790	0.8639	0.9504	0.9496	0.9358	0.9411	0.9498
3	1.2670e-04	6.4870e-05	0.0097	0.0018	1.6558e-04	1.8223e-04	0.0129	1.3028e-04	3.0337e-04	0.0133	0.0149	0.0662	0.0400	0.0396	0.0628	0.0613	0.0597
4																	
5																	
6																	
7																	
8																	
9																	
10																	
11																	

(c)

	52	53	54	55	56	57	58	59	60
1	0.0048	0.0056	0.0029	0.0026	0.0026	0.0069	0.0026	0.0025	0.0025
2	0.9157	0.8252	0.3144	0.1974	0.3997	0.1818	0.1676	0.0717	0.0546
3	0.1028	0.1969	0.6281	0.7770	0.6621	0.8308	0.7991	0.9545	0.9679
4									
5									
6									
7									
8									
9									
10									
11									

	61	62	63	64	65	66	67	68
1	0.0022	0.0025	0.0023	0.0023	0.0022	0.0023	0.0024	0.0022
2	0.0282	0.0076	0.0153	0.0202	0.0282	0.0264	0.0086	0.0162
3	0.9728	0.9947	0.9907	0.9893	0.9728	0.9712	0.9946	0.9906
4								
5								
6								
7								
8								
9								
10								
11								

(d)

	69	70	71	72	73	74
1	0.0021	0.0020	0.0017	0.0017	0.0021	0.0024
2	0.0044	0.0048	0.0019	3.0232e-04	1.5502e-04	9.4735e-05
3	0.9975	0.9968	0.9992	0.9999	0.9999	0.9999
4						
5						
6						
7						
8						
9						
10						

(e)

Figure 22: Recognition Rates for the system

Table-5 represents the results obtained from a run for the three different classes (Normal, mild and severe Asthma). This table below represents the number of records that were recognized by the network in the training and the testing phase. The number of recognized records was divided by the total number of records with respect to each case set (Normal, mild, and severe Asthma). The result of this fraction is called the recognition rate.

Table 5: Recognition Rate

Classes	Training sets (76 cases)	Testing sets (74 cases)	Total
Normal	100%	100%	100%
Mild	100%	100%	100%
Severe	90%	81.81%	81.81%
All Classes	96.6%	93.93%	93.93%

The total recognition rate for the preparation set is 96% and for the testing set is 93.93% which implies that some records were not perceived effectively. Accordingly, the total recognition rate is 93.93% and it is a satisfying result for such medical application.

4.4.2 Testing With 98% Training Ratio

Already mentioned before we had 15 hidden neurons, 0.1 as learning rate, 0.080 as momentum rate and the system ran on 9000 maximum iterations for the training performance. The following pictures show the testing result of the training performance.

train <3x74 double>

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0.4809	0.4375	0.4162	0.3618	0.3734	0.4507	0.3781	0.7800	0.3858	0.3903	0.3749	0.5020	0.3785	0.4872	0.5272	0.4516	0.4523
2	0.1092	0.0922	0.1051	0.0743	0.0774	0.0855	0.0705	0.1850	0.0613	0.0616	0.0556	0.0535	0.0555	0.0500	0.0564	0.0499	0.0519
3	0.0595	0.0446	0.0731	0.0417	0.0440	0.0518	0.0396	0.0507	0.0372	0.0527	0.0379	0.0219	0.0436	0.0217	0.0218	0.0265	0.0260

a

train <3x74 double>

	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1	0.4069	0.4337	0.5724	0.4317	0.4107	0.9891	0.8697	0.9778	0.8370	0.9807	0.9779	0.9603	0.9763	0.7747	0.9795	0.9506	0.9228
2	0.0550	0.0480	0.0763	0.0458	0.0433	0.3951	0.1121	0.3895	0.1223	0.3823	0.3702	0.2091	0.3654	0.1074	0.3223	0.1783	0.2237
3	0.0379	0.0242	0.0363	0.0232	0.0217	0.0881	0.1194	0.0525	0.0531	0.0210	0.0261	0.0740	0.0388	0.1539	0.0647	0.1557	0.2165

b

train <3x74 double>

	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51
1	0.9377	0.6518	0.5536	0.9833	0.7852	0.9945	0.9956	0.9341	0.8470	0.9102	0.9143	0.9051	0.9658	0.9445	0.9642	0.9459	0.8215
2	0.1762	0.0370	0.0588	0.5986	0.2256	0.7122	0.7400	0.2324	0.2165	0.3304	0.2509	0.2294	0.3501	0.3058	0.3444	0.3055	0.1145
3	0.0686	0.1436	0.3395	0.2610	0.2709	0.1726	0.1948	0.1093	0.2051	0.0302	0.2020	0.1870	0.1574	0.1699	0.1546	0.1742	0.1147

c

train <3x74 double>

	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68
1	0.9846	0.9190	0.9832	0.9788	0.9817	0.9859	0.9687	0.9403	0.9438	0.9218	0.9025	0.9015	0.8969	0.9479	0.9557	0.8948	0.9025
2	0.5358	0.1948	0.5452	0.4345	0.5516	0.5547	0.4497	0.4266	0.4431	0.3768	0.3601	0.3580	0.3471	0.3040	0.3318	0.3146	0.1908
3	0.1860	0.1001	0.1022	0.1501	0.0986	0.1954	0.2171	0.0148	0.0171	0.0136	0.0080	0.0081	0.0089	0.0623	0.0929	0.0172	0.0638

d

train <3x74 double>

	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75
1	0.9218	0.9025	0.9015	0.8969	0.9479	0.9557	0.8948	0.9025	0.9289	0.8908	0.8789	0.7089	0.5651	0.3992	
2	0.3768	0.3601	0.3580	0.3471	0.3040	0.3318	0.3146	0.1908	0.2565	0.1862	0.2127	0.0981	0.0652	0.0434	
3	0.0136	0.0080	0.0081	0.0089	0.0623	0.0929	0.0172	0.0638	0.0730	0.0496	0.0329	0.0245	0.0191	0.0146	

e

Figure 23: Recognition rates

The above Figure 23 a, b, c, d and e show the output of thissystem training series. The analysis of the results had shown that there were 28 unrecognized outputs based on 0.8 as a threshold value, which means that 37.85% of the system is unrecognized.

However, training results with 96% as regression has a testing performance with only 5.40% as errors. Thus, our asthma prediction systemhas been set and based on training with 96% as a regression rate and a satisfying performance with 93.93%.

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CHAPTER 5
RESULTS AND DISCUSSIONS

This asthma identification and predictive system has been tested using MATLAB software and tools. MATLAB is an established technical computing language for scientists and engineers and also an educative platform for developing algorithms and highly used in programming and data functions. The network has been tested on a dataset of 150 records; 75 for normal, 31 for mild and 44 for severe cases.

The rate of success of this project lies in the training results of the fed data and software tools; number of hidden neurons, momentum rate, learning rate and last number of iterations (epochs). Selection of Back-propagation methodology has facilitated and supplied the system with a high degree of precision due to its internal architecture and operation; MSE and training performance. None the less, the system could not identify and unable to recognize some outputs. Yet the three training trials and performance results performed during system testing have illustrated clearly the presence of an acceptable outcome one can rely on and continue its improvement.

The first trial with 95% as a ratio was not satisfying at all, thus we changed the parameters that affected the system in order to get better results. Moreover, the second trial with 98% as actual outputs didn't give satisfying recognized rates in the testing phase since we got 37.86% errors. By errors we mean that the output was not being recognized by either normal or mild or severe. Referring to figure 23, we were able to analyze the errors. Table 6 shows 9 unrecognized outputs from the total unrecognized outputs which is 28 as examples of the testing result for this training.

Table 6: Unrecognized outputs for 98% training ratio

Patient 1	**Patient 2**	**Patient 3**	**Patient 4**	**Patient 5**	**Patient 6**	**Patient 7**	**Patient 8**	**Patient 9**
0.4809	**0.4375**	**0.7852**	**0.3781**	**0.502**	**0.7089**	**0.5651**	**0.3992**	**0.78**
0.1092	**0.0922**	**0.2256**	**0.0705**	**0.0535**	**0.0981**	**0.0652**	**0.0434**	**0.185**
0.0595	**0.0446**	**0.2709**	**0.0396**	**0.0219**	**0.0245**	**0.0191**	**0.0146**	**0.0507**

As stated earlier the threshold for this project is 0.8, thus we can realize that the above outputs cannot be recognized as either normal (1 0 0) or mild (0 1 0) nor severe (0 0 1).

However, the chosen system with 96% as training ratio has fewer errors than other trials. Table 7 shows 4 unrecognized outputs in the full testing performance.

Refer to figure 22 to see the outputs of the system.

Table 7: Unrecognized outputs for 96% training ratio

Patient 1	**Patient 2**	**Patient 3**	**Patient 4**
0.0029	**0.0026**	**0.0026**	**0.0026**
0.3144	**0.1974**	**0.3997**	**0.1676**
0.6281	**0.7770**	**0.6621**	**0.7991**

Studying the difference between the errors, we realized that the testing performance of the 96% training ratio is better than the testing performance of the 98% ratio that was considered as the higher ratio. Thus, our intelligent asthma prediction system has a training performance of 96% with a testing result of 93.93%.

Why choosing 96% the training ratio instead of 98%?

As stated earlier, 98% is a satisfying training result for a similar medical application. However, the disadvantage of performing several trainings might cause problems in the neural network performance. The neural network will memorize instead of analyze. In this project the testing result of the 98% as training ratio showed that our neural network began to memorize since the error was 37.86% and such problem may prevent its ability to accept new parameters and identify the severity of asthma. Thus, we decided to choose the 96% training phase, since it gave a better testing performance with fewer errors (5.40%). This result is satisfying for this stage of the project.

CHAPTER 6
CONCLUSION

This project has several difficulties as any other project. The main risk was in collecting the suitable data used in the neural network system. Being able to find ready data on internet is something difficult since we are not able to have access on all the needed data because most of datasets are private to specific research centers and not easy to reach. Fortunately we were able to find the wanted data after several days of research. In addition, one of the difficulties was in the ability of stopping the training correctly when having the minimum square error (MSE) needed. Finally, finding the recognized testing results was also a problem since not every satisfying training result gives a suitable and recognized testing result.

Future work to improve the relevance of this new system should:

- Increase the database; increase in database size can yield better results.
- Use different algorithms to train and obtain higher performances for comparison purposes.
- Manipulate with the import of data in MATLAB; instead of importing all the parameters you have in training and repeating the same process in testing, import fewer number in training while a bigger number in testing and vice versa to avoid the memorizing of neural network.

In this project, an asthma prediction system based neural network was produced. Data mining technique proved useful in the recognition, classification, and search of consistent patterns and/or systematic relationships between variables, and then to validate the findings by applying the detected patterns to new subsets of data. The ultimate goal of data mining is prediction and predictive data mining is the most common type of data mining and one that has the most direct applications. The process of data mining consists of three stages: (1) the initial exploration, (2) model building or pattern identification with validation/verification, and (3) deployment to rate Asthma cases. The composed system isprogrammedto give assessments tothree diagnostic conditions: Normal, Mild and Severe Asthma after incorporating seven to aid in the proper prediction. The experimental results of the neural system were acceptable for such expectation assignment and they can be moreover progressed.

Our asthma prediction system has indicated a high rate of success at this stage of testing trials and performances. Still the system has to have more input data to be included such as patient weight, body surface area, existing chronic diseases, etc… More regional, intercontinental, and international data of patients of all walks of life; hard laborers, miners, prisoners, patients born with inherited asthma including babies and children, etc… should be brought in. One last suggestion to be made here and despite ANN can be used as an ultimate prediction system as input data grows is that testing trials and performances has to make differentiation between males and females so that we could minimize the errors to a minimum. Like any research project or study further work is always welcomed.

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APPENDICES

Appendix 1
CODE OF NEURAL NETWORK

- Neural Network Code Normalization

```
Close all
Clear all
PATERNS= []
PATERNS= xlsread ('dataset1.xlsx','sheet1');
PATERNS=[PATERNS(1,:);PATERNS(2,:);PATERNS(3,:);PATERNS(4,:);PATER
NS(6,:);PATERNS(7,:)];
Output= xlsread ('dataset1.xlsx','sheet2');
maxr = meshgrid(max(PATERNS),[1:size(PATERNS,1)]');
normdata=PATERNS./maxr;
```

- Training Phase

```
Clear all
Close all
clc
PATTERNS = [];
%[g,h]=size(PATTERNS);
%[m,h]=size(Dis_output);
%inputs
PATTERNS=  xlsread('IAPStrain.xlsx','sheet1')
%output
Dis_output = xlsread('IAPStrain.xlsx','sheet2')
net = newff(minmax(PATTERNS),[15,3],{'logsig''logsig'},'traingdx');
net = init(net); %only
net.LW{2,1} = net.LW{2,1}*0.1;
net.b{2} = net.b{2}*0.1;
% TRAINING THE NETWORK
net.trainParam.goal = 0.0001;
net.trainParam.show = 50;
```

```
net.trainParam.epochs = 5000;
net.trainParam.mc = 0.008;
net.trainParam.lr= 0.04;
[net,tr] = train (net,PATTERNS,Dis_output);%code of training
% for C=1: h
train = sim(net,PATTERNS)
```

- Testing Phase

```
Clear all
Close all
clc
% PATTERNS= [];
 % PATTERNS=  xlsread('IAPStest.xlsx','sheet1')
% net = newff(minmax(PATTERNS),[15,3],{'logsig' 'logsig'},'traingdx');
train = sim(net,PATTERNS)
```

Appendix 2

ASTHMA DATA BASE

Table 8: Asthma Database for Males

Age (yrs)	Height (cm)	FVC	FEV1	FEV1/FVC ratio	Frequency Range	Dose of steroids
35	175	4.2	0.9	0.21	350	1000
49	181	2	0.5	0.25	351	997
26	180	3.3	0.89	0.26	352	995
32	190	3.5	1	0.28	354	980
28	180	2.5	0.8	0.32	364	900
69	170	2.74	0.89	0.32	364	364
40	178	3.6	1.2	0.33	866	882
25	179	3.64	1.24	0.34	368	880
25	170	2.86	1.02	0.35	370	875
48	165	1.37	0.5	0.36	372	873
38	178	2.56	0.96	0.37	374	870
32	175	2.3	0.9	0.39	374	870
40	165	2.5	1	0.4	376	868
52	167	2.7	1.08	0.4	376	868
25	190	2.1	0.89	0.42	379	866
35	180	5.54	2.39	0.43	381	864
42	170	3.2	1.5	0.46	385	860
55	175	2.6	1.2	0.46	385	860
49	155	4.08	1.9	0.46	385	860
52	185	4.1	2	0.48	387	857
39	180	2.5	2.12	0.49	389	855
40	175	5.1	2.5	0.49	389	855
18	175	2.5	1.5	0.6	410	172.1
65	160	3.65	2.2	0.6	410	172.1
80	166	2	1.2	0.6	410	172.1

18	170	3.6	2.3	0.63	414	175
32	175	5.7	3.6	0.63	414	177
21	180	5	3.2	0.64	416	179.2
23	165	5.32	3.56	0.66	418	180.3
23	180	2.56	1.7	0.66	418	180.3
33	178	3	2	0.66	418	180.3
19	175	3.4	2.3	0.67	420	182.4
20	170	3.65	2.5	0.68	421	183.1
48	170	1.3	0.89	0.68	421	183.1
26	180	4.5	3.1	0.68	421	183.1
76	168	4.7	3.2	0.68	421	183.1
41	175	1.89	1.32	0.69	422	185.3
70	166	3	2.09	0.69	422	185.3
80	175	3.85	2.73	0.7	450	0
85	155	3.85	2.73	0.7	450	0
78	147	1.81	1.32	0.72	451	0
70	185	4.91	3.62	0.73	452	0
67	160	4.91	3.62	0.73	452	0
48	170	3.75	2.82	0.75	456	0
82	155	2.64	1.99	0.75	456	0
20	185	3.25	4.23	0.76	458	0
69	160	3.08	2.39	0.77	459	0
73	155	3.08	2.39	0.77	459	0
58	170	3.87	3.05	0.78	460	0
65	165	3.47	2.72	0.78	460	0
53	185	4.94	3.93	0.79	462	0
57	175	4.26	3.38	0.79	462	0
61	165	3.58	2.84	0.79	462	0
30	190	6.31	5.1	0.8	470	0
25	195	6.47	5.48	0.81	472	0
39	190	5.54	4.49	0.81	467	0
65	165	2.07	1.67	0.81	472	0

25	190	6.47	5.48	0.81	472	0
45	170	4.28	3.52	0.82	474	0
35	183	4.37	3.59	0.82	474	0
20	180	5.75	4.79	0.83	476	0
38	160	3.81	3.2	0.83	476	0
40	165	4.1	3.42	0.83	476	0
46	165	3.81	3.18	0.83	476	0
20	180	5.75	4.79	0.83	476	0
20	172	5.75	4.79	0.83	476	0
36	166	3.81	3.2	0.83	476	0
39	168	4.1	3.42	0.83	476	0
38	160	3.8	3.2	0.84	478	0
18	170	4.74	4.04	0.85	480	0
20	178	4.15	3.61	0.86	484	0
18	165	3.42	3.07	0.89	485	0
16	158	3.07	2.76	0.89	485	0
16	145	2.99	2.71	0.9	487	0
14	135	2.27	2.13	0.93	490	0

Table 9: Asthma Database for Females

Age (yrs)	Height (cm)	FVC	FEV1	FEV1/FVC ratio	Frequency Range	Dose of steroids
58	155	4.2	0.9	0.21	350	1000
35	165	4.2	0.9	0.21	350	1000
49	170	3.02	0.72	0.23	351	998
26	165	3.3	0.89	0.26	352	995
26	175	3.3	0.89	0.26	352	995
60	155	3.86	1.1	0.28	354	980
32	160	3.5	1	0.28	354	980
39	166	3.6	1.2	0.33	866	882
25	170	2.86	1.02	0.35	370	875
38	175	2.05	0.82	0.4	376	868
32	165	2.5	1	0.4	376	868
27	175	5.1	2.04	0.4	376	868
29	180	2.1	0.89	0.42	379	866
27	180	4.9	2.15	0.43	381	864
37	160	5.54	2.39	0.43	381	864
44	165	3.99	1.84	0.46	385	860
49	155	4.08	1.9	0.46	385	860
55	150	2.6	1.2	0.46	385	860
39	160	4.08	1.9	0.46	385	860
82	150	4.3	2	0.46	385	860
37	165	4.1	2	0.48	387	857
30	165	4.05	2	0.49	389	855
55	160	4.72	2.89	0.61	410	185.1
28	176	2.07	1.3	0.62	412	173.2
18	170	4	2.5	0.62	412	173.2
20	160	2.3	1.45	0.63	414	175
32	175	5.7	3.6	0.63	414	175
36	165	5.7	3.6	0.63	414	175
31	168	3.68	2.34	0.63	414	175

23	170	5	3.2	0.64	416	179.2
23	173	1.4	0.9	0.64	416	179.2
34	178	4.6	3.05	0.66	418	180.3
72	163	3.1	2.06	0.66	418	180.3
84	155	2.4	1.6	0.66	418	180.3
28	165	3.65	2.5	0.68	420	183.1
47	155	1.89	1.32	0.69	422	185.3
58	157	1.01	0.7	0.69	422	185.3
80	145	3.85	2.73	0.7	450	0
80	150	3.85	2.73	0.7	450	0
80	145	1.81	1.32	0.72	451	0
70	155	4.91	3.62	0.73	452	0
74	160	4.91	3.62	0.73	452	0
45	160	3.75	2.82	0.75	456	0
70	155	2.64	1.99	0.75	456	0
20	163	3.25	4.23	0.76	458	0
69	145	3.08	2.39	0.77	459	0
66	150	3.08	2.39	0.77	459	0
58	160	3.87	3.05	0.78	460	0
65	165	3.47	2.72	0.78	460	0
57	152	3.87	3.05	0.78	460	0
65	161	3.47	2.72	0.78	460	0
50	150	2.96	2.35	0.79	462	0
65	150	4.26	3.38	0.79	462	0
45	165	3.58	2.84	0.79	462	0
53	160	4.94	3.93	0.79	462	0
57	170	4.26	3.38	0.79	462	0
53	153	4.94	3.93	0.79	462	0
67	150	4.26	3.38	0.79	462	0
78	154	3.58	2.84	0.79	462	0
34	170	6.31	5.1	0.8	470	0
36	165	6.31	5.1	0.8	470	0

30	164	6.31	5.1	0.8	470	0
25	175	6.47	5.48	0.81	472	0
25	174	6.47	5.48	0.81	472	0
25	169	6.47	5.48	0.81	472	0
35	175	4.37	3.59	0.82	474	0
45	158	4.28	3.52	0.82	474	0
20	165	5.75	4.79	0.83	476	0
36	160	3.81	3.2	0.83	476	0
39	155	4.1	3.42	0.83	476	0
30	165	3.86	3.28	0.84	478	0
20	170	4.15	3.61	0.86	484	0
18	155	3.42	3.07	0.89	485	0
16	150	3.07	2.76	0.89	485	0
14	145	2.73	2.46	0.9	487	0