Expert Systems with Applications 37 (2010) 7648–7655

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Chest diseases diagnosis using artificial neural networks

Orhan Er [a,b], Nejat Yumusak [c], Feyzullah Temurtas [a,*]

[a] Bozok University, Department of Electrical and Electronics Engineering, 66200 Yozgat, Turkey
[b] Sakarya University, Department of Electrical and Electronics Engineering, 54187 Adapazari, Turkey
[c] Sakarya University, Department of Computer Engineering, 54187 Adapazari, Turkey

ARTICLE INFO

Keywords:
Chest disease diagnosis
Multilayer neural network
Probabilistic neural network
Learning vector quantization neural network
Generalized regression neural network
Radial basis function neural network

ABSTRACT

Chronic obstructive pulmonary, pneumonia, asthma, tuberculosis, lung cancer diseases are the most important chest diseases. These chest diseases are important health problems in the world. In this study, a comparative chest diseases diagnosis was realized by using multilayer, probabilistic, learning vector quantization, and generalized regression neural networks. The chest diseases dataset were prepared by using patient's epicrisis reports from a chest diseases hospital's database.

1. Introduction

The chest contains the main respiration and circulation organs which sustain some of the most critical life functions of the body. Millions of people are diagnosed every year with a chest disease in the world. Tuberculosis (TB), chronic obstructive pulmonary disease (COPD), pneumonia, asthma, lung cancer diseases are the most important chest diseases which are very common illnesses in the world (MedHelp: http://www.medhelp.org/Medical-Dictionary/Terms/2/8964.htm (accessed 18.03.09)).

TB is an infectious disease, caused in most cases by microorganisms called *Mycobacterium tuberculosis*. The microorganisms usually enter the body by inhalation through the lungs. They spread from the initial location in the lungs to other parts of the body via the blood stream, the lymphatic system, via the airways or by direct extension to other organs. TB is a major cause of illness and death worldwide and globally, 9.2 million new cases and 1.7 million deaths from tuberculosis occurred in 2006 (Enarson, Rieder, Arnadottir, & Trébucq, 2000; Royal College of Physicians of London, 2006; World Health Organization, 2008).

COPD is a disease state characterized by airflow limitation that is not fully reversible. The airflow limitation is usually both progressive and associated with an abnormal inflammatory response of the lungs to noxious particles or gases (Celli & MacNee, 2004). Clinically, patients with COPD experience shortness of breath (dyspnea) and cough, productive of an excess of mucus. There may also be wheeze (Jeffery, 1998). According to the World Health Organization (WHO) data is found 600 million patients who have COPD and every year 2.3 million persons die because of COPD in the world (Sönmez & Uzaslan, 2006).

Pneumonia is an inflammation or infection of the lungs most commonly caused by a bacteria or virus. Pneumonia can also be caused by inhaling vomit or other foreign substances. In all cases, the lungs' air sacs fill with pus, mucous, and other liquids and cannot function properly. This means oxygen cannot reach the blood and the cells of the body effectively. According to the World Health Organization (WHO) data, every year approximate 2.4 million persons die because of pneumonia (Global Action Plan for the Prevention, 2007).

Asthma is a chronic disease characterized by recurrent attacks of breathlessness and wheezing. During an asthma attack, the lining of the bronchial tubes swell, causing the airways to narrow and reducing the flow of air into and out of the lungs. Recurrent asthma symptoms frequently cause sleeplessness, daytime fatigue, reduced activity levels and school and work absenteeism. Asthma has a relatively low fatality rate compared to other chronic diseases. WHO estimates that 300 million people currently suffer from asthma. Asthma is the most common chronic disease among children (http://www.who.int/en/ (accessed 18.03.09)).

Lung cancer is a disease of uncontrolled cell growth in tissues of the lung. This growth may lead to metastasis, which is the invasion of adjacent tissue and infiltration beyond the lungs. The vast majority of primary lung cancers are carcinomas of the lung, derived from epithelial cells. Lung cancer, the most common cause of cancer-related death in men and the second most common in women, is responsible for 1.3 million deaths worldwide annually (http://www.who.int/en/ (accessed 18.03.09)).

Artificial neural network (ANN) structures for classification systems in medical diagnosis are increasing gradually. The multilayer neural network (MLNN), probabilistic neural network

* Corresponding author. Tel.: +90 532 207 56 33.
E-mail address: temurtas@gmail.com (F. Temurtas).

0957-4174/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2010.04.078

(PNN), learning vector quantization (LVQ) neural network, generalized regression neural network (GRNN), and radial basis function (RBF) neural network structures have been successfully used in replacing conventional pattern recognition methods for the disease diagnosis systems. As for other clinical diagnosis problems, the neural network classification systems have been used for chest diseases diagnosis problem also. There have been several studies reported focusing on chest diseases diagnosis using artificial neural network structures (Aliferis, Hardin, & Massion, 2002; Ashizawa et al., 2005; Coppini, Miniati, Paterni, Monti, & Ferdeghini, 2007; El-Solh, Hsiao, Goodnough, Serghani, & Grant, 1999; Er, Sertkaya, Temurtas, & Tanrikulu, 2009; Er & Temurtas, 2008; Er, Temurtas, & Tanrikulu, 2010; Hanif, Lan, Daud, & Ahmad, 2009; Paul, Ben, Thomas, & Robert, 2004; dos Santos, Pereira, & de Seixas, 2004; Temurtas, 2009). These studies have applied different neural networks structures to the various chest diseases diagnosis problem and achieved high classification accuracies using their various dataset.

The multilayer neural network structure are the most common neural network structure which have been successfully used for the disease diagnosis systems (Delen et al.,2005; Er & Temurtas, 2008; Kayaer & Yıldırım, 2003; Temurtas, 2009). The back-propagation (BP) algorithm (Rumelhart, Hinton, & Williams, 1986) is widely recognized as a powerful tool for training of the MLNN structures. However, BP algorithm suffers from a slow convergence rate and often yields suboptimal solutions (Brent, 1991; Gori & Tesi, 1992). A variety of related algorithms have been introduced to address that problem and a number of researchers have carried out comparative studies of MLNN training algorithms (Gulbag & Temurtas, 2006; Hagan, Demuth, & Beale, 1996; Hagan & Menhaj, 1994). Levenberg–Marquardt (LM) algorithm (Hagan & Menhaj, 1994) used in this study provides generally faster convergence and better estimation results than other training algorithms (Er & Temurtas, 2008; Gulbag & Temurtas, 2006).

The probabilistic neural network structures provide a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers. The PNN uses a supervised training set to develop distribution functions within a pattern layer. Training of the PNN is much simpler than that of the MLNN. However, the pattern layer can be quite huge if the distinction between categories is varied and at the same time quite similar in special areas (Speckt, 1990). Because the PNN provides a general solution to pattern classification problems, it is suitable for the disease diagnosis systems (Er, Sertkaya, et al., 2009; Temurtas, 2009; Temurtas, Yumusak, & Temurtas, 2009).

The classification of the learning vector quantization neural network structure is based on the similarity of the unknown data and these prototypes. An LVQ neural network has a competitive layer and linear output layer. The competitive layer learns to classify input vectors. The linear output layer transforms the competitive layer's classes into target classifications defined by the user. The classes learned by the competitive layer can be referred as subclasses and the classes of the linear output layer can be referred as target classes (Kohonen, 1990; Kohonen, 1997; Matlab Documentation, 2004). The LVQ network structures have been successfully used for the disease diagnosis systems (Er, Sertkaya, et al., 2009; Er, Temurtas, et al., 2010; Temurtas, 2009).

Like probabilistic neural networks, generalized regression neural networks are known for their ability to train in only one pass of the training set using sparse data sets. Rather than categorizing data like PNN, however, GRNN applications are able to produce continuous valued outputs. GRNN is especially useful for continuous function approximation, and can fit multidimensional surfaces through data (Speckt, 1991). There has been some studies reported focusing on the chest disease diagnosis using GRNN structure (El-Solh et al., 1999).

The radial basis functions greatly reduce the training time and make related analyses much easier. The RBF neural networks are quite suitable for implementing multi-class and high-dimensional classification problems (Chen & Lin, 1993; Daqi, Shuyan, & Yan, 2004). The RBF network structures have been successfully used for the disease diagnosis problems also (Hanif et al., 2009).

In this study, a comparative chest diseases diagnosis was realized by using multilayer, probabilistic, learning vector quantization, generalized regression, and radial basis function neural networks. The chest diseases dataset were prepared by using patient's epicrisis reports from a chest diseases hospital's database. The study aims also to provide machine learning based decision support system for contributing to the doctors in their diagnosis decisions.

2. Method

2.1. Data source

In order to perform the research reported in this article, the patient's epicrisis taken from Diyarbakir Chest Diseases Hospital from southeast of Turkey was used. The dataset were prepared using these epicrisis reports. The dataset which consists of the chest disease measurements contains six classes and 357 samples. The class distribution is

- Class 1: Tuberculosis (50).
- Class 2: COPD (71).
- Class 3: Pneumonia (60).
- Class 4: Asthma (44).
- Class 5: Lung Cancer (32).
- Class 6: Normal (100).

All samples have thirty eight features. These features are (Laboratory examination): complaint of cough, body temperature, ache on chest, weakness, dyspnoea on exertion, rattle in chest, pressure on chest, sputum, sound on respiratory tract, habit of cigarette, leucocyte (WBC), erythrocyte (RBC), trombosit (PLT), hematocrit (HCT), hemoglobin (HGB), albumin2, alkalen phosphatase 2 L, alanin aminotransferase (ALT), amylase, aspartat aminotransferase (AST), bilirubin (total + direct), CK/creatine kinase total, CK–MB, iron (SERUM), gamma–glutamil transferase (GGT), glukoz, HDL cholesterol, calcium (CA), blood urea nitrogen (BUN), chlorine (CL), cholesterol, creatinin, lactic dehydrogenase (LDH), potassium (K), sodium (NA), total protein, triglesid, uric acid.

2.2. Previous studies

There have been several studies reported focusing on chest disease diagnosis problem using artificial neural network structures as for other clinical diagnosis problems. These studies have applied different neural networks structures to the various chest diseases diagnosis problem using their various dataset (Aliferis et al., 2002; Ashizawa et al., 2005; Coppini et al., 2007; El-Solh et al., 1999; Er & Temurtas, 2008; Er, Temurtas, et al., 2010; Hanif et al., 2009; Paul et al., 2004; dos Santos et al., 2004).

El-Solh et al. used a generalized regression neural network (GRNN) using clinical and radiographic information to predict active pulmonary tuberculosis at the time of presentation at a health-care facility that is superior to physicians' opinion (El-Solh et al., 1999). The input patterns were formed by 21 distinct parameters which were divided into three groups: demographic variables, constitutional symptoms, and radiographic findings. The output of the GRNN provided an estimate of the likelihood of active pulmonary tuberculosis. The authors utilized

a 10-fold cross-validation procedure to train the neural networks. The authors reported approximately 92.3% diagnosis accuracy (El-Solh et al., 1999). Er et al. used multilayer, and generalized regression neural networks for diagnosis of tuberculosis (Er, Temurtas, et al., 2010). They used thirty eight features for the diagnosis and reported approximately 93.3% diagnosis accuracy for GRNN and 95% diagnosis accuracy for MLNN with LM algorithm and two hidden layer.

Ashizawa et al. used the MLNN with one hidden layer and they used BP training algorithm for diagnosis of COPD disease (Ashizawa et al., 2005). They used twenty six features for the diagnosis. The authors reported approximately 90% diagnosis accuracy. Coppini et al. used the MLNNs with one and two hidden layers and they used BP with momentum as the training algorithm for diagnosis of COPD disease (Coppini et al., 2007). The authors utilized a 10-fold cross-validation procedure to train the neural networks. The authors were obtained 90.6% diagnosis accuracy using the MLNN with two hidden layers as the best result. They used radiograph shape features for the diagnosis. Er and Temurtas used multilayer neural networks for diagnosis of COPD (Er & Temurtas, 2008). They used thirty eight features for the diagnosis and reported approximately 96% diagnosis accuracy for MLNN with LM algorithm and two hidden layer.

Er et al. used multilayer, probabilistic, and learning vector quantization neural networks for diagnosis of COPD and pneumonia diseases (Er, Sertkaya, et al., 2009). They used thirty eight features for the diagnosis and reported approximately 93.92% diagnosis accuracy for probabilistic neural network as the best result. Paul et al. used the MLNN with one and two hidden layers and they used BP with momentum as the training algorithm for predicting community-acquired pneumonia among patients with respiratory complaints (Paul et al., 2004). They performed genetic algorithms to search for optimal hidden layer architectures, connectivity, and training parameters for the neural network. The authors reported an ROC (Heckerling, 2002) accuracy ratio of 82.8% for the pneumonia disease diagnosis.

Hanif et al. used three different artificial neural networks to classify different severity of asthma and the suitable control measures to overcome it. These neural networks were feed forward back-propagation neural network (multilayer neural network), Elman back-propagation neural network and radial basis function neural network (RBF). The accuracy of the trained architectures was tested by inputting new sets of data to a created graphical user interface (GUI). They obtained best accuracy result (90%) using the radial basis function network (Hanif et al., 2009).

Aliferis et al. used KNN, decision tree induction, support vector machines and feed-forward neural networks for classify non-small lung cancers. The primary goal of their study was to develop machine learning models that classify non-small lung cancers according to histopathology types and to compare several machine learning methods in this learning task. The best multi-gene model found had a leave-one-out accuracy of 89.2% with feed-forward neural networks (Aliferis et al., 2002).

There have been several studies reported focusing on chest diseases diagnosis using artificial neural network structures as summarized in Table 1. These studies have applied different neural networks structures to the various chest diseases diagnosis problem and achieved high classification accuracies using their various dataset. On the other hand, direct comparison of the results is impossible. Because, the different data set were used by these studies. So, these neural networks were compared using the same data set which consists of the thirty eight features.

2.3. Diagnosis of the chest diseases using multilayer neural network

In the first stage of the study, the multilayer neural network structure with one and two hidden layers was used for the chest diseases diagnosis. This multilayer neural network structure (with one input layer, two hidden layers, and one output layer) is shown in Fig. 1. The hidden layer neurons (55 neurons for each hidden layer) and the output layer neurons use nonlinear sigmoid activation functions. In this system, thirty eight inputs are features, and six outputs are index of six classes (tuberculosis, COPD, pneumonia, asthma, lung cancer and normal). Equations used in the multilayer neural network structure with two hidden layers are shown in (1)–(3).

Outputs of the first hidden layer neurons are:

$$\vec{X}^{ih1}(n) = 1/\left(1+\exp\left(W^{ih1}(n)^{*}\vec{f}(n)+\vec{b}^{ih1}(n)\right)\right), \quad (1)$$

Outputs of the second hidden layer neurons are:

$$\vec{X}^{ih2}(n) = 1/\left(1+\exp\left(W^{ih2}(n)^{*}\vec{X}^{ih1}(n)+\vec{b}^{ih2}(n)\right)\right), \quad (2)$$

Outputs of the network are:

$$\vec{Y}(n) = 1/\left(1+\exp\left(W^{ho}(n)^{*}\vec{X}^{ih2}(n)+\vec{b}^{ho}(n)\right)\right), \quad (3)$$

where $W^{ih1}(n)$ are the weights from the input to the first hidden layer and $\vec{b}^{ih1}(n)$ are the biases of the first hidden layer, $W^{ih2}(n)$ are the weights from the first hidden layer to the second hidden layer and $\vec{b}^{ih2}(n)$ are the biases of the second hidden layer, $W^{ho}(n)$ are the weights from the second hidden layer to the output layer and $\vec{b}^{ho}(n)$ are the biases of the output layer, $\vec{f}(n)$ values are the features, $\vec{Y}(n)$ values are the outputs for the class index, and n is training pattern index.

The back-propagation (BP) algorithm (Rumelhart et al., 1986) is widely recognized as a powerful tool for training of the MLNNs. But, since it applies the steepest descent method to update the weights, it suffers from a slow convergence rate and often yields suboptimal solutions (Brent, 1991; Gori & Tesi, 1992). A variety of related algorithms have been introduced to address that problem. A number of researchers have carried out comparative studies of MLNN training algorithms (Hagan & Menhaj, 1994; Hagan et al., 1996; Sagiroglu et al., 2000). Levenberg–Marquardt (LM) algorithm (Hagan & Menhaj, 1994) used in this study is one of the fastest types of these algorithms. Detailed computational issues about

Table 1
The best classification accuracies of the previous studies using neural networks.

Study	Disease	Method	Training algorithm	Classification accuracy (%)
El-Solh et al. (1999)	Tuberculosis	GRNN with one hidden layer		92.30
Er, Temurtas, et al. (2010)	Tuberculosis	MLNN with two hidden layers	LM	95.08
Ashizawa et al. (2005)	COPD	MLNN with one hidden layer	BP	90.00
Coppini et al. (2007)	COPD	MLNN with two hidden layers	BP with momentum	90.60
Er and Temurtas (2010)	COPD	MLNN with two hidden layers	LM	96.08
Er, Sertkaya, et al. (2009)	COPD, pneumonia	PNN		93.92
Paul et al. (2004)	Pneumonia	MLNN with two hidden layers	BP with momentum	82.8 (ROC accuracy ratio)
Hanif et al. (2009)	Asthma	NN – radial basis function	BP	90.00
Aliferis et al. (2002)	Lung cancers	NN – feed forward		89.20

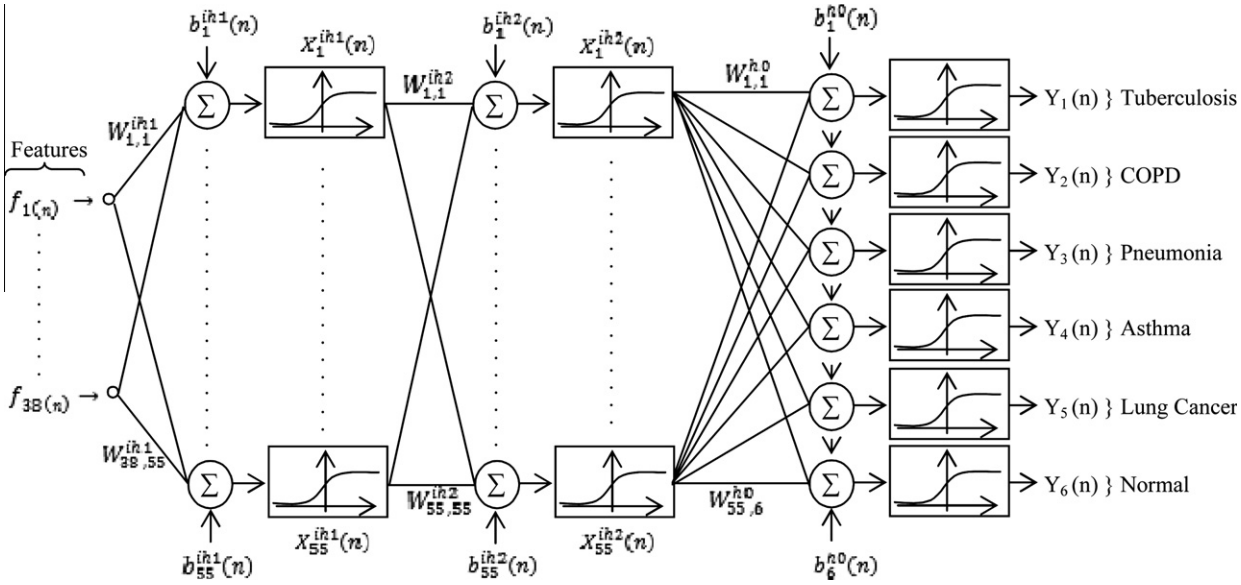

Fig. 1. Implementation of multilayer neural network for the chest disease diagnosis.

the application of the training algorithms to MLNN structures can be found in references (Gulbag & Temurtas, 2006; Matlab Documentation, 2004).

2.4. Diagnosis of chest disease using probabilistic neural network

At the second stage of this study, a probabilistic neural network was used for the chest diseases diagnosis. The network structure used for this purpose is shown in Fig. 2.

The PNN structure (Speckt, 1990) used in this study has a multilayer structures consisting of an input layer, a single hidden layer (radial basis layer), and an output layer (competitive layer) as shown in Fig. 2. In this system, real valued input vector is feature's vector, and six outputs are index of six classes (tuberculosis, COPD, pneumonia, asthma, lung cancer and normal). All hidden units simultaneously receive the 38-dimensional real valued input vector. Equations which used in the neural network model are shown in (4)–(8) (Gulbag, Temurtas, & Yusubov, 2008; Temurtas, 2009):

$$X_j = \phi\left(\|\vec{f} - \vec{c}_j\| * b^{ih}\right), \tag{4}$$

$$\phi(x) = \exp(-x^2), \tag{5}$$

$$b^{ih} = 0.833/s, \tag{6}$$

$$S_i = \sum_{j=1}^{h} W_{ji}^{ho} * X_j, \tag{7}$$

$$Y_i = \begin{cases} 1, & \text{if } S_i \text{ is max of } \{S_1, S_2, S_3\} \\ 0, & \text{else} \end{cases}, \tag{8}$$

where $i = 1, 2, ..., 6$, $j = 1, 2, ..., h$, Y_i is the ith output (classification index), $\vec{f}$ is the 38-dimensional real valued input vector, W_{ji}^{ho} is the

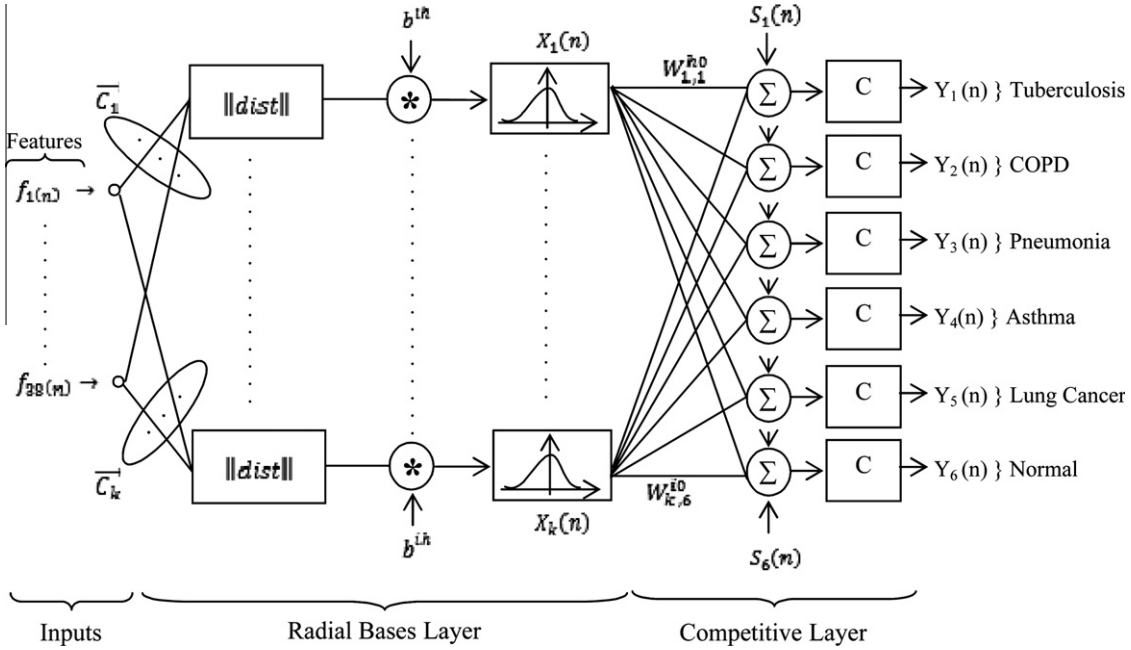

Fig. 2. Implementation of probabilistic neural network for the chest disease diagnosis.

weight between the jth hidden node and the ith output node, $\vec{c}_j$ is the center vector of the jth hidden node, s is the real constant known as spread factor, $b$ih is the biasing term of radial basis layer, and $\varphi(.)$ is the nonlinear radial basis function (Gaussian).

The PNN structures employed in the study utilized the newpnn function implemented in MATLAB. Detailed information about the realisation of the PNN structures can be found in the neural network toolbox part of MATLAB Documentation (Matlab Documentation, 2004).

2.5. Diagnosis of the chest disease using learning vector quantization neural network

At the third stage of this study, a learning vector quantization neural network was used for the chest disease diagnosis. The network structure used for this purpose is shown in Fig. 3.

The LVQ structure (Kohonen, 1990) used in this study has a multilayer structures consisting of a single hidden layer (competitive layer) and an output layer (linear layer) of six units, as shown in Fig. 3. In this system, real valued input vector is feature's vector, and six outputs are index of six classes (tuberculosis, COPD, pneumonia, asthma, lung cancer and normal). The hidden layer consists of a set of competition functions. Equations which used in the neural network model are shown in (9)–(11) (Gulbag et al., 2008; Temurtas, 2009):

$$S_j = \|\vec{f} - \vec{c}_j\|, \tag{9}$$

$$X_j = \begin{cases} 1, & \text{if } S_j \text{ is max of } \{S_1, \ldots, S_h\} \\ 0, & \text{else} \end{cases}, \tag{10}$$

$$Y_i = \sum_{j=1}^{h} W_{ji}^{ho} * X_j, \tag{11}$$

where $i = 1, 2, \ldots, 6$, $j = 1, 2, \ldots, h$, Y_i is the ith output (classification index), $\vec{f}$ is the 38-dimensional real valued input vector, W_{ji}^{ho} is the weight between the jth hidden node and the ith output node, $\vec{c}_j$ is the center vector of the jth hidden node.

The LVQ structures employed in the study utilized the newlvq function implemented in MATLAB. Detailed information about the realisation of the LVQ structures can be found in the neural network toolbox part of MATLAB Documentation (Matlab Documentation, 2004).

2.6. Diagnosis of the chest disease using generalized regression neural network

At the fourth stage of this study, a generalized regression neural network (GRNN) was used for the chest disease diagnosis. The network structure used for this purpose is shown in Fig. 4.

Bayesian networks, which often called generalized regression neural networks (GRNNs), were devised by Speckt (1990), Speckt (1991). The GRNN structure used in this study has a multilayer structures consisting of an input layer, a single hidden layer (radial basis layer), a layer of regression units, and an output layer as shown in Fig. 4. The regression layer must have exactly 1 unit more than the output layer. The regression layer contains linear units. In this system, real valued input vector is feature's vector, and six outputs are index of six classes (tuberculosis, COPD, pneumonia, asthma, lung cancer and normal). All hidden units simultaneously receive the 38-dimensional real valued input vector. Equations which used in the neural network model are shown in (12)–(15):

$$X_j = \phi\left(\|\vec{f} - \vec{c}_j\| * b^{ih}\right), \tag{12}$$

$$\phi(x) = \exp(-x^2), \tag{13}$$

$$b^{ih} = 0.833/s, \tag{14}$$

$$Y_i = \frac{\sum_{j=1}^{h} W_{ji}^{ho} * X_j}{\sum_{j=1}^{h} X_j}, \tag{15}$$

where $i = 1, 2, \ldots, 6$, $j = 1, 2, \ldots, h$, Y_i is the ith output (classification index), $\vec{f}$ is the 38-dimensional real valued input vector, W^{ho} are the regression layer weights, $\vec{c}_j$ is the center vector of the jth hidden node, s is the real constant known as spread factor, b^{ih} is the biasing term of radial basis layer, and $\varphi(.)$ is the nonlinear radial basis function (Gaussian).

The GRNN structures employed in the study utilized the newgrnn function implemented in MATLAB. Detailed information about the realisation of the GRNN structures can be found in the neural network toolbox part of MATLAB Documentation (Matlab Documentation, 2004).

2.7. Diagnosis of the chest disease using radial based function neural network

At the fifth stage of this study, a radial based function (RBF) neural network was used for the chest disease diagnosis. The network structure used for this purpose is shown in Fig. 5.

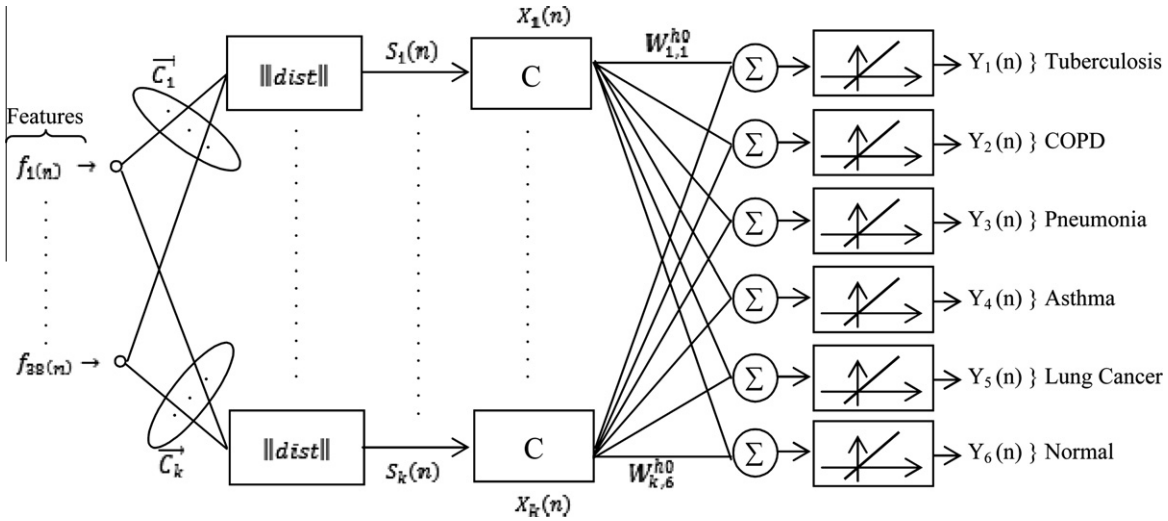

Fig. 3. Implementation of learning vector quantization neural network for the chest disease diagnosis.

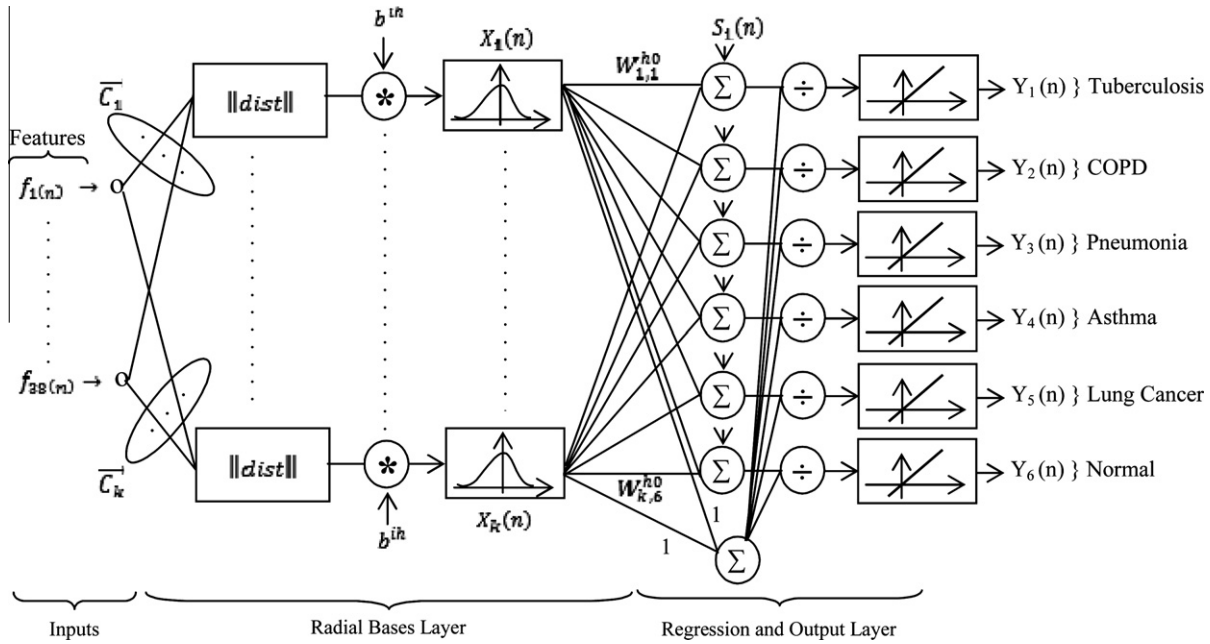

Fig. 4. Implementation of generalized regression neural network for the chest disease diagnosis.

The RBF structure used in this study has a multilayer structures consisting of an input layer, a single hidden layer (radial basis layer), and an output layer as shown in Fig. 5. In this system, real valued input vector is feature's vector, and six outputs are index of six classes (tuberculosis, COPD, pneumonia, asthma, lung cancer and normal). All hidden units simultaneously receive the 38-dimensional real valued input vector. Equations which used in the neural network model are shown in (16)–(19):

$$X_j = \phi\left(\|\vec{f} - \vec{c}_j\| * b^{ih}\right), \tag{16}$$

$$\phi(x) = \exp(-x^2), \tag{17}$$

$$b^{ih} = 0.833/s, \tag{18}$$

$$Y_i = \sum_{j=1}^{h} W_{ji}^{ho} * X_j, \tag{19}$$

where $i = 1, 2, ..., 6$, $j = 1, 2, ..., h$, Y_i is the ith output (classification index), $\vec{f}$ is the 38-dimensional real valued input vector, W^{ho} are the output layer weights, $\vec{c}_j$ is the center vector of the jth hidden node, s is the real constant known as spread factor, b^{ih} is the biasing term of radial basis layer, and $\varphi(.)$ is the nonlinear radial basis function (Gaussian).

The RBF structures employed in the study utilized the newrb function implemented in MATLAB. Detailed information about the realisation of the RBF structures can be found in the neural network toolbox part of MATLAB Documentation (Matlab Documentation, 2004).

3. Results

The classification accuracies obtained by neural network structures for chest diseases were presented in Table 2. The table shows classification accuracies for each chest diseases and average values.

From Table 2, it can be seen easily that, the best result for tuberculosis was obtained using MLNN with LM (two hidden layers). For

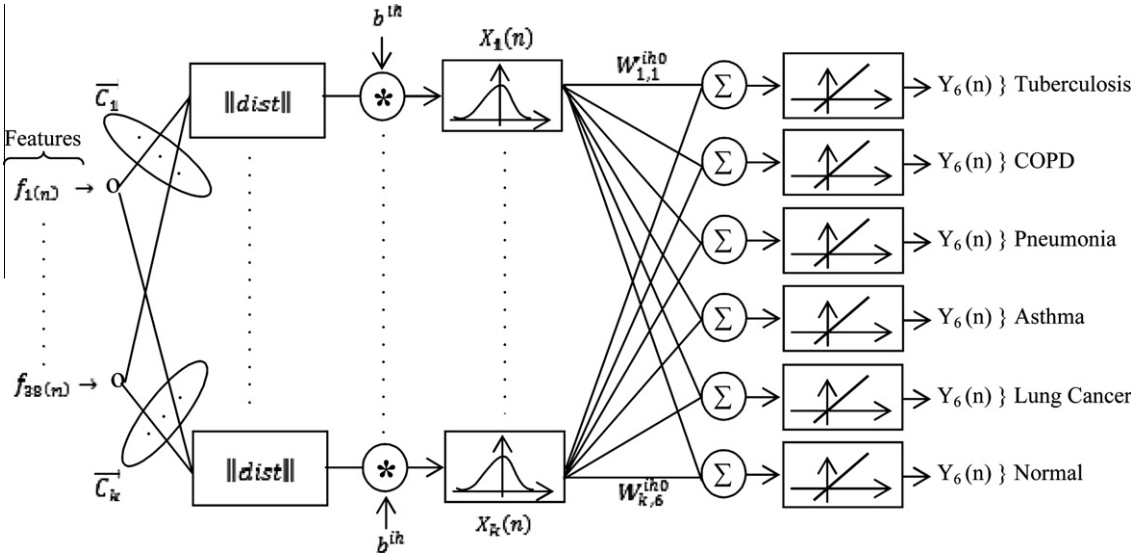

Fig. 5. Implementation of radial based function neural network for the chest disease diagnosis.

Table 2
Average of classification accuracies for each disease.

Method	Classification accuracy (%)						
	Tuberculosis	COPD	Pneumonia	Asthma	Lung cancer	Normal	Average
MLNN with BPwM (one hidden layer)	84.00	84.51	88.33	88.64	87.50	96.00	89.08
MLNN with BPwM (two hidden layers)	84.00	87.32	90.00	90.91	87.50	98.00	90.76
MLNN with LM (one hidden layer)	84.00	87.32	91.67	88.84	93.75	95.00	90.48
MLNN with LM (two hidden layers)	90.00	88.73	90.00	90.91	90.63	96.00	91.60
PNN	88.00	88.73	88.33	90.91	93.75	99.00	92.16
LVQ	84.00	84.51	86.67	86.37	93.75	94.00	88.52
GRNN	86.00	83.10	88.33	86.37	84.38	95.00	88.24
RBF	86.00	87.32	90.00	88.64	90.63	95.00	90.20

COPD and asthma, the best results were obtained using PNN and MLNN with LM (two hidden layers). For pneumonia, the best result was obtained using MLNN with LM (one hidden layers). For lung cancer, the best result was obtained using PNN.

In this study, the best result for the average classification accuracy was obtained using PNN structure as seen in the same table. The second best result for the classification accuracy was obtained using MLNN with LM (two hidden layers). The classification accuracy performances of GRNN and LVQ were similar and closer to that of MLNN with BPwM (one hidden layer).

From the same table, it can be seen also that the results obtained using MLNN with two hidden layers were better than the results obtained using MLNN with one hidden layer and the best result for the classification accuracy of MLNN structures were obtained from MLNN with two hidden layers trained by LM training algorithm in this study. So we can easily say that MLNN with two hidden layers is better than MLNN with one hidden layer and Levenberg–Marquardt (LM) training algorithm converges better than BP with momentum training algorithm for chest disease diagnosing.

4. Conclusions

There have been several studies reported focusing on chest diseases diagnosis using artificial neural network structures. These studies have applied different neural networks structures to the various chest diseases diagnosis problem using their various dataset. Because of the different dataset used by the studies, the direct comparison of the results was impossible. So, these neural networks were compared using the same dataset which consists of the thirty eight features.

As the conclusion, the following results can be summarised:

- It was seen that neural network structures could be successfully used to help diagnosis of chest disease.
- The best results for the average classification accuracy were obtained using PNN for the chest disease diagnosis problem.
- The results obtained using MLNN with two hidden layers were better than the results obtained using MLNN with one hidden layer for chest disease diagnosing.
- LM training algorithm converges better than BP with momentum training algorithm for MLNN structures for the diagnosis of chest disease.
- And, it was obtained that neural network structures could be successfully used to help diagnosis of chest disease. So, these structures can be helpful as learning based decision support system for contributing to the doctors in their diagnosis decisions.

References

Aliferis, C. F., Hardin, D., & Massion, P. P. (2002). Machine learning models for lung cancer classification using array comparative genomic hybridization. In *Proceedings of the AMIA symposium on biomedical informatics* (pp. 7–11). Nashville, TN, USA: Vanderbilt University.

Ashizawa, K., Ishida, T., MacMahon, H., Vyborny, C. J., Katsuragawa, S., Doi, K., et al. (2005). Artificial neural networks in chest radiography: Application to the differential diagnosis of interstitial lung disease. *Academic Radiology, 11*(1), 29–37.

Brent, R. P. (1991). Fast training algorithms for multi-layer neural nets. *IEEE Transactions on Neural Networks, 2*, 346–354.

Celli, B. R., & MacNee, W. (2004). Standards for the diagnosis and treatment of patients with COPD: A summary of the ATS/ERS position paper. *European Respiratory Journal, 23*(6), 932–946.

Chen, F. C., & Lin, M. H., (1993). On the learning and convergence of the radial basis networks. In *Proceedings of the IEEE international conference on neural networks, March 28* (pp. 983–988). San Francisco, CA.

Coppini, G., Miniati, M., Paterni, M., Monti, S., & Ferdeghini, E. M. (2007). Computer-aided diagnosis of emphysema in COPD patients: Neural-network-based analysis of lung shape in digital chest radiographs. *Medical Engineering & Physics, 29*, 76–86.

Daqi, G., Shuyan, W., & Yan, J. (2004). An electronic nose and modular radial basis function network classifiers for recognizing multiple fragrant materials. *Sensors and Actuators B – Chemical, 97*, 391–401.

Delen, D., Walker, G., & Kadam, A. (2005). Predicting breast cancer survivability: A comparison of three data mining methods. *Artificial Intelligence in Medicine Artificial Intelligence in Medicine, 34*(2), 113–127.

dos Santos, A. M., Pereira, B. B., de Seixas, J. M., (2004). Neural networks: An application for predicting smear negative pulmonary tuberculosis. In *Proceedings of the statistics in the health sciences*.

El-Solh, A. A., Hsiao, C.-B., Goodnough, S., Serghani, J., & Grant, B. J. B. (1999). Predicting active pulmonary tuberculosis using an artificial neural network. *Chest, 116*, 968–973.

Enarson, D. A., Rieder, H. L., Arnadottir, T., & Trébucq, A. (2000). *A guide for low income countries*. 2-914365-00-4. 68, Boulevard, Saint-Michel, 75006 Paris, France: International Union Aagainst Tuberculosis and Lung Disease.

Er, O., Sertkaya, C., Temurtas, F., & Tanrikulu, A. C. (2009). A comparative study on chronic obstructive pulmonary and pneumonia diseases diagnosis using neural networks and artificial immune system. *Journal of Medical Systems, 33*(6), 485–492.

Er, O., & Temurtas, F. (2008). A study on chronic obstructive pulmonary disease diagnosis using multilayer neural networks. *Journal of Medical Systems, 32*(5), 429–432.

Er, O., Temurtas, F., & Tanrikulu, A. C. (2010). Tuberculosis disease diagnosis using artificial neural networks. *Journal of Medical Systems, 34*(3), 299–302.

Global Action Plan for the Prevention and Control of Pneumonia (GAPP), (2007). *Report of an informal consultation*, 5–7 March 2007, La Mainaz, Gex, France.

Gori, M., & Tesi, A. (1992). On the problem of local minima in backpropagation. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 14*, 76–85.

Gulbag, A., & Temurtas, F. (2006). A study on quantitative classification of binary gas mixture using neural networks and adaptive neuro fuzzy inference systems. *Sensors and Actuators B – Chemical, 115*, 252–262.

Gulbag, A., Temurtas, F., & Yusubov, I. (2008). Quantitative discrimination of the binary gas mixtures using a combinational structure of the probabilistic and multilayer neural networks. *Sensors and Actuators B – Chemical, 131*, 196–204.

Hagan, M. T., Demuth, H. B., & Beale, M. H. (1996). *Neural network design*. Boston, MA: PWS Publishing.

Hagan, M. T., & Menhaj, M. (1994). Training feed forward networks with the Marquardt algorithm. *IEEE Transactions on Neural Networks, 5*, 989–993.

Hanif, N. H. H. M., Lan, W. H., Daud, H. B., & Ahmad, J. (2009). *Classification of control measures for asthma using artificial neural networks*. Malaysia: Scientific and Technical Publishing Company, ACTA Press.

Heckerling, P. S. (2002). Parametric receiver operating characteristic (ROC) curve analysis using mathematica. *Computer Methods and Programs in Biomedicine, 69*, 65–73.

Jeffery, P. K. (1998). Structural and inflammatory changes in COPD: A comparison with asthma. *Thorax, 53*(2), 129–136.

Kayaer, K., & Yıldırım, T. (2003). Medical diagnosis on pima indian diabetes using general regression neural networks. In *Proceedings of international conference on artificial neural networks and neural information processing (ICANN/ICONIP)* (pp. 181–184). Istanbul.

Kohonen, T. (1990). Improved versions of learning vector quantization. In *Proceedings of the IEEE international joint conference on neural networks* (pp. 545–550). New York.

Kohonen, T. (1997). *Self-organizing maps* (2nd ed). Berlin: Springer-Verlag.

Matlab Documentation, (2004). *Version 7.0, Release 14*. The MathWorks, Inc.

MedHelp, (2009). *Thoracic organs*. <http://www.medhelp.org/Medical-Dictionary/Terms/2/8964.htm> (accepted 18.03.09).

Paul, S. H., Ben, S. G., Thomas, G. T., & Robert, S. W. (2004). Use of genetic algorithms for neural networks to predict community-acquired pneumonia. *Artificial Intelligence in Medicine, 30*, 71–84.

Royal College of Physicians of London, (2006). *Tuberculosis*. 11 St. Andrews Place, London NW1 4LE. ISBN: 1 86016 277 0.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning internal representations by error propagation. In D. E. Rumelhart & J. L. McClelland (Eds.). *Parallel distributed processing: Explorations in the microstructure of cognition* (Vol. 1, pp. 318–362). Cambridge, MA: MIT Press.

Sönmez, S., & Uzaslan, E. (2006). Kronik Obstrüktif Akciğer Hastalığı'nın Genetiği ve Sitokin Gen Polimorfizmi–Derleme. *Archives of Lung, Cilt 7*, 75–78.

Speckt, D. F. (1990). Probabilistic neural networks. *Neural Networks, 3*, 109–118.

Speckt, D. F. (1991). A generalized regression neural network. *IEEE Trans Neural Networks, 2*(6), 568–576.

Temurtas, F. (2009). A comparative study on thyroid disease diagnosis using neural networks. *Expert Systems with Applications, 36*, 944–949.

Temurtas, H., Yumusak, N., & Temurtas, F. (2009). A comparative study on diabetes disease diagnosis using neural networks. *Expert Systems with Applications, 36*, 8610–8615.

World Health Organization, (2008). Global tuberculosis control 2008 surveillance planning financing. Geneva. ISBN: 978 92 4 156354 3.