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Classification of the Frequency of Carotid Artery Stenosis With MLP and RBF Neural Networks in Patients With Coroner Artery Disease

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For the classification of left and right Internal Carotid Arteries (ICA) stenosis, Doppler signals have been received from the patients with coroner arteries stenosis by using 6.2–8.4 MHz linear transducer. To be able to classify the data obtained from LICA and RICA in artificial intelligence, MLP and RBF neural networks were used. The number of obstructed veins from the coroner angiography, intimal thickness, and plaque formation from the power Doppler US and resistive index values were used as the input data for the neural networks. Our findings demonstrated that 87.5% correct classification rate was obtained from MLP neural network and 80% correct classification rate was obtained from RBF neural network. MLP neural network has classified more successfully when compared with RBF neural network.

KEY WORDS: carotid arteries stenosis; coroner arteries stenosis; Doppler ultrasonography; MLP neural network; RBF neural network.

INTRODUCTION

Angiography is being used for extracranial vascular disease diagnosis as the main method for years. However, for this method is invasive and it has high morbidity and mortality rates, new methods such as Doppler Ultrasonography (US) and MR angiography have formed.

For the time being, duplex Doppler US is accepted as the standard noninvasive examination method for vascular system. Its common use has facilitated the evaluation of morphologic and hemodynamic variations in the carotid arteries.[1,2]

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Carotid lesions causing hemodynamic flow changes are important risk factors in coroner artery patients recovering from by-pass operation. Degradation in many levels in the central nerve system are proved to occur after coroner by-pass.[3]

Artificial neural network, more often simply called "neural networks," are non-parametric pattern recognition techniques that can recognize "hidden patterns" between independent and dependent variables.[4] Neural networks have been used in a number of applications such as remote sensing,[5] dynamic modeling and medicine,[6] and pattern classification.[7–9] In many cases, neural network results have been achieved relative to standard statistical models.[10] Recently, neural networks have been used for the classification of several diseases. Some researchers demonstrated their predictive reliability of a neural networks model in medical diagnosis. In this case, we utilize the ability of neural network to recognize complex and nonlinear relationship in characterizing medical circumstances.[11,12]

Recently RBF neural networks have been found to be very attractive for many engineering problems. An important property of the RBF neural networks is that they form a unifying link among many different research fields such as function approximation, regularization, noisy interpolation, pattern recognition,[13] and medicine.[14] The increasing popularity of the RBFNNs is partly due to their simple topological structure, their locally tuned neurons, and their ability to have a fast learning algorithm in comparison with other multilayer feed forward neural networks.[15,16]

In this study, 80 cases in which coroner artery disease is determined with coroner angiography have been examined with Doppler US, and determination of the incidence of carotid artery disease in these patients and classification of such with MLP and RBF neural network. The determination of the incidence of carotid lesions and levels of hemodynamic changes in these patients will lead the way to surgical procedures and radiologic methods prior to bypass operation and also will contribute to avoidance of possible cerebro vascular complications as a result of bypass operation.

MATERIALS AND METHOD

Between November 2002 and May 2003, 80 patients in which surgery has been planned after coroner angiography, have been examined with power Doppler US for carotid artery disease in Radiology clinics of the Medical Center of Fırat University for carotid artery disease. For these examinations, Toshiba SSA-770 Aplio 80 (Toshiba, Tokyo, Japan) power Doppler US apparatus with multifrequency 6.2–8.4 MHz linear transducer has been used.

Patients were examined in supine position, head contralaterally turned. Examination of both sides started right above the claviculas, as the transducer was cranially moved, Left Internal Carotid Artery (LICA) and Right Internal Carotid Artery (RICA) were examined. Intimal thickening and plaque formation were determined with saggital examination. With spectral examination, peak systolic and end diastolic velocity measurements were performed and resistive index was obtained.

Further on, color Doppler was performed to record the narrowing percentage of the carotid arteries—1–39% narrowing was low stenosis, 40–59% was moderate stenosis, and 60–79% was severe stenosis.

To be able to classify the data obtained from LICA and RICA in artificial intelligence, MLP and RBF neural networks were used. The number of obstructed veins from the coroner angiography, intimal thickness and plaque formation from the power Doppler US, and resistive index values were used as the input data for the neural networks. Output data were given according to the percentage of narrowing in the carotid arteries as—severe stenosis, moderate stenosis, low stenosis, and normal.

MLP Neural Network

Neural networks are complex systems, which are formed with the different connection geometry of artificial networks produced like the neurons in the human brain and with their interconnection. Feed forward neural networks have a wide application field.[4,17] Some researchers demonstrated their predictive reliability of a neural networks model in medical diagnosis. In this case, we utilize the ability of neural network to recognize complex and nonlinear relationship in characterizing medical circumstances.[18]

The tangent hyperbolic (tanh) function may be selected as the transfer function that is used to determine the outputs according to the neuron inputs. One of the most important topics that should be applied during the learning process of the neural networks is to adjust learning rate and momentum term.[4] The momentum coefficient and the size of the step were taken as 0.7 and 0.1, respectively.

The value of the neuron at the output of neural network (calculated diagnosis) is compared with the real diagnosis information that is determined by expert radiologist using magnetic resonance imaging and the difference between them is calculated as the error. Mean Square Error (MSE) is used to decide if the expected and calculated values of network output are approximate. Then normalized mean square error (NMSE), mean square error (MSE), and mean average error (MAE) are computed. The correlation coefficient r gives information about the training of network, having a value between –1 and 1. If the correlation coefficient is close to (1), it shows how much the learning is successful. MSE is used to determine how much the network has reached to desired output values. The stopping criterion for the supervised learning is set over the curve of MSE.[19]

In this work, feed forward multilayered perceptron neural network was used. The back propagation feed forward neural network is shown in Fig. 1. The reason for using this type of neural network is that it is a standard in the solution of problems related with identifying figures by applying the supervised learning and the back propagation of errors together.

RBF Neural Network

The RBF neural network[20–22] is a fully connected feed forward neural network with one hidden layer and an output layer. The hidden layer of nodes uses a Gaussian density function as its activation function.

RBF neural networks share features of the back propagation neural networks (BPNNs) for pattern recognition. They are being extensively used for on- and off-linear-adaptive modeling and control applications. RBF neural networks store

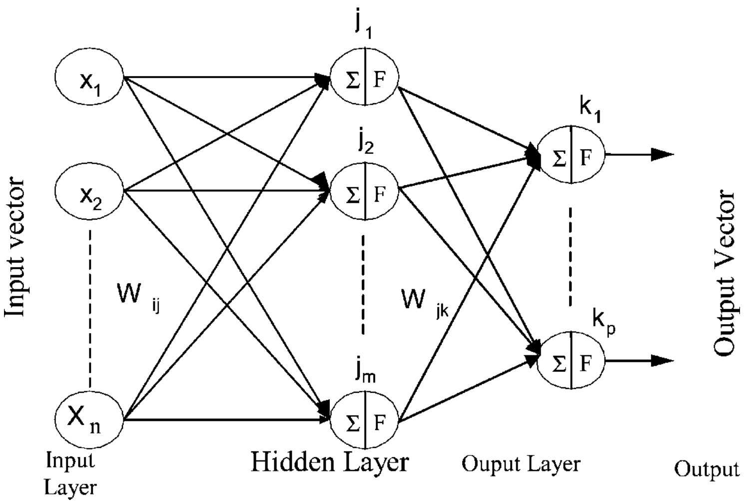

Fig. 1. Feed forward back propagation neural network architecture.

information locally whereas the conventional BPNNs store the information globally.

Like the more commonly used MLP neural network, RBF neural networks comprise three layers of nodes but with the middle (hidden) layer being made up of Gaussian or asymmetric kernels (Fig. 2). A number of kernels are positioned in the input space using one of a number of possible placement algorithms. As in MLPs, the inputs to the network are nodes that simply pass each of the input signals to the middle layer kernels. The architecture consists of one hidden and one output layer. This shallow architecture has great advantage in terms of computing speed compared to multiple hidden layer nets.

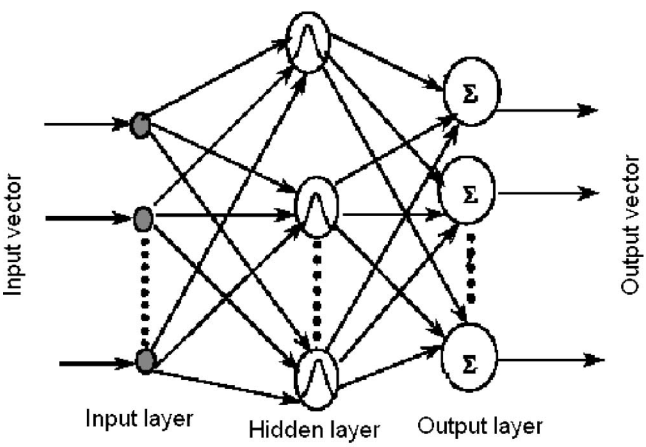

Fig. 2. RBF neural network structure.

The RBF architecture consists of a feed forward two layer network in which the transfer function of each hidden node is radially symmetric in the input space. We will focus our attention on Gaussian basis functions, which are the most commonly used functions and have many useful analytical properties.

The input layer simply transfers the input vector to the hidden neurons. The only hidden layer consists of j locally tuned units and each unit has a radial basis function acting like a hidden node. The hidden node output $\varphi_i(x)$ calculates the closeness of the input and projects the distance to an activation function. The activation function of the jth hidden node used in this study is the Gaussian function given by

$$\varphi_i(x) = \exp\left(-\frac{\|x - c_i\|^2}{\sigma_i^2}\right) \quad (i = 1, \ldots, n_\mathrm{h}) \tag{1}$$

where x is the n-dimensional input vector; c_i is the center of the radial basis function for hidden node j; and $\|x - c_i\|$ denotes the Euclidean distance between the center of the radial basis function and input; σ_i is a parameter for controlling the smoothness properties of the radial basis functions; n_h is the number of hidden neurons.

The jth output y_j of the RBF neural network will be

$$y_j = \sum_{i=1}^{n_\mathrm{h}} w_{ij}\varphi_i(x) \quad (j = 1, \ldots, n_\mathrm{o}) \tag{2}$$

where w_{ij} is the connection weight from the ith hidden neuron to the jth output neuron and n_o is the total number of output neurons.

Sensitivity, Specificity, and Receiver Operating Characteristic Curve Analysis

The simplest classification problem is that of separating one-dimensional feature vectors into two groups. In this situation the only choice that needs to be made is where to locate the decision threshold. If there is no overlap between the magnitudes of the vectors obtained from patients belonging to the two classes, the threshold can simply be chosen to separate the classes completely. In general, the results from these two classes do overlap. That is depending on where the threshold of some signals from normal subjects will be adjudged abnormal and/or some signals from abnormal will be adjudged normal. The best choice of threshold will then depend on a number of factors. There are two important measures of the performance of a diagnostic test; sensitivity (or true positive fraction) and specificity (or true negative fraction) that are defined as

$$\begin{aligned}\text{Sensitivity (TPF)} = {} & \text{Number of true positive decisions/} \\ & \text{Number of actually positive cases}\end{aligned} \tag{3}$$

and

$$\begin{aligned}\text{Sensitivity (TNF)} = {} & \text{Number of true positive decisions/} \\ & \text{Number of actually positive cases}\end{aligned} \tag{4}$$

These measures are dependent since they are both affected by the position of the decision threshold and as the threshold is moved to increase sensitivity, so specificity decreases. The best method of assessing the value of a test and defining an appropriate decision threshold is to plot a receiver operating characteristic (ROC) curve for the test.(23)

RESULTS AND DISCUSSION

In this study, to solve the pattern classification problem MLP and RBF neural network were used. Selection of network input parameters and performance of systems are important for the prediction of stenosis degrees of carotid arteries by MLP and RBF neural network.

During training, the input and desired data will be repeatedly presented to the network. When using MLP and RBF neural network, decision must be taken for how to divide data into a training set and a test set. In this study, 40 of 80 subjects were used for training and the rest of them were used for testing. The outputs are represented by unit basis vectors as

[1 0 0 0] = Severe stenosis of carotid arteries
[0 1 0 0] = Moderate stenosis of carotid arteries
[0 0 1 0] = Low stenosis of carotid arteries
[0 0 0 1] = Normal

Selection of network input parameters plays an important role in classifying systems. During this study, the number of obstructed veins from the coroner angiography, intimal thickness and plaque formation from the power Doppler US, and resistive index values were used as the input data for the neural networks.

Before applying the data to MLP and RBF neural network, all the data used in this work were diagnosed by the expert radiologist using magnetic resonance imaging method as 20 samples of data were severe stenosis of carotid artery, 20 samples of data were moderate stenosis of carotid artery, 20 samples of data were low stenosis of carotid artery, and 20 samples of data were normal.

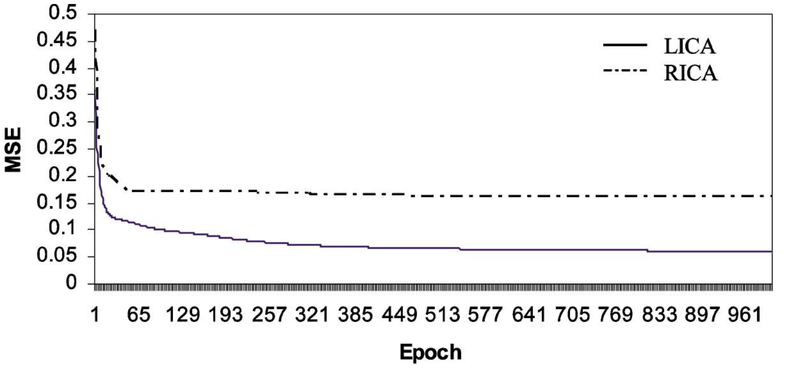

Fig. 3. Training MSE curves of MLP neural network.

Table I. Test Results of MLP Neural Network

	Severe stenosis		Moderate stenosis		Low stenosis		Normal	
	LICA	RICA	LICA	RICA	LICA	RICA	LICA	RICA
Severe stenosis	9	8	1	1				
Moderate stenosis	1	2	8	8		1		
Low stenosis			1	1	9	8	1	1
Normal					1	1	9	9

In patients evaluated for their coroner artery pathologies, 18 had single vein coroner artery, 27 had double vein coroner artery, 28 had triple vein coroner artery, and 7 had four vein coroner artery disease. A significant relation was found between the degree of the coroner artery disease and carotid artery stenosis ($p < 0.05$).

Results of MLP Neural Network

One of the simplest methods is to observe how the square difference between the network's output and the desired response changes over training iterations. The curve of the MSE versus iteration is called as the training curve. Training MSE curve of MLP neural network in 1000 epochs is shown in Fig. 3. As the network learns, the error is converging to zero.

After the learning, test vectors were applied to neural network, and the obtained results are shown on Tables I and II. As it is seen in Table I, 35 of the total 40 LICA testing data and 33 of the total 40 RICA testing data were classified correctly.

In this study, MSE, NMSE, MAE, and correlation coefficient (r) were used for measuring performance of the neural network. Performance evaluation parameters and their values in this neural network are given for subjects having stenosis (severe, moderate, and low), and normal subjects in Table II. From the results of performance evaluation and statistical measures, the neural network was found to be successful.

To measure the classification performance, these results should be evaluated statistically. Sensitivity, specificity, area under ROC curve, and correct classification values reached after the application of test vectors to the MLP have been given in Table III. As it is seen in Table III, correct classification size of LICA is 87.5% and correct classification size of RICA is 82.5%. As a result of the studies made by MLP, the receiver operating characteristic (ROC) curve has been obtained. To find out the prediction capacity of MLP, the output data of test results are analyzed and ROC

Table II. Test Performances of MLP and RBF Neural Networks

	MLP		RBF	
Performance	LICA	RICA	LICA	RICA
MSE	0.0601	0.1623	0.0647	0.1346
NMSE	0.1566	0.3243	0.1748	0.3024
MAE	0.0471	0.0826	0.0562	0.0718
r	0.8934	0.8163	0.8627	0.8131

Table III. Statistics of MLP and RBF Neural Networks

	MLP		RBF	
Statistic type	LICA	RICA	LICA	RICA
Specificity	90%	90%	90%	80%
Sensitivity	86.7%	80%	83.3%	80%
Area under ROC curve	0.863	0.817	0.846	0.805
Correct classification rate	87.5%	82.5%	85%	80%

curve is obtained. By examining data related with correct and false classification, the relation between the specificity and sensitivity is shown in Fig. 4.

ROC curve is one of the best method of evaluating the performance of a test and defining an appropriate decision threshold. The best choice of threshold will then depend on a number of factors including the consequences of making both types of false classification (false positive and false negative) and the prevalence of disease in the target population. For a given result obtained by a classifier system, four possible alternatives exist that describe the nature of the result: (a) true positive (TP), (b) false positive (FP), (c) true negative (TN), and (d) false negative (FN). In this study, a TP decision occurred when the positive diagnosis of the system coincided with a positive diagnosis according to the physician. A FP decision occurred when the system made a positive diagnosis that did not agree with the physician. A TN decision occurred when both the system and the physician suggested the absence of a positive diagnosis. A FN decision occurred when the system made a negative diagnosis that did not agree with the physician. Also the best choice of threshold for any test depends on the shape of the ROC curve. A good test is one for which sensitivity rises rapidly and one-specificity hardly increases at all until sensitivity becomes high. Hence, the closer the curve is to the upper left corner, the higher the

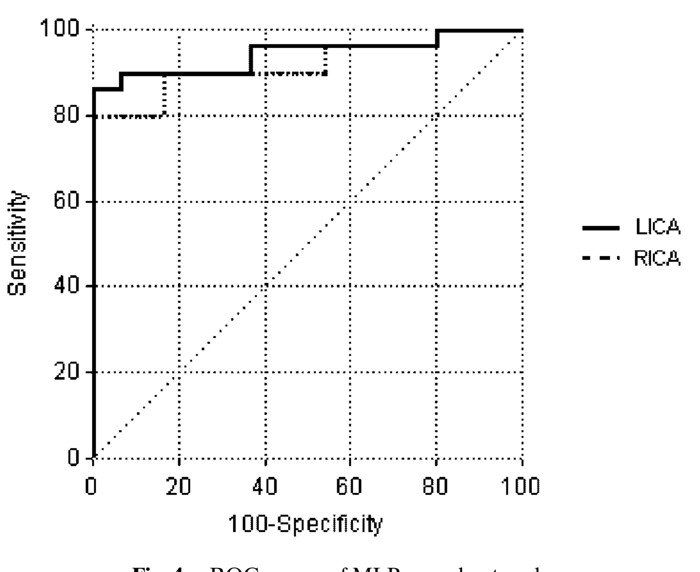

Fig. 4. ROC curves of MLP neural network.

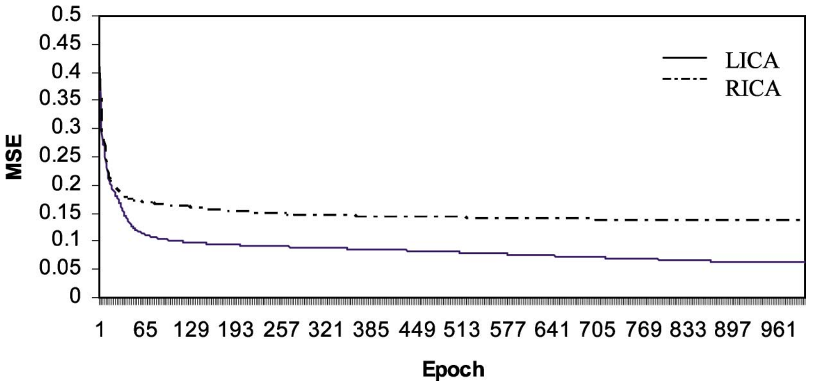

Fig. 5. Training MSE curves of RBF neural network.

overall accuracy of the test. ROC curve that is seen in Fig. 4 represents the network performance on the test file of 80 subject records.

Furthermore, the performance of the neural network can be measured by computing the area under the ROC curve. The area under the ROC curve is 0.863 and 0.825 for LICA and RICA, respectively. This shows that MLP neural network is successful.

Results of RBF Neural Network

Training MSE curve of RBF neural network in 1000 epochs is shown in Fig. 5. As the network learns, the error is converging to zero.

After the learning, test vectors were applied to neural network, and the obtained results are shown on Tables II and IV. Performance evaluation parameters and their values in this neural network are given for subjects having stenosis (severe, moderate, and low), and normal subjects in Table II. As it is seen in Table IV, 34 of the total 40 LICA testing data and 32 of the total 40 RICA testing data were classified correctly.

To measure the classification performance, these results should be evaluated statistically. Sensitivity, specificity, area under ROC curve, and correct classification values reached after the application of test vectors to the RBF have been given in Table III. As it is seen in Table III, correct classification size of LICA is 85% and correct classification size of RICA is 80%. As a result of the studies made by RBF, the receiver operating characteristic (ROC) curve has been obtained. To find out the

Table IV. Test Results of RBF Neural Network

	Severe stenosis		Moderate stenosis		Low stenosis		Normal	
	LICA	RICA	LICA	RICA	LICA	RICA	LICA	RICA
Severe stenosis	9	8	1					
Moderate stenosis	1	2	8	8	1	1		
Low stenosis			1	2	8	8	1	2
Normal					1	1	9	8

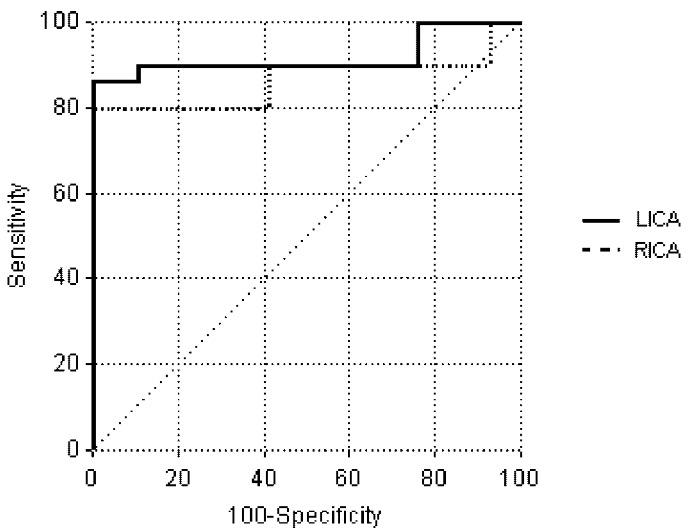

Fig. 6. ROC curves of RBF neural network.

prediction capacity of RBF, the output data of test results are analyzed and ROC curve is obtained. By examining data related with correct and false classification, the relation between the specificity and sensitivity is shown in Fig. 6.

In this study, the diagnosis performance of carotid arteries stenosis with coroner artery diseases shows the advantages of MLP and RBF neural network: it is rapid, easy to operate, noninvasive, and not expensive.

CONCLUSION

In this work, the classification systems were developed with the application of degrees of carotid arteries stenosis with coroner artery diseases in MLP and RBF neural network. Our findings demonstrated that 87.5% correct classification rate was obtained from MLP neural network and 80% correct classification rate was obtained from RBF neural network.

These results demonstrate that the classification performance of carotid arteries stenosis with RBF is lower than that of MLP neural network.

REFERENCES

1. Steinke, W., and Kloetzsch, C., Hennereci, Carotid artery disease assessed by color Doppler flow imaging: Correlation with standard Doppler sonography and angiography. *Ann. J. Roentgenol.* 154:1061–1068, 1990.
2. Wagner, W. H., Treiman, R. L., Cossman, D. V., *et al.*, The diminishing role of diagnostic arteriography in carotid artery disease: Duplex scanning as definitive preoperative study. *Ann. Vasc. Surg.* 5:105–110, 1991.
3. Blossom, G. B., Fietsam, R. J., Bassets, J. S., *et al.*, Characteristics of cerebrovascular accidents after coronary artery bypass grafting. *Ann. Surg.* 58:584–589, 1992.

4. Beale, R., and Jackson, T., *Neural Computing: An Introduction*, Institute of Physics Publishing, Bristol, UK, 1990.
5. Bruzzone, L., Prieto, D. F., and Serpico, S. B., A neural-statistical approach to multitemporal and multisource remote-sensing image classification. *IEEE Trans. Geosci. Remote Sensing* 30:1350–1359, 1999.
6. Hwang, J. N., Kung, S. Y., Niranjan, M., and Principe, J. C., The past, present, and future of neural networks for signal processing. *IEEE Signal Process. Mag.* 14:28–48, 1997.
7. Grudin, M. A., On internal representation in face recognition systems. *Pattern Recognit.* 33(6):1161–1177, 2000.
8. Yung, M. H., Kreigman, D. J., and Ahuja, N., Detecting face in images: A survey. *IEEE Trans. Pattern Anal. Mach. Int.* 34(1):34–58, 2002.
9. Haddadnia, L., and Faez, K., Human face recognition based on shape information and pseudo Zernike moment. *Proc. 5th Int. Fall Workshop Vision, Model. Visual.,* Saarbrucken, Germany, November 22–24, pp. 113–118, 2000.
10. White, H., Learning in artificial neural networks: A statistical approach. *Neural Comput.* 1:425–464, 1989.
11. Baxt, W. G., Application of neural networks to clinical medicine. *Lancet* 346:1135–1138, 1995.
12. Mobley, B. A., Schecter, E., Moore, W. E., McKee, P. A., and Eichner, J. E., Predictions of coronary artery stenosis by artificial neural network. *Artif. Intell. Med.* 18:187–203, 2000.
13. Bishop, C. M., *Neural Network for Pattern Recognition*, Oxford University Press, New York, 1995.
14. Bezerianos, A., Papadimitrious, S., and Alexopoulos, D., Radial basis function neural networks for the characterization of heart rate variability dynamics. *Artif. Intell. Med.* 15:215–234, 1999.
15. Zhou, W., Verification of the nonparametric characteristics of backpropagation neural networks for image classification. *IEEE Trans. Geo. Remote Sensing* 37(2):771–779, 1999.
16. Yingwei, L., Sundarajan, N., and Saratchandran, P., Performance evaluation of a sequential minimal radial basis function (RBF) neural network learning algorithm. *IEEE Trans. Neural Netw.* 9(2):308–318, 1998.
17. Fredric, M. H., and Inica, K., *Principles of Neurocomputing for Science and Engineering*, McGraw-Hill, New York, 2001.
18. Ergün, U., Serhatlýoǝlu, S., Hardalaç, F., and Güler, Ý., Classification of carotid artery stenosis of the patients with diabetes by neural network and logistic regression. *Comput. Biol. Med.*, 34:389–405, 2004.
19. McClelland, J. L., and Rumelhart, D. E., *Explorations in Parallel Distributed Processing: A Handbook of Models, Programs and Exercises*, MIT Press, Cambridge, MA, 1986.
20. Powell, M. J. D., Radial basis functions for multivariable interpolation: A review. In Cox, M. G., and Mason, J. C. (eds.), *Algorithms for the Approximation of Functions and Data*, Oxford University Press, New York, 1985.
21. Broomhead, D. S., and Lowe, D., Multivariable functional interpolation and adaptive networks. *Complex Syst.* 2:321–355, 1988.
22. Moody, J., and Darken, C. J., Fast learning in networks of locally tuned processing units. *Neural Comput.* 1:281–294, 1989.
23. Zweig, M. H., and Campbell, G., Receiver-operating characteristic (ROC) plots: A fundamental evaluation tool in clinical medicine. *Clin. Chem.* 39:561–577, 1993.