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Classification of Breast Cancer using Artificial Neural Network Algorithms

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A B S T R A C T

Breast cancer is a malignant tumor that has developed from cells of the breast. Breast cancer is one of the most fatal diseases in the world and a relatively common cancer in Turkey. Breast cancer diagnosis has been approached by various machine learning techniques for many years. In this study, two different probabilistic neural network (PNN) structures were used for breast cancer’s diagnosis. The PNN results were compared with the results of the multilayer, learning vector quantization neural networks and the results of the previous reported studies focusing on breast cancer’s diagnosis and using the same dataset. It was observed that the PNN is the best classification accuracy with 98.10% accuracy obtained via 3-fold cross validation. The present paper describes how this technique can be applied to the breast tissue classification and the breast cancer detection for medical devices. The purpose of this study is the classification of the variability of impedivity observed in normal and pathological breast tissue.

1. Introduction

Breast cancer is the cancer of breast tissue, and constitutes malignant tumor that has developed from cells of the breast. It has become a major cause of death among women in developed countries [1]. Breast cancer is one of the most fatal diseases in the world and a relatively common cancer in Turkey. Scientifically medical diagnosis for this disease is very important in the digital age. Thus, this paper represents efficient machine learning techniques using soft computing methods in order to diagnose cancer.

In order to recognize the breast tissue characteristics or get data, set electrical impedance techniques are used. The tissue is tested with different frequencies and data set is plotted. The specific impedance of a tissue is determined by its electrical and dielectric properties, which depend, among other things, on the cell concentration, membrane capacitance, electric conductivity in interstitial area and the intracellular medium [2].

Early diagnosis of the cancers lessen the sad results and is an efficient way of its treatment. Because of these reasons, computer aided diagnosis is essential. When several tests are involved, the ultimate diagnosis may be difficult to be obtained, even for a medical expert. This has given rise, over the past few decades, to computerized diagnostic tools, intended to aid the doctor in making sense out of the confusion of data [3]. In the paper, data sets, which belong to breast tissue, is gotten by this electrical impedance technique.

Moreover, breast cancer diagnosis is an important classification issue. Classification is often a very important part of the process in many different fields like medicine. The use of artificial intelligence methods in medical diagnosis have been increasing gradually. There is no doubt that the evaluations of data taken from patients and the decisions of experts are the most important factors in diagnosis. However, sometimes different artificial intelligence techniques are needed for classification of the disease [4].

The PNN 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 the other ANNs structures. 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 [5]. Because the PNN provides a general solution to pattern classification problems, it is suitable for the disease diagnosis systems [6-10].

Some advantages of the PNN are as followed:

1. It is a very fast learning and recalling process,
2. There is no iteration for weight regulations in learning process,
3. No pre-decision for the number of hidden layers and the number of hidden nodes in each layer with the predetermined,
4. Training samples, the number of hidden nodes could be effectively determined.
5. It needs a limited number of samples for training;
6. It has adaptability to architectural changes.

The multilayer neural network (MLNN) structure is the most common neural network structure, which has been successfully used for the disease diagnosis systems [10-12]. The back-propagation (BP) algorithm is widely recognized as a powerful tool for training of the MLNN structures [13]. However, BP algorithm suffers from a slow convergence rate and often yields suboptimal solutions [14-15]. 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 [16-17]. Levenberg-Marquardt (LM) algorithm [16] used in this study provides generally faster convergence and better estimation results than other training algorithms [18-19].

The classification of the learning vector quantization (LVQ) neural network structure is based on the similarity of the unknown data and these prototypes. A LVQ neural network has a competitive layer and a 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 [20-21]. The LVQ network structures have been successfully used for the disease diagnosis systems [6-10].

Computer simulation shows that the PNN-based disease diagnosis system could be very effective in processing the diagnosis information. Certainly our previous works [6-10] show that good performance was achieved by PNN with regards to other disease diagnosis problems [10,22-23]. Therefore in this paper, a study of PNN on breast tissue cancer diagnosis was realized. The breast cancer dataset which was created by Silva and Jossinet was used [2,24]. Also, the PNN results were compared with the results of the MLNN and LVQ neural networks, focusing on breast cancer diagnosis and using the same database.

The aim of this work was to investigate the electrical impedance characteristics of breast tissue by soft computing in order to pattern recognition. This study offers the alternative approach that breast cancer may be diagnosed early and therefore be cured. Another focus of the study is providing a machine learning based decision support system that can contribute to the doctors' diagnosis decisions.

2. Method

2.1. Data source

In this paper, the data set of breast cancer which was created by Silva and Jossinet is used [2,24]. This is a data set with electrical impedance measurements in samples of freshly excised tissue from the breast. It consists of 106 instances, and 10 attributes that consist of 9 features and1 class attribute. Six classes of freshly excised tissue were studied using electrical impedance measurements. Table 1 presents the details about the 6 classes and the number of cases that belong to those classes.

Table 1: Description about the 6 classes of breast tissue dataset.

	CLASSES	# OF CASES
Normal Tissue Classes	Connective (Con)	14
	Adipose (Adi)	22
	Glandular (Gla)	16
Pathological Tissue Classes	Carcinoma (Car)	21
	Fibro-Adenoma (Fad)	15
	Mastopathy (Mas)	18

The initial data set consisted of 120 spectra recorded in samples of breast tissue from 64 patients undergoing breast surgery. Each spectrum consisted of twelve impedance measurements taken at different frequencies ranging from 488 Hz to 1 MHz. Details concerning the procedure for the aforementioned data collection, as well as the classification of the used cases and frequencies are given in the work of Jossinet [25-26].

2.2. Previous Studies

Considerable work has been done on applying machine learning techniques to study breast cancer, one of the most common kinds of cancer in the world. In the machine learning repository of UCI (University of California, Irvine) there are four data sets whose main target of study is breast cancer [27]. One of the first works on applying machine learning techniques to breast cancer data dates back to 1990. At this time, the first data set donated to the UCI repository was created by Wolberg and Mangasarian after their work on a multi-surface method of pattern separation for medical diagnosis that was applied to breast cytology [28].

Breast cancer data is analyzed by various researchers within the framework of medical diagnosis of breast cancer in neural network literature [29-35]. In Ref [3] breast cancer is diagnosed using feed forward neural networks by comparing the hidden neurons. In Ref [36], the performance comparison of the multilayered perceptron networks using various back propagation algorithms for breast cancer diagnosis is discussed. The used training algorithms are gradient descent with momentum and adaptive learning, resilient back propagation, Quasi-Newton and Levenberg-Marquardt. The performances of these four algorithms are compared with the standard steepest descent back propagation algorithm. The MLP network using the Levenberg-Marquardt algorithm displays the best performance.

More recently, Ref [37] evaluated whether an artificial neural network, which was trained on a large prospectively collected data set of consecutive mammography findings, could discriminate between benign and malignant disease, and accurately predict the probability of breast cancer for individual patients.

In this study, we use the same data set used by Ref [2] and Ref [24]. Ref [2] made a classification stage consisted in discriminating between the three classes of carcinoma, mastopathy/ fibro- adenoma and glandular tissue. The classification results (training set) revealed 83.33% correctly classified cases for carcinoma, 78.57% for glandular tissue and 56.25% for the others. The selected features were NOTCH, IP_{MAX}, D_R. Then they used seven-point spectra and the classification performance results are shown in Table 2.

Table 2: Six class, four variable classification matrix. Rows: observed classification; columns: predicted classification.

	Percent Correct	Carcinoma (Car)	Fibro-Adenoma (Fad)	Mastopathy (Mas)	Glandular (Gla)	Connective (Con)	Adipose (Adi)
Carcinoma (Car)	81,82	18	0	4	0	0	0
Fibro-Adenoma (Fad)	66,67	1	10	3	1	0	0
Mastopathy (Mas)	16,67	3	8	3	4	0	0
Glandular (Gla)	54,54	0	3	7	12	0	0
Connective (Con)	85,71	0	0	1	0	12	1
Adipose (Adi)	***90,91***	***0***	***0***	***0***	***0***	***2***	***20***
Total	66,37	22	21	18	17	14	21

Ref [24] studied the performance criterion of machine learning tools in classifying breast cancer, and compared the data mining tools to analyze the performance of supervised learning algorithms, such as Naive Bayes, Support vector machines, Radial basis neural Networks, Decision trees J48 and simple CART. The aim of this research was to find out the best classifier with respect to accuracy, precision, sensitivity and specificity in detecting breast cancer. Table 3 shows the results about the accuracy percentage for breast tissue data set.

Table 3: Accuracy percentage for breast tissue data set.

Algorithm	**Accuracy (%)**
Naive Bayes	94,33
RBF Networks	***92,45***
Trees- J48	95,28
Trees- CART	96,22
SVM- RBF Kernel	99,00

2.3. Diagnosis of the breast cancer using probabilistic neural network

The PNN provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers. The network paradigm also uses Parzen Estimators, which were developed to construct the probability density estimation that was required by Bayes theory [5]. The PNN structure that was used in this study has a multilayer structure consisting of an input layer, a single hidden layer (radial basis layer), and an output layer (competitive layer) as shown in Fig. 1 [6-10,22-23].

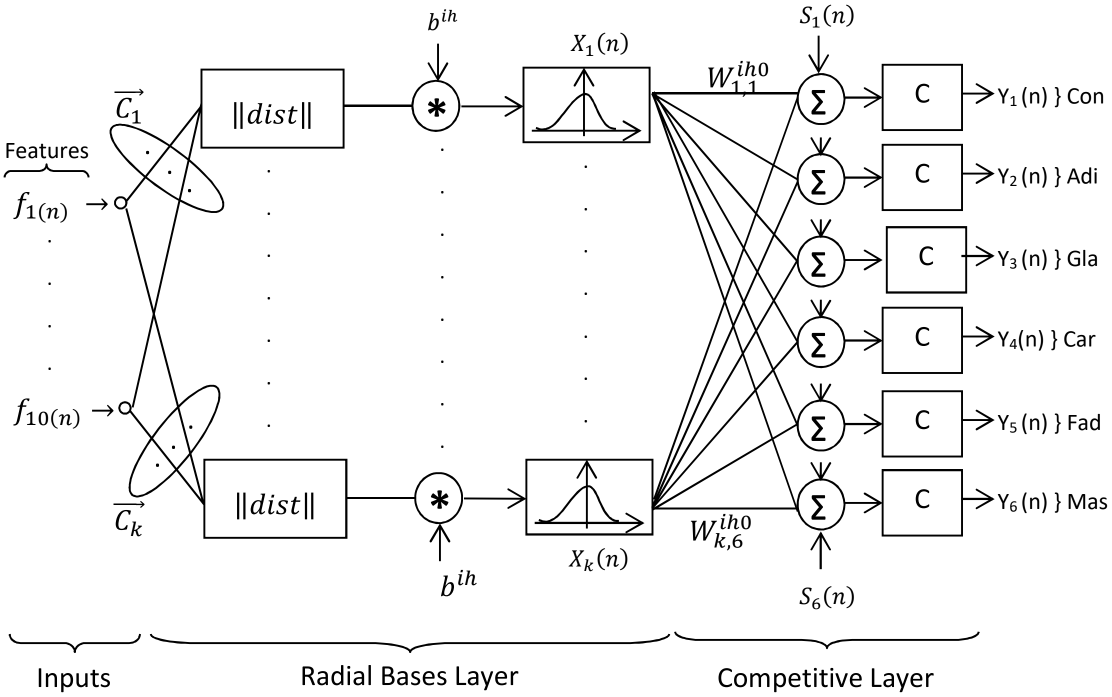

Figure 1: Architecture of PNN.

In this system, the real valued input vector is the feature's vector and the six outputs are the index of the six classes, namely Connective (Con), Adipose (Adi), Glandular (Gla), Carcinoma (Car), Fibro-Adenoma (Fad), and Mastopathy (Mas). All hidden units simultaneously receive the 10-dimensional real valued input vector. The pattern layer consists of a set of radial basis functions. All of the radial basis functions are the same type (Gaussian) [5]. The architecture of PNN is shown in Fig. 1.

The equations which were used in the neural network model are given as (1), (2), (3), (4), and (5) [10].

$$X_j = \phi\left(\left\|\vec{f} - \vec{c}_j\right\| * b^{ih}\right) \tag{1}$$

$$\phi(x) = \exp\left(-x^2\right) \tag{2}$$

$$b^{ih} = 0.833 / s \tag{3}$$

$$S_i = \sum_{j=1}^{h} W_{ji}^{ho} * X_j \tag{4}$$

$$Y_i = \begin{cases} 1, & if\ S_i\ is\ \max\ of\ \{S_1, S_2\} \\ 0, & else \end{cases} \tag{5}$$

where $i = 1,2,..,6$, $j = 1,2,..,6$, Y_i is the i^{th} output (classification index), $\vec{f}$ is the 34-dimensional real valued input vector, W_{ji}^{ho} is the weight between the j^{th} hidden node and the i^{th} output node, $\vec{c}_j$ is the centre vector of the j^{th} hidden node, s is the real constant known as spread factor, b^{ih} is the biasing term of radial basis layer, and $\phi(.)$ is the nonlinear radial basis function (Gaussian) [6-11].

Probabilistic neural network is a kind of radial basis network suitable for classification problems. PNN uses the supervised learning, where the data is divided into two parts, namely the training and the testing part. The performance of PNN is related to two procedures: the training and the recall procedure [38].
In the training procedure, the training data is given to the network and passes from the input layer through the pattern layer to the output layer. PNN uses training input data to set up the weights (W^i) between input and pattern layer as follows:

$$\begin{aligned} &\overrightarrow{c_{ij}} = \overrightarrow{f_j} \\ &\overrightarrow{f_j} = [f_1, f_2, f_3, \dots, f_{34}] = W^i = [w_{ij}]_{ixj} \\ &i = 1,2,3,\dots,34 \qquad j = 1,2,3,\dots,324 \end{aligned} \tag{6}$$

Where w_{ij} is the j^{th} weight value of weight (W^i). Then the network will define the weight (W^o) among the pattern layer and output layer as follows:

$$W_{ji}^{iho} = \begin{cases} 1, & \textit{if the } j^{ih} \textit{ sample and neuron belong to the same class} \\ 0, & \textit{others} \end{cases} \tag{7}$$

if the j^{th} sample is associated with class *c*, $c=1,2,..,6$ the weight value is defined as 1 and others are 0.
In the recall procedure, the testing data is given to the network and the weights between the input and pattern layer calculates the Euclidean norm (Ed_j) of training and testing data. The Euclidean norm function can be described as:

$$Ed_j = \sqrt{\sum (w_{ij} - f_i)^2} \tag{8}$$

Where *w* is the weight vector and *f* is the input vector.

The pattern units generate the probabilistic vectors and after calculating the probabilities of each condition, the weight W^o transports these probabilities to the summation layer. The summation layer neurons sum the inputs from the pattern layer, and transmit them to the output layer. The output layer uses a ‘winner takes all’ attitude to compare the probability density of each condition in the output layer [38].

2.4. Diagnosis of the breast cancer using multilayer neural network

In the second stage of the study, a MLNN with two hidden layers was used for the breast cancer’s diagnosis. This MLNN structure (with one input layer, two hidden layers, and one output layer) is shown in Fig. 2.

The hidden layer neurons (20 neurons for each hidden layer) and the output layer neurons use nonlinear sigmoid activation functions. In this system, the ten inputs are features, and the six outputs are the index of six classes, namely Connective (Con), Adipose (Adi), Glandular (Gla), Carcinoma (Car), Fibro-

Adenoma (Fad), and Mastopathy (Mas). The equations used in the MLNN structure with the two hidden layers are shown in (9), (10), and (11).

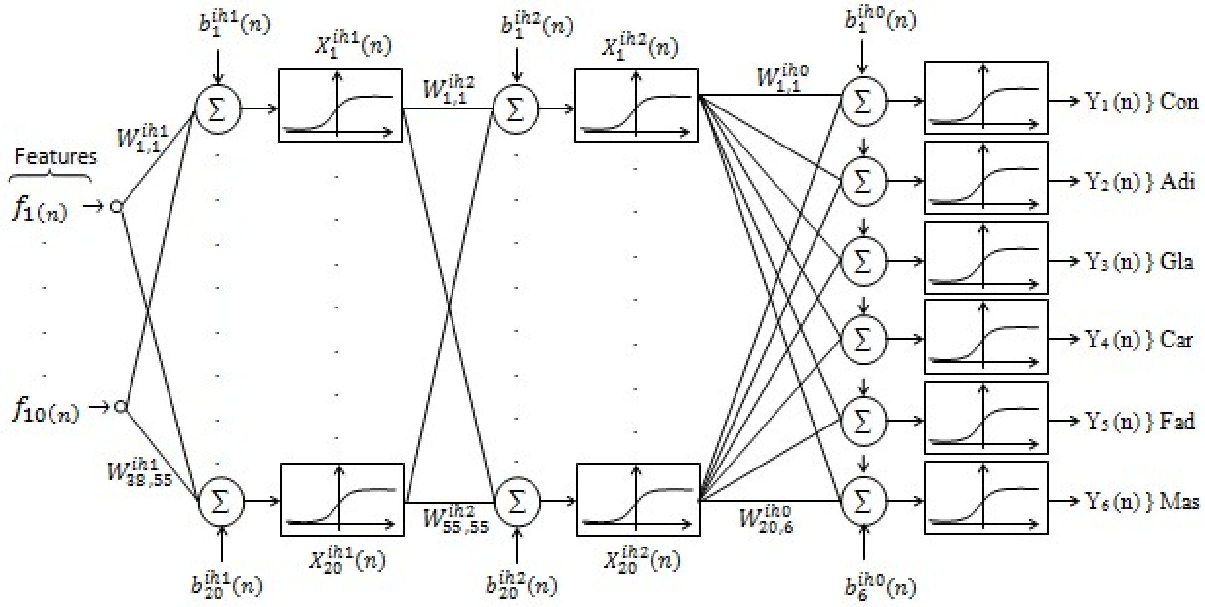

Figure 2: Implementation of multilayer neural network for the breast cancer's diagnosis.

The outputs of the first hidden layer neurons are,

$$\vec{X}^{ih1}(n) = 1 \Big/ \left(1 + \exp\left(W^{ih1}(n) * \vec{f}(n) + \vec{b}^{ih1}(n)\right)\right) \tag{9}$$

The outputs of the second hidden layer neurons are,

$$\vec{X}^{ih2}(n) = 1 \Big/ \left(1 + \exp\left(W^{ih2}(n) * \vec{X}^{ih1}(n) + \vec{b}^{ih2}(n)\right)\right) \tag{10}$$

The outputs of the network are,

$$\vec{Y}(n) = 1 \Big/ \left(1 + \exp\left(W^{ho}(n) * \vec{X}^{ih2}(n) + \vec{b}^{ho}(n)\right)\right) \tag{11}$$

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 the training pattern index.

The back-propagation (BP) algorithm [13] is widely recognized as a powerful tool for the 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 [14-15]. 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 [16-17]. The Levenberg-Marquardt (LM) algorithm [16] that is used in this study is one of the fastest types of these algorithms. Detailed computational issues about the application of the training algorithms to the MLNN structures can be found in the reference [39].

2.5. Diagnosis of the breast cancer using learning vector quantization neural network

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

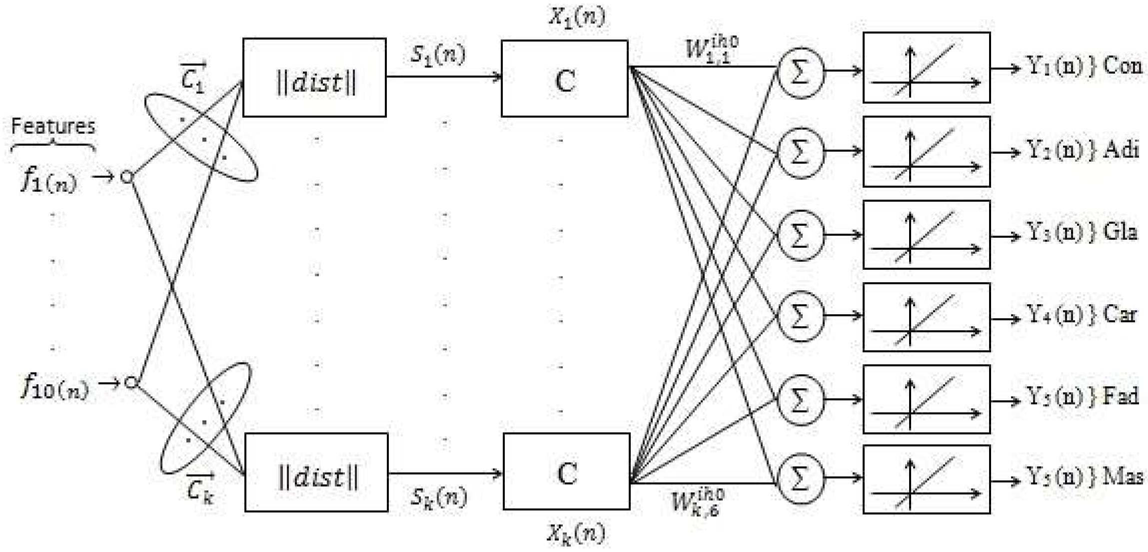

Figure 3: Implementation of learning vector quantization neural network for the breast cancer's diagnosis.

The LVQ structure [20] that was used in this study has a multilayer structure consisting of a single hidden layer (competitive layer) and an output layer (linear layer) of two units, as shown in Fig. 3. In this system, the real valued input vector is the feature's vector, and the six outputs are the index of six classes, namely Connective (Con), Adipose (Adi), Glandular (Gla), Carcinoma (Car), Fibro-Adenoma (Fad), and Mastopathy (Mas). The hidden layer consists of a set of competition functions. The equations which were used in the neural network model are shown in (12), (13), and (14) [6-11, 22].

$$S_j = \left\| \vec{f} - \vec{c}_j \right\| \tag{12}$$

$$X_j = \begin{cases} 1, & \text{if } S_j \text{ is max of } \{S_1,...,S_h\} \\ 0, & \text{else} \end{cases} \tag{13}$$

$$Y_i = \sum_{j=1}^{h} W_{ji}^{ho} * X_j \tag{14}$$

where $i = 1,2,..,6$, $j = 1,2,...,h$, Y_i is the i^{th} output (classification index), $\vec{f}$ is the 10-dimensional real valued input vector, W_{ji}^{ho} is the weight between the j^{th} hidden node and the i^{th} output node, $\vec{c}_j$ is the center vector of the j^{th} hidden node. Detailed information about the realisation of the LVQ structures can be found in the references [6-10, 39].

2.6. Measures for performance evaluation

2.6.1. Classification accuracy

Classification accuracy [42] has been used for the study on breast cancer's diagnosis. The equations that were used in the classification accuracies are shown in (15) and (16):

$$classification\ accuracy(N) = \frac{\sum_{i=1}^{|N|} assess(n_i)}{|N|} \quad , \quad n_i \in N \tag{15}$$

$$assess(n) = \begin{cases} 1 & if\ \ classify(n) = nc \\ 0 & otherwise \end{cases} \tag{16}$$

where N is the set of data items to be classified (the test set), $n \in N$, nc is the class of the item n, and $classify(n)$ returns the classification of n by NNs [6-11].

All the computations were implemented using MATLAB V7. The function newpnn, newlvq and newff were used to create the PNN, LVQ and MLNN networks respectively. The architecture used in these applications consisted of nonlinear sigmoid hidden units and one output unit. The learning rate of 0.7 was used. The number of maximum allowable epochs was 1000.

2.6.2. Validation of the estimated results

The conventional (one training and one test) validation [23] and the 3-fold cross-validation techniques were performed to compute the accuracy of the neural networks for breast cancer's diagnosis. For the conventional validation (CV) method, the 70 cases where used as the training set, and the remaining 35 cases were used as the test set.

In k-fold cross-validation [6-10,12,18-19,22-23,40], the whole data are randomly divided to k mutually exclusive and approximately equal size subsets. The classification algorithm is trained and tested k times. In each case, one of the folds is taken as test data and the remaining folds are added to form the training data. Thus, k different test results exist for each training-test configuration [12]. The average of these results gives the test accuracy of the algorithm. If a neural network learns the training set of a problem, it makes generalization to that problem. So, this type of a trained neural network can give similar result for untrained test sets. But, if a neural network starts to memorize the training set, its generalization starts to decrease and its performance may not be improved for untrained test sets [19]. The k-fold cross-validation method shows how good generalization can be made using neural network structures [41].

3. Results

This work presents an application of the PNN with random search (RMS) method (using 3xFC) on breast cancer's diagnosis. Also, the PNN results were compared with the results of the MLNN and LVQ neural networks focusing on breast cancer's diagnosis and using the same database. The classification accuracies obtained by PNN, MLNN and LVQ structures for breast cancer are presented in Table 4.

Table 4: Average of classification accuracies of test dataset for breast cancer.

Experimental results ***Methods***	***Accuracy (%)*** ***1.FC (35 Samples)***	***2.FC (35 Samples)***	***3.FC (35 Samples)***	**Average**
PNN (with 3xFC, RSM)	97.14	100.00	97.14	98.10
MLNN (with LM, 3xFC, two hidden layers)	94.29	97.14	94.29	95.24
LVQ (with 3xFC)	88.57	97.14	91.43	92.38
PNN (with CV)		96.77		96.77
MLNN (with CV)		94.29		94.29
LVQ (with CV)		88.57		88.57

In this study, the best result for the average classification accuracy was obtained using PNN (with 3xFC, RSM) structure by %98,10, as seen in Table 4. This result is quite good for breast cancer's diagnosis problem. The second best result for the classification accuracy was obtained using PNN (with 1xFC) by %96,77. The third best result for the classification accuracy was obtained using MLNN (with LM, 3xFC, two hidden layers) by %95,24.

4. Conclusions

This study applied three different ANNs structures to the breast cancer's diagnosis problem for medical devices. As it can be seen from this study, a patient can be classified based on the person's breast tissue type. According to the overall results, it was seen that the most suitable neural network structure for classifying breast tissue data is the PNN structure. It was also observed that the neural network structures generally show good performances for breast cancer's diagnosis problem. This classification accuracy is highly reliable for such a problem, because only a few samples were misclassified by the system. Finally, the 3-fold cross-validation technique is more suitable for the diagnosis of breast cancer than the conventional validation algorithm for PNN structures.

The model used in this study will be embedded in medical devices via developed software. Finally, the ANN structures can be helpful as a learning based decision support system that can contribute to the doctors' diagnosis decisions.

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