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BREAST CANCER DIAGNOSIS BY ARTIFICIAL NEURAL NETWORKS (ANN'S)

A project thesis submitted to the college of engineering in particularfulfillmentof the requirement for the B.Sc (honor) in biomedical engineering

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Dedication

We dedicate our research to our whole beloved family, to dear fathers who has never left our heart and thought.

To the dearest of them all great women who filled us with love, strength and power our dear mothers.

To our faithful brothers and our lovely sister.

To all my dear friends, who have always been there for me in good and bad moments. Toall the people who have a special space in my life.

Acknowledgement

We thank Allah for blessing us to make possible doing this research.

Wewould like to give our deepest appreciation to our spiritual father and supervisor DR.ELTAHER M HUSSIEN, who was always there to listen and to give advice, whose support, direction and leadership from the

beginning till the end helped us in doing a lot of research and we came to know about so many new things.

Special and deepest thanks with respect to teacher SAMI FATHI who guided us properly and really helped us.

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Abbreviation

ANNs   Artificial Neural Networks

BPNN Back Propagation Neural Network

RBF Radial Basis Function

GRNN Generalized Regression Neural Network

nntool   Neural network tool box

nprtool   neural pattern recognition

CAD   Computer Aided Diagnosis

Abstract

Breast cancer is the second largest cause of cancer deaths among women. This project aim for early diagnosis of breast cancer and reduce the human diagnosis errorsthrough (ANN's).

Here we canstudy the performance of different Neural Network structures: Radial Basis Function(RBF), General Regression Neural Network (GRNN)and Back propagation NeuralNetwork(BPNN), are examined on the Wisconsin Breast Cancer Data (WBCD).The result demonstrated that; the BPNN is the best classification accuracy.

□□□□□□□□

يعتبر سرطان الثدي هو ثاني أكبر سبب للوفيات بين النساء. يهدف هذا المشروع إلى التشخيص المبكر لسرطان الثدي وت قليل اخطاء الانسان من خلال إستخدام ت قنية الشبكات العصبيه الإصناعيه.

في هذا المشروع نـ قارن بين أداء ثلاث من أنواع الشبكات الاصطناعية
التي تم إختبارها على بيانات مأخوذه من جامعة (BPNN,GRNN and RBF)
ويسكونسن. حيث وجد أن الشبكة متعددة الطبـ قات تعطينا أفضل د قة في النتائج.

CHAPTER ONE

1.1 General view:

Breast cancer is one of the major causes of death in women. Although screening mammography has been demonstrated to effectively detect early breast cancer, differentiating between malignant and benign cases is still challenging for radiologists.

Computer –aided diagnosis (CAD) schemes for breast cancer have been investigated with the hope to provide "second opinion" to radiologists so that their diagnostic accuracy and efficiency can be significantly improved. To data, many CAD schemes have been investigated to identify suspicious regions for specific breast abnormalities on mammograms.

Nowadays neural network (NN) is used in medical diagnosis especially in breast cancer, they are not affected such as human fatigue, emotional states and habituation .They are capable of rapid identification, analyses of condition and diagnosis in real time.

1.2 Statement of the problem:

The diagnosis of mammography images done by the radiologist by viewing the images using different plain of mammogram , this subjectivity lead to a miss interpretation of some pathology in the images therefore to reduce the high miss detection rate an objective method to classify and identify the pathology on the mammogram is need it .

1.3 Objectives:

The objectives of this research are to:-

1-Design an algorithm to diagnose breast cancer (early detection cause better therapy) .

2-Reduce the human diagnose errors, cost, time and minimize radiation in takes.

3-Choose the best method that can be used for diagnose breast cancer.

1.4 Methodology:

This project used MATLAB to diagnosis the tumor by using artificial neural network toolbox, by using the neural pattern regression and neural network toolbox .First, a clinical database of 699 cases was collected from Wisconsin breast cancer data (WBCD). [1-4].We explored an ANN using 9 features to determine the probability for the presence of breast cancer. Then, the ANN was trained and examined using radial basis function neural network, general regression neural network and feed-forward back propagation.

1.5 literature review:

A number of researchers have investigated various approaches to integrate mammographic findings, as well as patient-related information, in developing CAD schemes.

Artificial neural networks (ANNs) were most commonly used and have been demonstrated to be potentially useful for solving medical problems and decision making [5-8]. For breast cancer diagnosis, Lo JY et al. investigated an ANN on the basis of 8 mammographic findings and patient age [9].

Baker JA et al. investigated an ANN using the Breast Imaging Recording and Data System (BIRADS) with 10 lesion descriptors and 8 inputs from patient% medical history [10].

In addition to ANN applications, Kahn et al. explored a Bayesian network (MammoNet) that integrated 5 patient-history features, 2 physical findings, and 15 mammographic findings to determine the probability of breast cancer malignancy [11].

CHAPTER TWO

2.1 ANATOMY OF BREAST:

Each breast has 15 to 20 sections, called lobes, which are arranged like the petals of a daisy. Each lobe has many smaller lobules, which end in dozens of tiny bulbs that can produce milk.

The lobes, lobules, and bulbs are all linked by thin tubes called ducts. These ducts lead to the nipple in the center of a dark area of skin called the areola. Fat fills the spaces between lobules and ducts.

There are no muscles in the breast, but muscles lie under each breast and cover the ribs.

Each breast also contains blood vessels and vessels that carry lymph. The lymph vessels lead to small bean-shaped organs called lymph nodes, clusters of which are found under the arm, above the collarbone, and in the chest, as well as in many other parts of the body.

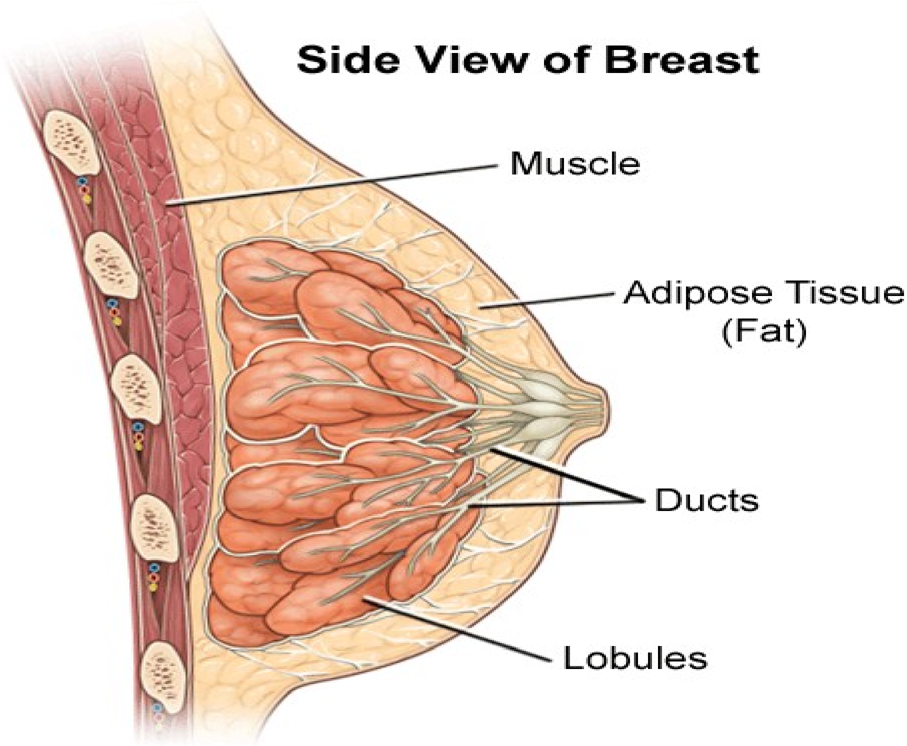

Figure 2.1 Female Breast Anatomy

2.2 Risk Factors and Causes of Breast Cancer:

Research is ongoing to identify the exact causes of breast cancer. Researchers have, however, identified several breast cancer risk factors. A risk factor is something that increases the chance that a person will develop a disease. It is *not* a guarantee and does not predict a future diagnosis. Risk factors for breast cancer include:

- **Age:** As we grow older, our risk of developing breast cancer increases. It is estimated that 80% of women diagnosed with breast cancer are 50 or older. This doesn't mean that younger women aren't at risk. Young women are diagnosed with breast cancer, just much less frequently.
- **Family and Personal History of Breast Cancer:** Having a mother, sister, or daughter with breast cancer doubles your risk of the disease. While family history can play a role in breast cancer development, women shouldn't subscribe to the popular belief that women without a family history of breast cancer aren't at risk. The American Cancer Society estimates that 70 to 80% of women with breast cancer do not have a family history that includes breast cancer. Women who have previously been diagnosed and treated for breast cancer are at a greater risk of developing breast cancer again.
- **Race:** Of all women, Caucasian women are diagnosed more frequently than women of other races. Though Caucasian women are the most at risk, it is African American women who die of the disease the most. Asian, Native American, and Hispanic women have less of a risk.
- **Alcohol Consumption:** Women who drink alcohol increase their breast cancer risk and the risk is heightened with the amount of alcohol consumed. Women who drink 2-5 drinks a day increase their risk by 1 1/2 when compared to women who do not drink alcohol. One drink a day only slightly elevates a woman's risk.
- **Family Planning Choices:** Women who choose not to have children or have them after age 30 somewhat increase their risk of breast cancer.
- **Genetics:** Genetics may play a role in up to 10% of women diagnosed with breast cancer. Hereditary breast cancer occurs when a mutated gene has been passed down from a parent.

2.3 MAMMOGRAPHY:

Mammography is a specific type of imaging that uses a low-dose x-ray system to examine breasts. A mammography exam, called a mammogram, is used to aid in the early detection and diagnosis of breast diseases in women.

An x-ray (radiograph) is a non-invasive medical test that helps physicians diagnose and treat medical conditions. Imaging with x-rays involves exposing a part of the body to a small dose of ionizing radiation to produce pictures of the inside of the body. X-rays are the oldest and most frequently used form of medical imaging.

Three recent advances in mammography include digital mammography, computer-aided detection and breast tom synthesis.

2.4 DIGITAL MAMMOGRAPHY:

Also called full-field digital mammography (FFDM) is a mammography system in which the x-ray film is replaced by solid-state detectors that convert x-rays into electrical signals. These detectors are similar to those found in digital cameras. The electrical signals are used to produce images of the breast that can be seen on a computer screen or printed on special film similar to conventional mammograms. From the patient's point of view, having a digital mammogram is essentially the same as having a conventional film mammogram.

Figure 2.2 Digital Mammography [12]

2.5 THE RISKS OF MAMMOGRAPY:

- There is always a slight chance of cancer from excessive exposure to radiation. However, the benefit of an accurate diagnosis far outweighs the risk.
- False Positive Mammograms Five percent to 15 percent of screening mammograms require more testing such as additional mammograms or ultrasound.
- Most of these tests turn out to be normal. If there is an abnormal finding, a follow-up or biopsy may have to be performed. Most of the biopsies confirm that no cancer was present. It is estimated that a woman who has yearly mammograms between ages 40 and 49 has about a 30 percent chance of having a false-positive mammogram at some point in that decade and about a 7 percent to 8 percent chance of having a breast biopsy within the 10-year period.

CHAPTER THERE

3.1 ARTIFICIAL NEURAL NETWOR:

An Artificial Neural Network is a mathematical structure which consists of interconnected artificial neurons that mimics , in a much smaller scale , the way a biological neural network (or brain) works .An ANN has the ability to learn from data , either in a supervised or an unsupervised fashion and can used in takes such as regression , classification , clustering and more .

An ANN is typically defined by three types of parameters:

- The interconnection pattern between different layers of neurons
- The learning process for updating the weights of the interconnections
- The activation function that converts a neuron's weighted input to its output activation.
- "A neural network can be defined as a model of reasoning based on the human brain".

3.2 STRUCTURE OF ANNs:

A typical artificial neuron is depicted in figure 1.The scalar inputs pi are transmitted through connections that multiply their strength by the scalar weight wi to form the product wipi , again a scalar.All the weighted inputs wipi are added and to Σ wipi we also add the scalar bias b.The result is the argumet of the transfer function f. which produce the output a . The bias is much like a weight , except that it has a constant input of 1.

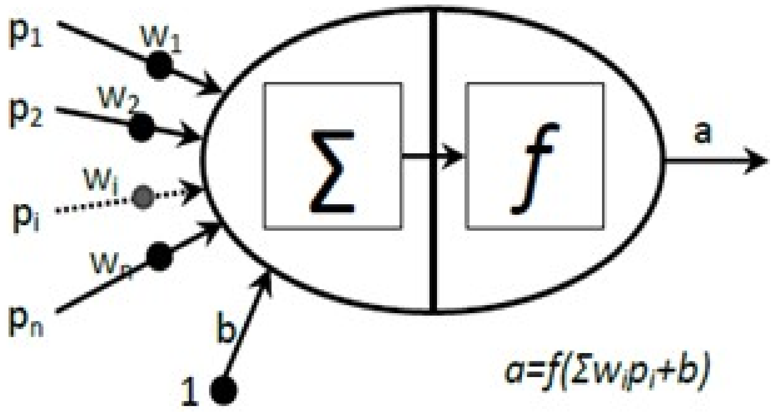

Figure 3.1: An artificial neuron with one input and bias. [13]

Note that wi and bi are both adjustable scalar parameters of the neuron. The central idea of neural networks is that such parameters can be adjusted so that the network exhibits some desired or interesting behavior. Thus, you can train the network adjusting the weight or bias parameters, or perhaps the network itself will adjust these parameters to achieve some desired end. The most commonly used transfer functions are the hard – limit i.

3.3 Artificial Neural Network Architecture:

Neurons can be referred as arranged in layers. Normally neurons in the same layer behave in the same manner. The main factors which decide the behavior of a neuron are its activation function and pattern of weighted connections over which it sends and receives signals. The arrangement of neurons into layers and the connection patterns within and between the layers is called the net architecture.

Based on the no of layers the network structure is broadly classified into 2 categories depends on the connection establishment in the network. They are:

3.3.1 Feed-forward network:

- **Single layer network:**

It has only one layer of connection weights. The input unit will receive signals from the outside world and the response to a signal can be read from the output unit. The input units are directly connected with the output unit and they are generally used for pattern classification.

Figure 3.2: show Single layer network [15]

- **Multilayer network:**

A multilayer network has more layers of nodes between the input units and output units. Typically there is a layer of weights between 2 adjacent levels of units. Multilayer nets can solve more complicated than single-layer nets, but its training is more difficult.

Figure 3.3: show Multilayer network [15]

3.3.2 Recurrent network:

Here each node is a processing element or unit; it may be anyone of the 2 states (Black-Active, White-Inactive). Units are connected to each other with weighted symmetric connection. A positive weighted connection indicates that 2 units tend to activate each other. A negative connection allows an active unit to deactivate from a neighboring unit.

Figure 3.4: Recurrent network [15]

3.4 Activation Functions:

There are a number of common activation functions in use with neural networks. This is not an exhaustive list.

Figure 3.5: activation function [15]

3.5 Training of ANNs:

Training is a very important process for a neural network. There are two forms of training that can be employed, supervised and unsupervised. Supervised training involves providing the neural network with training sets and the anticipated output. In unsupervised training, the neural network is also provided with training sets, but not with anticipated outputs.

Figure 3.6: show the training of ANNs [15]

3.5.1 Unsupervised Training

As previously mentioned, the neural network is provided with training sets, which are collections of defined input values. The unsupervised neural network is not provided with anticipated outputs.

Unsupervised training is typically used to train classification neural networks. A classification neural network receives input patterns, which are presented to the input neurons. These input patterns are then processed, causing a single neuron on the output layer to fire. This firing neuron provides the classification for the pattern and identifies to which group the pattern belongs.

Another common application for unsupervised training is data mining. In this case, you have a large amount of data to be searched, but you may not know exactly what you are looking for. You want the neural network to classify this data into several groups. You do not want to dictate to the neural network ahead of time which input pattern should be classified into which group. As the neural network trains, the input patterns fall into groups with other inputs having similar characteristics. This allows you to see which input patterns share similarities.

Unsupervised training is also a very common training technique for self-organizing maps (SOM), also called Kohonen neural networks.

Figure 3.7: Unsupervised training.[16]

3.5.2 Supervised Training:

The supervised training method is similar to the unsupervised training method, in that training sets are provided. Just as with unsupervised training, these training sets specify input signals to the neural network. The primary difference between supervised and unsupervised training is that in supervised training the expected outputs are provided. This allows the neural network to adjust the values in the weight matrix based on the differences between the anticipated output and the actual output.

There are several popular supervised training algorithms. One of the most common is the back propagation algorithm. It is also possible to use simulated annealing or genetic algorithms to implement supervised training. We will now discuss how errors are calculated for both supervised and unsupervised training algorithms.

Figure 3.8: Supervised training. [16]

3.6 Root Mean Square (RMS) Error:

The RMS method is used to calculate the rate of error for a training set based on predefined ideal results. The RMS method is effective in calculating the rate of error regardless of whether the actual results are above or below the ideal results. To calculate the RMS for a series of n values of x, consider Equation (3.1).

Equation (3.1): Root Mean Square Error (RMS):

.... (3.1)

The values of x are squared and their sum is divided by n. Squaring the values eliminates the issue associated with some values being above the ideal values and others below, since computing the square of a value always results in a positive number.

Equation (3.2): RMS for a Neural Network:

.... (3.2)

To calculate the RMS for the arrays in the previous section, you would calculate the difference between the actual results and the ideal results, as shown in the above equation. The square of each of these would then be calculated and the results would be summed. The sum would then be divided by the number of elements, and the square root of the result of that computation would provide the rate of error.

Chapter four

This project used MATLAB to diagnosis the tumor by using artificial neural network toolbox, by using the neural pattern regression and neural network toolbox.

Pattern recognition: Task performed by a network trained to respond when an input vector close to a learned vector is presented. The network "recognizes" the input as one of the original target vectors.

The work flow in artificial neural network to solve any problems has seven primaries:

4-1 NEURAL NETWORK DESIGN STEPS:

Figure 4.1 neural network design steps

4.2 Collect data:

Breast cancer Wisconsin data names:-

Before beginning the network design process, you first collect and prepare sample data. It is generally difficult to incorporate prior knowledge into a neural network; therefore the network can only be as accurate as the data that are used to train the network.

It is important that the data cover the range of inputs for which the network will be used. Multilayer networks can be trained to generalize well within the range of inputs for which they have been trained. However, they do not have the ability to accurately extrapolate beyond this range, so it is important that the training data span the full range of the input space.

4.2.1About data set:-

This breast cancer database is downloaded from the UCI machine-learning repository [5], which was collected by Dr. William H. Wolberg from the University of Wisconsin Hospitals, Madison [6]. The dataset is comprised of elements that consist of various scalar observations. The total number of the original samples is 699 with 16 samples contain missing values. The dataset contains two classes referring to benign and malignant samples. There are 458 samples in the dataset that are assigned to benign and the other 241 samples are malignant. The original dataset contains 11 attributes including both sample id number and class label, which are removed in the actual dataset that are used in our experiments. The remaining 9 attributes represent 9 cytological characteristics of breast fine-needle aspirates (FNAs), as shown in Table 1. The cytological characteristics of breast FNAs were valued on a scale of one to ten, with one being the closest to benign and ten the most malignant.

Table 1: These attributes measure the external appearance and internal chromosome changes in nine different scales

Domain	Attributes	No
1-10	Clump thickness	1
1-10	Uniformity of cell size	2
1-10	Uniformity of cell shape	3
1-10	Marginal adhesion	4
1-10	Signal epithelial cell size	5
1-10	Bara nuclei	6
1-10	Bland chromatin	7
1-10	Normal nucleli	8
1-10	Mitoses	9
2 for benign and 4for malignant	Class	10

4.2.2 The descriptions of the features:-

- Clump thickness:

Benign cells tend to be grouped in monolayers, while cancerous cells are often grouped in multilayers.

-Uniformity of cell size/shape:

Cancer cells tend to vary in size and shape. That is why these parameters are valuable in determining whether the cells are cancerous or not.

-Marginal adhesion:

Normal cells tend to stick together. Cancer cells tend to loose this ability. So loss of adhesion is a sign of malignancy.

-Single epithelial cell size:

Is related to the uniformity mentioned above. Epithelial cells that are significantly enlarged may be a malignant cell.

-Bare nuclei:

This is a term used for nuclei that is not surrounded by cytoplasm (the rest of the cell). Those are typically seen in benign tumours.

-Bland Chromatin:

Describes a uniform "texture" of the nucleus seen in benign cells. In cancer cells the chromatin tends to be more coarse.

-Normal nucleoli:

Nucleoli are small structures seen in the nucleus. In normal cells the nucleolus is usually very small if visible at all. In cancer cells the nucleoli become more prominent, and sometimes there are more of them.

The code for intery the data:

```
%   assumes these variables are defined:
%   X - input data.
%   Y- target data.
Inputs = X;
Target=Y;
```

Figure 4.2: show the cancer Input

Figure 4.3: show the cancer target

4.3 Create the network:

We are going to use pattern recognition network , which is feed-forward network with tan-sigmoid transfer function in both the hidden layer and the output layer .

The network has two output neurons, because there are two categories associated with each input vector .Each output neuron represent a category. When an input vector of the appropriate category is applied to the network ,the corresponding neuron should produce a 1 and the other neurons should output a 0.

This is a code use in a command line:-

```
% Create a Pattern Recognition Network
hiddenLayerSize = 10;
net = patternnet(hiddenLayerSize);
```

4.3.1 Radial basis function network

Is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. They are used in function approximation, time series prediction, and control. Neural network that can be designed directly by fitting special response elements where they will do the most good.

Network Architecture

Radial basis networks consist of two layers: a hidden radial basis layer of S^1 neurons, and an output linear layer of S^2 neurons.

Figure 4.4: RBF Architecture

The || dist || box in this figure accepts the input vector **p** and the input weight matrix $\mathbf{IW}^{1,1}$, and produces a vector having S_1 elements. The elements are the distances between the input vector and vectors ${}_i\mathbf{IW}^{1,1}$ formed from the rows of the input weight matrix.

The bias vector $\mathbf{b}^1$ and the output of || dist || are combined with the MATLAB operation.*, which does element-by-element multiplication.

RBF method:

The transfer function for a radial basis neuron is

Figure 4.5: Transfer Function for a Radial Basis Neuron

Notice that the expression for the net input of a radbas neuron is different from that of other neurons. Here the net input to the radbas transfer function is the vector distance between its weight vector **w** and the input vector **p**, multiplied by the bias *b*. (The || dist || box in this figure accepts the input vector **p** and the single row input weight matrix, and produces the dot product of the two.)

The transfer function for a radial basis neuron is:

$$radbas(n) = e^{-n^2} \quad \text{...}(4.1)$$

Here is a plot of the radbas transfer function

Figure 4.6 radial basis transfer function

The radial basis function has a maximum of 1 when its input is 0. As the distance between **w** and **p** decreases, the output increases. Thus a radial basis neuron acts as a detector which produces 1 whenever the input **p** is identical to its weight vector **p**.

The bias *b* allows the sensitivity of the radbas neuron to be adjusted. For example, if a neuron had a bias of 0.1 it would output 0.5 for any input vector **p** at vector distance of 8.326 (0.8326/*b*) from its weight vector **w**.

4.3.2 Generalized Regression Networks

A generalized regression neural network (GRNN) is often used for function approximation. It has a radial basis layer and a special linear layer.

Network Architecture

The architecture for the GRNN is shown below. It is similar to the radial basis network, but has a slightly different second layer.

Figure 4.7: GRNN Architecture

Here the nprod box shown above (code function normprod) produces S^2 elements in vector n^2. Each element is the dot product of a row of $LW^{2,1}$ and the input vector a^1, all normalized by the sum of the elements of a^1

GRNN Method:

$$\mathbf{y(x) = \frac{\sum_k t_k \exp\{-||x-x_k||^2 / 2h^2\}}{\sum_k \exp\{-||x-x_k||^2 / 2h^2\}}} \quad \text{.............................(4.2)}$$

GRNNs share a special property, namely that they do not require iterative training; the hidden to-output weights are just the target values *tk*, so the output *y*(*x*), is simply a weighted average of the target values *tk* of training cases *xk* close to the given input case *x*. It can be viewed as a normalized RBF network in which there is a hidden unit centered at every training case. These RBF units are called “kernels” and are usually probability density functions such as the Gaussians considered in (4).The only weights that need to be learned are the widths of the RBF units *h*. These widths (often a single width is used) are called “smoothing parameters” or “bandwidths” and are usually chosen by cross validation. GRNN is a universal approximate for smooth functions, so it should be able to solve any smooth function approximation problem given enough data. The main drawback of GRNNs is that, like kernel methods in general, they suffer seriously from the curse of dimensionality. GRNNs cannot ignore irrelevant inputs without major modifications to the basic algorithm.

4.3.3 Back propagation network:

In, the assigned weights for each connector of node resemble the long term memory. They contain information of the input's importance and ANN learns by repeated adjustments of these weights. The weight adjustments are carried out according to the mathematical functions known as learning or activation functions known as learning or activation functions, which will be compared to the threshold value of the network. A feed forward back propagation artificial can learn a function of mapping inputs to outputs by being trained with cases of input-output pairs.

Network Architecture

Figure 4.8: BPNN Architecture

BPNN method:

………………………(4.3)

where *xi* is the input to the node and *wi* is the corresponding input weight, q is a value which is usually called the threshold, *n* is the number of inputs to the node. The network performance and convergence depends on many parameters like initial weights, learning rate and momentum used during the training process.

4.4 Configure the network:-

The configuration step consists of examining input and target data, setting the network's input and output sizes to match the data, and choosing settings for processing inputs and outputs that will enable best network performance. The configuration step is normally done automatically, when the training function is called. However, it can be done manually, by using the configuration function.

The code for configuration:

net = configure (net, x,t) takes input data x and target data t, and configures the network's inputs and outputs to match.

4.5 Validate the network:-

These are used to measure network generalization, and to halt training when generalization stops improving.

The pattern recognition network uses the default Scaled Conjugate Gradient algorithm for training. The application randomly divides the input vectors and target vectors three sets for training, validation and testing.

```
% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
```

4.6 Train the network:-

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function net. The default performance function for feed forward networks is mean square error MSE —the average squared error between the networks outputs a and the target outputs t. It is defined as follows:

F= mse = 1N i=1N(ei)2 = 1N i=1N(ti-ai)2 …………………(4.4)

To train the network, enter the command:

Net = train (net, Inputs, Targets);

During the training, the training window opens; this window displays training progress. To interrupt loing training at any point, click 'stop training'.

Figure 4.9: Train network

This training window it will presents the performance, training state, error histogram, confusion and receiver operating characteristic.

The training stopped when the validation error increased for 6 iterations, which occurred at epoch 21.

Performance:

Performance is to find validation error. Performance is measured in terms of mean squared error, and shown in log scale. It rapidly decreased as the network was trained. To see how the network's performance improved during training, either click the "Performance" button in the training tool, or call PLOTPERFORM. Performance is shown for each of the training, validation and test sets. The version of the network that did best on the validation set is was after training.

The network outputs will be in the range 0 to 1, so we can use **vec2ind** function to get the class indices as the position of the highest element in each output vector.

testX = x(:,tr.testInd);

testT = t(:,tr.testInd);

testY = net(testX);

testIndices = vec2ind(testY)

Figure 4.10: Best validation performance

The trained neural network can now be tested with the testing samples we partitioned from the main dataset. The testing data was not used in training in any way and hence provides an "out-of-sample" dataset to test the network on. This will give us a sense of how well the network will do when tested with data from the real world.

Confusion:

It's to analyze the network response. The confusion matrix shows the percentages of correct and incorrect classifications. Correct classifications are the green squares on the matrices diagonal. Incorrect classifications form the red squares. If the network has learned to classify properly, the percentages in the red squares should be very small, indicating few misclassifications. If this is not the case then further training, or training a network with more hidden neurons, would be advisable.

```
plotconfusion(testT,testY)
```

Figure 4.11: Plot confusion

Receiver operating characteristic:

Another measure of how well the neural network has fit data is the receiver operating characteristic plot. This shows how the false positive and true positive rates relate as the thresholding of outputs is varied from 0 to 1.

The farther left and up the line is, the fewer false positives need to be accepted in order to get a high true positive rate. The best classifiers will have a line going from the bottom left corner, to the top left corner, to the top right corner, or close to that.

Plotroc(testT,testY)

Figure 4.12: Receiver Operating Characteristic

4.7 Use the network

After the network is trained and validated, the network object can be used to calculate the network response to any input.

CHAPTER FIVE

5.1 Simulation results:

One of the most difficult problems for neural network modeling is selection of proper neural network structure .The three neural network structure, back propagation (BPNN), generalized regression neural network (GRNN) and radial basis Function neural network (RBF) were applied to WBCD data sets to show the performance of neural network on breast cancer data. The simulations were developed using MATLAB 7.12.0 (R2012) Neural Network Toolbox. The results are shown in table . 2.

5.2 Radial basis Function result:

Figure 5.1: Performance of RBF

The diagonal cells show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red) (97.7%).

5.3 Back propagation neural network result:

Figure (5-2): Performance Of Bpnn

The diagonal cells show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). The results show very good recognition (99.0 %)

5.4 Generalized regression neural network result:

Figure (5-3): Performance of GRNN

The diagonal cells show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red) (98.4%)

Table (5-1): Performance of ANNs Type:

Performance	Type
99.0	BPNN
98.1	GRNN
97.7	RBF

Here we found the performance of Back Propagation is the best one.

CHAPTER SIX

6.1 CONCLUSION:

Variability among radiologists in tumor diagnosis is a very important issue that needs to be taken into account when it comes to the patient health.

In this study neural network are used in actual clinical diagnosis of breast cancer to help operators avoiding misdiagnosis.

The performance of three networks BPNN, GRNN and RBF was investigated for breast cancer diagnosis.

According to the overall results, it is seen that the most suitable neural network model for classifying WBCD data is BPNN.

Further work is needed to increase the accuracy of classification of breast cancer diagnosis

6.2 RECOMMANDATION:

The network has to be trained with more input patterns, so that the generalization ability of network will be enhanced.

This method can be used for the diagnosis of breast cancer.

```
% Solve a Pattern Recognition Problem with a Neural Network
% Script generated by NPRTOOL
% Created Tue Sep 11 23:22:29 AST 2012
%
% This script assumes these variables are defined:
%
%   cancerInputs - input data.
%   cancerTargets - target data.

inputs = cancerInputs;
targets = cancerTargets;

% Create a Pattern Recognition Network
hiddenLayerSize = 10;
net = patternnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};


% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% For help on training function 'trainlm' type: help trainlm
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainlm';  % Levenberg-Marquardt

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
  'plotregression', 'plotfit'};
```

```
% Train the Network
[net,tr] = train(net,inputs,targets);

% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs)

% Recalculate Training, Validation and Test Performance
trainTargets = targets .* tr.trainMask{1};
valTargets = targets  .* tr.valMask{1};
testTargets = targets  .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,outputs)
valPerformance = perform(net,valTargets,outputs)
testPerformance = perform(net,testTargets,outputs)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotconfusion(targets,outputs)
%figure, ploterrhist(errors)
```

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