Optimization of Artificial Neural Networks for Cancer Detection

Amandeep Kaur Author1[†], J K Sharma Author2[††] and Sunil Agrawal Author3[†††]

RIEIT Railmajra and Panjab University Chandigarh

Summary
This paper presents a feed-forward back-propagation Neural Network (NN) model to detect and locate early breast cancer/tumor efficiently through the investigation of Electromagnetic (EM) waves. A spherical tumor of radius 0.25 cm was created and placed at arbitrary locations in a breast model using an EM simulator. Directional antennas were used to transmit and receive Ultra-Wide Band (UWB) signals in 4 to 8GHz frequency range. Small training and validation sets were constructed to train and test the NN. The received signals were fed into the trained NN model to find the presence and location of tumor. Very optimistic results (about 100% and 97% presence and location detection rate of tumor respectively) have been observed for early received signal components with the NN model. Hence, the proposed model is very potential for early tumor detection to save human lives in the future.

Key words:
Artificial neural networks, UWB, Tumor, Multi-layer perceptron.

1. Introduction

Ultrawideband (3.1–10.6 GHz) microwave imaging is a promising method for biomedical applications such as cancer detection because of their good penetration and resolution characteristics. The underlying principle of Ultrawideband (UWB) cancer detection is a significant contrast in dielectric properties, which is estimated to be greater than 2: 1 between normal and cancerous tissue. UWB imaging systems have shown encouraging results in the detection of tumors for early breast-cancer detection [1-4].

In the UWB imaging systems, a very narrow pulse is transmitted from a UWB antenna to penetrate the body. As the pulse propagates through the various tissues, reflections and scattering occur at the interfaces. A particular interest is in the scattered signal from a small size-tissue representing a tumor. The reflected and scattered signals can be received using an UWB antenna, or array of antennas, and used to map different layers of the body [9, 10].

Artificial Neural Networks have emerged as a major paradigm for Data Mining applications. Neural nets have gone through two major development periods -the early 60's and the mid 80's. They were a key development in the field of machine learning. Artificial Neural Networks were inspired by biological findings relating to the behavior of the brain as a network of units called neurons. The human brain is estimated to have around 10 billion neurons each connected on average to 10,000 other neurons. Each neuron receives signals through synapses that control the effects of the signal on the neuron. These synaptic connections are believed to play a key role in the behavior of the brain.

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does [5]. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

On the other hand, multi-layered perceptron means a feed-forward net with one or more layers of nodes between the input and output nodes. The additional layers contain hidden nodes that are not directly connected to both the input and output nodes. The multi-layer perceptron overcomes many limitations of single layer perceptron (Lippmann, 1987). Their capabilities stem from the non-linear relationships among the nodes.

The fundamental building block in an Artificial Neural Network is the mathematical model of a neuron as shown in Figure 1.1

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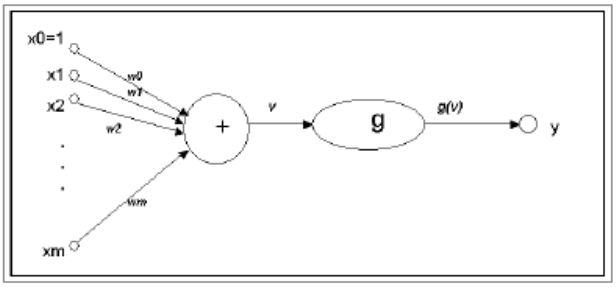


Fig 1.1 Mathematical model of a neuron

The three basic components of the (artificial) neuron are:
1. The synapses or connecting links that provide weights, wj , to the input values, xj for j = 1, ...m;
2. An adder that sums the weighted input

$$w_o + \sum_{j=1}^{m} w_j x_j \quad (1)$$

values to compute the input to the activation function

$$v = \sum_{j=0}^{m} w_j x_j \quad (2)$$

where w_o is called the bias is a numerical value associated with the neuron. It is convenient to think of the bias as the weight for an input xo whose value is always equal to one, so that an activation function g (also called a squashing function) that maps v to g(v) the output value of the neuron. This function is a monotone function.

The most successful applications in data mining of neural networks have been multilayer feedforward networks. These are networks in which there is an input layer consisting of nodes that simply accept the input values and successive layers of nodes that are neurons as depicted in Figure 1.1. The outputs of neurons in a layer are inputs to neurons in the next layer. The last layer is called the output layer. Layers between the input and output layers are known as hidden layers. Figure 1.2 is a diagram for this architecture.

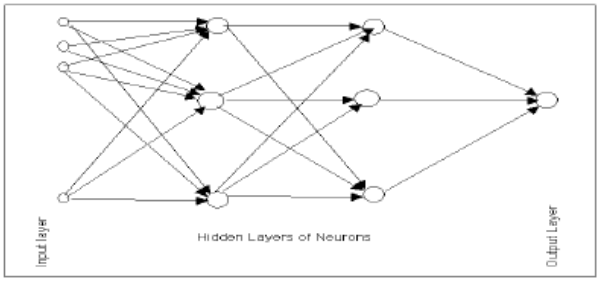


Fig 1. 2 Architecture of neural network

Back propagation, or backdrop has been the most popular and widely implemented of all neural network paradigms. It is based on a multi-layered feed forward topology with supervised learning. The propagation of error operates into two modes: 1) mapping; and 2) learning.
In the mapping mode, information flows forward through the network, from inputs to the outputs.
In the learning mode, the information flow alternates between forward and backward. A key element in the back-propagation paradigm is the existence of a hidden layer of nodes [6-8]. This frees the network from the linear limitations of the perceptron.

2. Work Done

Matlab has been used as the simulation tool. The objective of this work is to develop an Artificial Neural Networks based system for Breast Cancer Detection. The neural networks provide artificial intelligence techniques for solution for real life problems and being flexible in nature allows representation of many types of data for analysis. Since the training in based on the past as well as existing data of different parameters the results obtained can be more reliable. Also the computational difficulty is reduced by considerable extent and recent data can be obtained for further analysis. Thus it is appropriate to adopt the neural network technique for the cancer detection to ensure simplicity, reliability and flexibility in modeling process. The system will input the signatures of Ultra Wide Band Signals and train itself and determine whether the patient has breast cancer or not. Thus the objectives of the paper work are

1. Develop an ANN based system to detect cancer using UWB technique
2. Optimise the ANN and reduce the error rate and time taken to detect cancer from UWB signals by varying the number of layers
3. Optimise the ANN and reduce the error rate and time taken to detect cancer from UWB signals by varying the number of neurons.

Training
The term "training" or "learning" can be one of, or a combination of the following definitions:

1) Training means a process whereby error is used to modify the weights so that the network gives a more correct answer the next time
2) Learning is a mechanical process which may be decision trees, called explanation trees. It is used for providing decision rules.
3) Learning is the process whereby the ANN learns from its mistake. It usually involves three tasks: 1) computes outputs; 2) compare outputs with desired

outputs; and 3) adjusts the weights and repeats the process.

In this research, the two terms "training" and "learning" are used interchangeably. Training (or learning) is the process by which the weights and biases are initialized randomly. It deals with splitting the samples prior to feeding them to the networks. These also include the algorithm used for minimizing the system error, and criteria for stopping training.

Testing

Another process in neural network modelling is called testing or classifying. It can be one of or a combination of the following definitions.

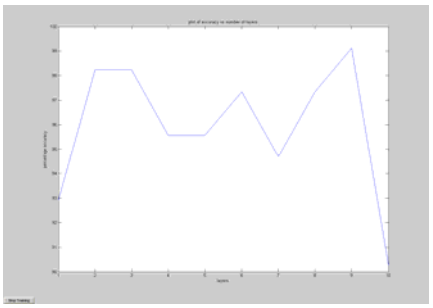
1) Testing is to determine how well a network has captured the nature of a function. It is to validate the network on additional samples that are not used in training the network, called testing set. The network which can yield the best performance on the validation samples would be the best accurate model among the other networks which are trained all the way to converge on the training samples.
2) Testing is a phase to examine the performance of the network by using the derived weights. It is to measure the ability of the network to classify the testing samples correctly.
3) Testing is a process by which the testing samples are used to determine how well the network performs on data it has not seen before during training. A properly built and trained network will exhibit similar levels of performance on both the training and testing sets. If performance differs widely, appropriate corrective action should be taken to the architecture, composition, or size of the training and testing sets.

Training process used in this research conforms to all the definitions given above. It deals with feeding the remaining samples to the trained networks to validate their generalization capability. Among the number of successfully trained networks, the best network may yield minimum error when it is validated by the test samples.

3. Results and Discussion

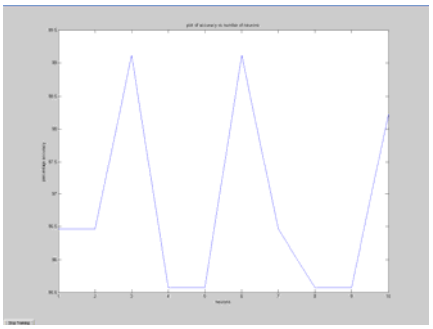
Following graph plots the percentage accuracy achieved by varying the number of layers used to construct the artificial neural network. It can be seen that best result was obtained when 9 layers were used to construct the neural network.

Percentage Correct Cancer Detection : 98.123008%
Percentage Incorrect Cancer Detection : 1.876992%



Following graph plots the percentage accuracy achieved by varying number of neurons used to construct the artificial neural network

Percentage Correct Cancer Detection : 98.230088%
Percentage Incorrect Cancer Detection : 1.769912%



It is evident that maximum 3 neurons are required to give the best result.

Thus it can be concluded from this work that ANN with 9 layers and 3 neurons is ideally suitable for predicting cancer. And it can achieve 98 % accuracy.

4. Conclusion

A feed-forward NN model using back-propagation algorithm is developed to identify the existence and location of tumor tissue in a breast model. This work was successfully done with a tumor size of 0.25 cm in radius. UWB signals were used to construct the feature vector patterns for 3.1 to 10.6 GHz center frequencies range. The NN model is able to detect the presence of tumor successfully. The detection performance could reach up to 100% showing its efficiency.

At the same time, it is able to find out the tumor location with average accuracy 97 %. This model shows also that early stage received signals (0.35–1 ns) are enough to

detect and locate the tumor signature. Discrimination between malignant and benign tissues is currently under investigation. More complex and realistic breast model can also be tested using this method.

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