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Efficient design of feedforward network for pattern classification

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Abstract: *A feedforward neural network is a computing device whose processing units (the nodes) are distributed in adjacent layers connected through unidirectional links (the weights).Feedforward networks are widely used for pattern recognition. Here two feedforward networks are taken into consideration, Multi Layer Perceptron and Radial Basis Network. while designing these networks problem involves in finding the architecture which is efficient in terms of training time. In this paper different data samples will be presented to RBF and Multi Layer network and the best network selection will be done on the basis of minimum time taken by the network for training.*
Keywords- *Feed forward network, Multi Layer Perceptron Neural Networks, Radial Basis Network, Spread.*

I. INTRODUCTION

Pattern recognition is the study of how machines can observe the environment, learn to explore patterns of interest from their background, and make reasonable decisions about the classes of the patterns. the main properties of neural networks are that they have the ability to learn nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data. the most commonly used neural network family for pattern classification tasks is the feed-forward network, which includes Multi Layer Perceptron(MLP) and Radial-Basis Function (RBF) networks[9]. Neural networks can be viewed as massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. Neural network models attempt to use some organizational principles (such as learning, generalization, adaptivity, fault tolerance and distributed representation. computation) in a network of weighted directed graphs in which the nodes are artificial neurons and directed edges (with weights) are connections between neuron outputs and neuron inputs. The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data.

Feed-Forward Networks

In a feed-forward neural network, information flows from the inputs to the outputs, without any cycle in their structure.The source nodes in the input layer of the network supply input vector, which constitute the input signal applied to that neuron in the second layer. The output of second layer are used as input to the third layer. Typically the neurons in each layer of the network have the inputs as outputs of preceding layer only[4].Here two types of feedforward networks have been used:-
1)Radial Basis Network.
2)Multi Layer Perceptron.

Radial Basis Network(RBF)

A feedforward neural network is a computing device whose processing units (the *nodes*) are distributed in adjacent layers connected through unidirectional links (the *weights*). In particular, a RBF network is a fully connected network with on hidden layer, whose nodes have some radially symmetric function as activation function[3]. Radial Basis Function Network (RBFN), with the simplicity of its single-hidden layer structure have Linear output layer and the radial basis hidden layer structure of RBFN provide the possibility of learning the connection weights efficiently without local minima problem in a hierarchical procedure so that the linear weights are learned after determining the centers[2].

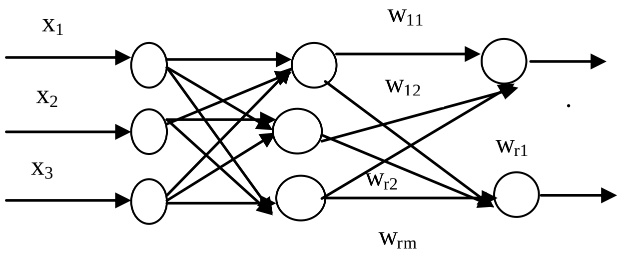

Figure 1:Network Topology of RBF Neural Network.

A function is a RBF function if its output depends on the distance of the input sample from another stored vector, referred to as the center of the RBF[8]. RBF network is three layer network where the hidden layer performs a nonlinear transformation and maps the input space onto a new space. The output layer then implements a linear combiner on this space, where the only adjustable parameters are the weights of the linear combiner[5]. Basic architecture of RBF network is shown in figure 1 which consists of one hidden layer, and the output neuron is the weighted sum of all output items of hidden layer. The transfer function of the hidden layer is the radial basis function, the weight between the input and hidden layer is fixed at 1, which means the weights between the hidden layer and the output layer are adjustable[10].

Multi Layer Perceptron(MLP)

The most popular class of multilayer feed-forward networks is *multilayer perceptrons* in which each computational unit employs either the thresholding function or the sigmoid function. Multilayer perceptrons can form arbitrarily complex decision boundaries and represent any Boolean function. The development of the *back-propagation* learning algorithm for determining weights in a multilayer perceptron has made these networks the most popular. For classification purposes, *m* is the number of classes. The squared error cost function most frequently used in the ANN literature is defined as

$$E = 1/2 \sum_{i=1}^{p} (y^{(i)} - d^{(i)})^2$$

The back-propagation algorithm is a gradient-descent method to minimize the squared-error cost function in Equation[1]**.**Below figure 2 shows architecture of MLP where connection weights are present in both the layers.

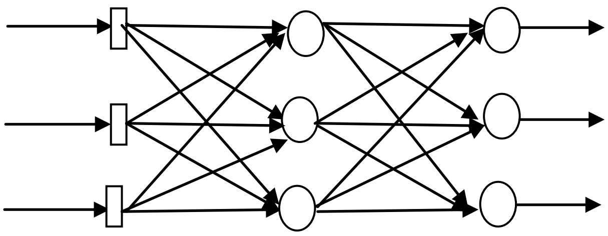

Figure 2: Architectural graph of MLP

II. EXPERIMENTAL RESULTS

Dataset

1)Below Poverty Line(BPL) dataset : In this dataset input consist of 13 features are there named as:

1)Land Holding
2)Types of house
3)Availability of clothing
4)Food security
5)Sanitation
6)Consumable durables
7)Literacy status of highest literate
8)Status of household labour

9)Means of livelihood
10)Status of children
11)Types of indebtedness
12)Reason for migration
13)Preference for assistance[6].

Target is specified using 2 values as
1)Belonging to BPL
2)Not belonging to BPL.

Here 293 samples are constructed . For performing training using RBF and MLP same number of neurons will be used in the hidden layer.

2)Breast cancer dataset: In this dataset 9 inputs features are present, these features are:
1)Clump thickness
2)Uniformity of cell size
3)Uniformity of cell shape
4)Marginal adhesion
5)Single Epithelial cell size
6)Bare nuclei
7)Bland chromatin
8)Normal nucleoli
9)Mitosis

Target value is specified as:
1)Benign
2)Malignant [7]

Here 699 instances are constructed. For performing training using RBF and MLP same number of neurons will be used in the hidden layer.

Simulation for this experiment was done using Matlab neural network toolbox version 7.1.

1)Using BPL dataset :As shown in table 1 for BPL data RBF and MLP uses same number of hidden neurons but time taken to train RBF is very less than MLP. For simulation *newff* is used to train MLP with 1 neuron in output layer and *newrbe* function is used to train RBF with spread 1.6.

Network used	Activation function (Hidden, Output)	Time (in seconds)	Number of hidden neurons
Radial Basis Network	Gaussian, Purelin	.522	293
Multi Layer Perceptron	Logsig, Logsig	7	293

Table 1: Architecture and training time taken for BPL data.

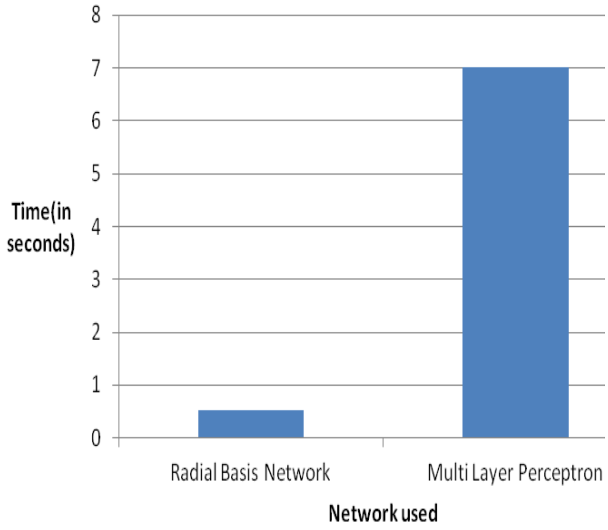

Figure 3: Relation between network used and training time for BPL data.

2) Using Breast cancer dataset: As shown in table 2 for cancer data RBF and MLP uses same number of hidden neurons but time taken to train RBF is very less than MLP. For simulation *newff* is used to train MLP with 2 neurons in output layer and *newrbe* function is used to train RBF with spread 1.6.

Network used	Activation function (for both layers)	Time (in seconds)	Number of hidden neurons
Radial Basis Network	Radbas	1.323	699
Multi Layer Perceptron	Logsig	17	699

Table 2: Architecture and training time taken for breast cancer data.

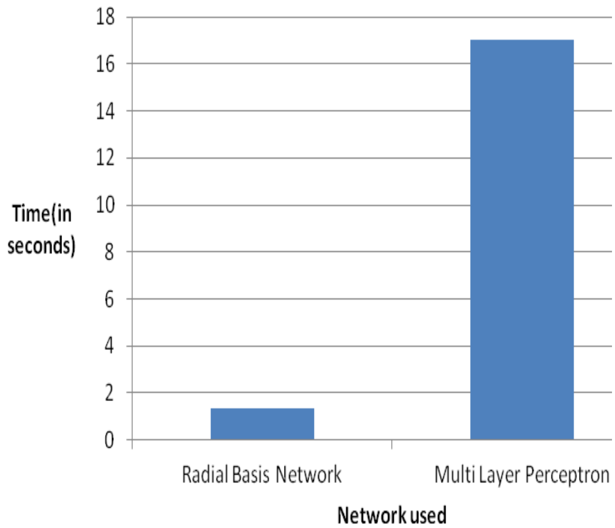

Figure 4: Relation between network used and training time for breast cancer data.

III. CONCLUSION

In this work comparative analysis of training time is done between RBF and MLP by using BPL dataset and breast cancer dataset. In both the datasets RBF performs training faster than MLP using same number of neurons without affecting performance.

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