

A DECISION SUPPORT SYSTEM FOR PREDICTION OF THYROID DISEASE - A COMPARISON OF MULTILAYER PERCEPTRON NEURAL NETWORK AND RADIAL BASIS FUNCTION NEURAL NETWORK

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ABSTRACT

Thyroid disease is a major cause of concern in medical diagnosis and the prediction / onset of which is a difficult proposition in medical research. In this research, we use two Neural Network models Multilayer perceptron (MLP) and Radial Basis Function Networks (RBF) for the prediction of onset of thyroid disease using the data generated in real life. The MLP is trained and tested with Back-propagation algorithm whereas RBF networks was trained and tested with SPSS software. Thyroid disease database which had been published and was used for empirical comparisons and the results show that MLP and RBF show the almost same kind of results in diagnosing the thyroid disease.

Keywords: *Neural networks, Radialbasisfunction Network, Multilayer Perceptron, Thyroid Disease, Back-Propagation, Medical Diagnosis.*

1. INTRODUCTION

The thyroid is a gland in the neck that produces the hormones that help regulate many body processes, including growth, energy balance, body temperature, and heart rate [1]. The thyroid gland is located at the lower front of the neck. Thyroid function involves the interaction of many hormones, including triiodothyronine (T3) and thyroxine (T4). Both of these hormones exist in two forms in the blood and this research can help diagnose hyperthyroidism (when the thyroid gland produces too much thyroid hormone) and hypothyroidism [2] (when the thyroid gland isn't producing enough thyroid hormone). A thyroid stimulating hormone (TSH) test is a common blood test used to evaluate how well the thyroid gland is working. TSH is produced by the pituitary, a pea-sized gland located at the base of the brain. The defects of thyroid function are one production of too little thyroid hormone (hypothyroidism) and second one is production of too much thyroid hormone (hyperthyroidism). In this proposed research, we try to compare two neural network models one is an Multilayer Perceptron Neural Network with sigmoidal activation function and the other is a Radialbasis function network with Gaussian function as the activation function.

1.1 Related Work

Many theoretical works have been proposed for thyroid disease diagnosis. Jacquelin Margret et al proposed a decision tree splitting rule for this disease diagnosis [3]. Farhad Soleimani Gharehchopogh et al performed a case study in diagnosis of thyroid disease using artificial neural network [4]. S.B.Patel worked to predict the diagnosis of heart disease using classification mining techniques [5]. Chang et al adopted seven feature extraction technique viz., co-occurrence matrix, grey level run-length matrix, laws textures energy measures, wavelet and Fourier features based on local Fourier coefficients[6]. Savelonas et al in 2005 proposed variable background active contour model for detection of thyroid nodules in USG images [7,8]. Isa et al has experimented for several activation functions such as sigmoid, Hyperbolic tangent, Neuronal, Logarithmic and Sine activation function for the MLP Neural Network and determined the most suitable function to classify the thyroid disease as Hypothyroid and Hyperthyroid[9]. Senol et al proposed a hybrid structure in which Neural Networks and Fuzzy logic are combined to diagnose the thyroid disease [10]. Anupam Shukla et al in 2009, has presented the diagnosis of thyroid disorders using ANN's[11],

Saiti et al in 2009, has proposed SVM and probabilistic Neural Network as classifier for diagnosing the disease[12]. Rohani et al compared several ANN models for diagnosing the thyroid disease [13]. Eyratios et al proposed an USG image analysis technique for boundary detection of thyroid nodule [14].

1.2 Dataset Description/Thyroid Data Set

The dataset of thyroid gland database taken from the UCI machine learning repository was used as one of the benchmark datasets for testing classifiers. The thyroid data set consists of 215 instances and each instance has five attributes plus the class attribute. All samples have five features. We used attributes of the thyroid disease along with network parameter bias were considered as a set of inputs and assessed the performance of the networks in predicting the thyroid disease. Three scales of measurement was considered as outputs of the network in this research and they were considered as Normal, Hypothyroidism and Hyperthyroidism respectively [15]. The inputs and outputs were taken as follows.

- T3: Resin uptake test
- Total serum thyroxin as measured by the isotopic displacement method
- Total serum triiodothyronine as measured by radio immuno assay
- Basal thyroid stimulating hormone (TSH) as measured by radio immune assay
- Maximal absolute difference of TSH value after injection of 200micro grams of thyrotropin-releasing hormone as compared to the basal value
- Class attribute in which 1 for Normal, 2 for hyperthyroid and 3 for Hypothyroid were taken as outputs.

All attributes are continuous and each of the instances has to be categorized into one of the three classes. Class-1: Normal (150 instances) Class-2 Hyperthyroidism (35 instances) and Class-3: Hypothyroidism (30 instances).

The table-1 below describes the class distribution of each type of disease

Type of disease	Number of samples	class
Normal	150	1
Hyperthyroidism	35	2
Hypothyroidism	30	3
Total	215	

2. MULTILAYER PERCEPTRON NEURAL NETWORKS

Artificial Neural Networks is an important application of Artificial Intelligence and is an attempt to model the functioning of the human brain. Single Layer Perceptrons (SLP) are those that have only one input and one output layer. SLP's are normally used in developing filters. Input layer is a layer which consists of input neurons and output layer is a layer consists of output neurons. Input layer is responsible for taking the inputs and output layer is responsible for generating the outputs. Neural Networks provide a mapping between input neurons in the input layer and output neurons in the output layer. This mapping provided by the network varies with the data set used for the network. An inbuilt function will be developed internally by the network. The connection between Neurons in the input layer and the neurons in the output layer are called as synapses and each synapse is associated with a weight called as a synaptic weight. Multi Layer Perceptron is a feed-forward neural network with one or more number of hidden layers between input and output layer. Feed-forward networks are those networks where the information flows from input to output layer in a forward direction. This network is trained with the supervised learning algorithm called as a back-propagation learning algorithm and classified the data into 3 subclasses. The back propagation algorithm is as follows.

2.1 After presenting input data to the input layer, information propagates through the network to the output layer (forward propagation). During this time, input and output states for each neuron will be set.

$$x_j^{[s]} = f(I_j^{[s]}) = f\left(\sum_i w_{ij}^{[s]} * x_i^{[s-1]}\right) \quad [16]$$



Where

$X_j [s]$ - Denotes the current input state of the j th neuron in the current $[s]$ layer.

$I_j [s]$ - Denotes the weighted sum of inputs to the j th neuron in the current layer $[s]$.

f is conventionally the sigmoid function.

$w_{ij}[s]$ - denotes the connection weight between the i th neuron in the current layer $[s]$ and j th neuron in the previous layer $[s-1]$. [16]

2.2 Global error is generated based on the summed difference of required and calculated output values of each neuron in the output layer. The Normalized System error E (glob) is given by the equation [16]

$$E(\text{glob}) = 0.5 * (r_k - o_k)^2$$

and $(r_k - o_k)$ denotes the difference of required and calculated output values.

2.3 Global error is back propagated through the network to calculate local error values and delta weights for each neuron. Delta weights are modified according to the delta rule that strictly controls the continuous decrease of synaptic strength of those neurons that are mainly responsible for the global error. In this manner the regular decrease of global error can be assured. [16]

$$E_j^{[s]} = X_j^{[s]} * (1.0 - X_j^{[s]}) * \sum (e_k^{[s+1]} * w_{kj}^{[s+1]})$$

Where

$E_j^{[s]}$ = Scaled local error of the j th Neuron in the current layer $[s]$

$$\Delta w_{ji}^{[s]} = \text{lcoef} * e_j^{[s]} * x_i^{[s-1]}$$

$\Delta w_{ji}^{[s]}$ = Denotes the delta weight of the connection between the current neuron and joining neuron. lcoef denotes the learning co-efficient / learning constant of the training parameters [16]

2.4 Synaptic weights are updated by adding delta weights to the current weights

3. RADIAL BASIS FUNCTION NETWORKS

In this article an attempt is made to study the applicability of a general purpose, supervised feed forward neural network with one hidden layer, namely, Radial Basis Function (RBF) neural network. It uses relatively smaller number of locally tuned units and is adaptive in nature. It is an artificial neural networks that uses radial basis functions as activation functions. The output of a network is a linear combination of radial basis functions of the inputs and neuron parameters. These type of networks are used in classification, function approximation, time series prediction and

system control. The methodology of Radial Basis Function network is as follows. [17]

The RBF network has a feed forward structure consisting of a single hidden layer of J locally tuned units, which are fully interconnected to an output layer of L linear units. All hidden units simultaneously receive the n -dimensional real valued input vector X (Figure 2). The main difference from that of MLP is the absence of hidden-layer weights. The hidden-unit outputs are not calculated using the weighted-sum mechanism/sigmoid activation; rather each hidden-unit output Z_j is obtained by closeness of the input X to an n -dimensional parameter vector m_j associated with the j th hidden unit. The response characteristics of the j th hidden unit ($j = 1, 2, \dots, J$) is assumed as,

$$Z_j = K \left(\frac{\|X - \mu_j\|}{\sigma_j^2} \right) \quad \text{---(1)}$$

Where K is a strictly positive radially symmetric function (kernel) with a unique maximum at its 'centre' m_j and which drops off rapidly to zero away from the centre. The parameter σ_j is the width of the receptive field in the input space from unit j . This implies that Z_j has an appreciable value only when the distance

$$\|X - \mu_j\| \text{ is smaller than the width } \sigma_j. \quad \text{[17]}$$

Given an input vector X , the output of the RBF network is the L -dimensional activity vector Y , whose l th component ($l = 1, 2, \dots, L$) is given by,

$$Y_l(X) = \sum_{j=1}^J W_{lj} Z_j(X) \quad \text{---(2)}$$

For $l = 1$, mapping of eq. (1) is similar to a polynomial threshold gate. However, in the RBF network, a choice is made to use radially symmetric kernels as 'hidden units'. RBF networks are best suited for approximating continuous or piecewise continuous real-valued mapping $f: R^n \rightarrow R^L$, where n is sufficiently small. These approximation problems include classification problems as a special case. From eqs (1) and (2), the RBF network can be viewed as approximating a desired function $f(X)$ by superposition of non-orthogonal, bell-shaped basis functions. The degree of accuracy of these RBF



networks can be controlled by three parameters: the number of basis functions used, their location and their width. In the present work we have assumed a Gaussian basis function for the hidden units given as Z_j for $j = 1, 2, \dots, J$ where

$$Z_j = \exp \left(- \frac{\|X - \mu_j\|^2}{2\sigma_j^2} \right) \quad (3)$$

and μ_j and σ_j are mean and the standard deviation respectively, of the j th unit receptive field and the norm is the Euclidean.[17]

A training set is an m labelled pair $\{X_i, d_i\}$ that represents associations of a given mapping or samples of a continuous multivariate function. The sum of squared error criterion function can be considered as an error function E to be minimized over the given training set. That is, to develop a training method that minimizes E by adaptively updating the free parameters of the RBF network. These parameters are the receptive field centres m_j of the hidden layer Gaussian units, the receptive field widths s_j , and the output layer weights (w_{ij}). Because of the differentiable nature of the RBF network transfer characteristics, one of the training methods considered here was a fully supervised gradient-descent method over E . In particular, μ_j, σ_j and w_{ij} are updated as follows: [17]

$$\Delta\mu_j = -\rho_\mu \nabla_{\mu_j} E \quad (4)$$

$$\Delta\sigma_j = -\rho_\sigma \frac{\partial E}{\partial \sigma_j} \quad (5)$$

$$\Delta w_{ij} = -\rho_w \frac{\partial E}{\partial w_{ij}} \quad (6)$$

where ρ_μ, ρ_σ , and ρ_w , are small positive constants. This method is capable of matching or exceeding the performance of neural networks with back-propagation algorithm, but gives training comparable with those of sigmoidal type of FFNN.

The training of the RBF network is radically different from the classical training of standard FFNNs. In this case, there is no changing of weights with the use of the gradient method aimed at function minimization. In RBF networks with the chosen type of radial basis function, training resolves itself into selecting the centres and dimensions of the functions and calculating the

weights of the output neuron. The centre, distance scale and precise shape of the radial function are parameters of the model, all fixed if it is linear. Selection of the centers can be understood as defining the optimal number of basic functions and choosing the elements of the training set used in the solution. It was done according to the method of forward selection. Heuristic operation on a given defined training set starts from an empty subset of the basis functions. Then the empty subset is filled with succeeding basis functions with their centres marked by the location of elements of the training set; which generally decreases the sum-squared error or the cost function. In this way, a model of the network constructed each time is being completed by the best element. Construction of the network is continued till the criterion demonstrating the quality of the model is fulfilled. The most commonly used method for estimating generalization error is the cross-validation error. [17]

4. RESULTS

4.1 RBF Neural Network

The RBF Neural Network was trained and tested with SPSS software. The table given below (Table -1) describes percentage of sample taken by the network for classification purpose.

Table-1: The Case Processing Summary Of The Network

		N	Percent
Sample	Training	152	76.8
	Testing	46	23.2
Valid		198	100
Excluded		17	
Total		215	

The following table (Table-2) describes the architecture of the RBF network. The number of neurons considered input layer are 6, the number of hidden units considered are 288 (identified by the software) and the number of output neurons considered are 3. The softmax activation function is used by the RBF network and finally sum of squares error function is used for classification purpose.

Table-2: The Network Information Of The RBF

Network		
Input Layer Factors	1	Inp 1
	2	Inp 2
	3	Inp 3
	4	Inp 4
	5	Inp 5
	6	bias
Hidden Layer	Number of Hidden Units	181
	Activation Function used	Exponential
Output layer	Number of Units	3
	Error Function	Sum of Squares

The following table (Table-3) describes the error generated by the network along with percentage of incorrect predictions during testing and training phases of the network.

Table-3: The Model summary of the RBF network is as follows

Training	Sum of squares error	10.501
	Percent incorrect predictions	7.9%
Testing	Sum of squares error	5.057
	Incorrect predictions	13.0%

The following table (Table-4) gives the entire classification made by the RBF network during training and testing phases. It is observed that RBF network classified the entire dataset into 77.6% as Normal, 11.2% as Hypothyroidism and finally 11.2% as Hyper-thyroidism during training phase.

In testing phase, 84.8% was considered for Normal, 13.0% and 2.2% was considered for Hypothyroidism and Hyperthyroidism individually respectively.

In a nut shell, the RBF network classified 92.1% during training phase and 87% during testing phase respectively.

Table-4: The classification of the RBF Network is as follows

Sample	Observed	Predicted			
		0.33	0.66	1.00	Percent Correct
Training	0.33	109	2	1	97.3
	0.66	7	15	0	68.2
	1.00	2	0	16	88.9
	Overall percent	77.6 %	11.2%	11.2%	92.1
Testing	0.33	34	1	0	97.1
	0.66	3	5	0	62.5
	1.00	2	0	1	33.3
	Overall percent	84.8 %	13.0%	2.2%	87.0%

4.2 MLP Neural Network

The MLP Neural Network was developed using back-propagation algorithm. Many Network parameters were considered during training and testing phases of the network. The network parameters considered are number of input samples, number of output samples, learning rate, momentum rate, maximum individual error, maximum total error, number of iterations respectively. The input to the MLP network was taken from a data (.dat) file. Six input neurons including the bias were considered in the input layer and 3 neurons were considered in the output layer respectively. The output generated by the network is predicted by considering the Normalized System Error values of the network. The following table gives the Normalized System Error (NSE) values generated by MLP Neural Network for different input samples and for different neurons in each hidden layer.

Table-5(NSE values of the MLP Network w.r.t input samples and hidden neurons)

Table-5 Placed at the end of paper

The following table (Table-6) gives the accuracy given by the network. Here Input-1 to Input-6 was taken as inputs and the actual value is the value generated by the network during testing phase. It is observed that, 99% accuracy is maintained by the MLP for Normal, 49.5% for Hypothyroidism and finally 33% for Hyperthyroidism for predicting the disease. When compared with RBF, MLP is slightly more accurate in predicting the disease. The testing of the MLP Network is given in the following table.

Table-6:(Accuracy of the MLP Network)



Table-6 Placed at the end of paper

Limitations of the work

As any project consists of pros and cons, this proposed research also consists of some limitations.

- Usually the problem given to the neural network is described as a set of examples rather than a function. Therefore the number of points in the problem space is finite. Neural networks which are trained properly have a good interpolation performance, but a very poor extrapolation performance. Unfortunately there is no general rule to find out if a new pattern is within the interpolation space
- The prediction accuracy could be more had we considered more number training and testing samples.
- The system can be enhanced to any desired level if we provide more number of inputs and outputs.
- The proposed system can also be used for different kinds of disease diagnosis given the set of input and output variables.

DISCUSSION:

The Multilayer Perceptron Neural Network has been trained by back propagation algorithm and Radial Basis Function Network has been trained by SPSS software to predict thyroid disease using biological variables. Neural Network models have been employed in a variety of clinical medicine settings, but this is the first time it is being used to predict the onset of thyroid disease [18]. The comparison of two models (MLP & RBF Networks) had been done to predict the onset of thyroid disease. The results indicate that, Normal outcome had been recognized /classified by both the networks accurately whereas which is not the same for Hypothyroidism and Hyperthyroidism labels. This is because; both the networks have not been trained and tested with more number of Hypothyroidism and Hyperthyroidism variables and which is due to lack of values for these

variables in the dataset gathered from UCI library. The development of our model is a practical tool to predict thyroid onset variables and as more data are generated the system improves in precision and can be widely employed in patient care and research.

CONCLUSION

It is seen that radial basis network can be successfully used for the diagnosis of thyroid disease. Diagnosing the thyroid disease is an important yet difficult task from both clinical diagnosis and statistical classification point of view. In summary, in this proposed research, we developed two Neural Network models using the available information on thyroid disease diagnosis demonstrated that it gave results consistent with our recent application of the method to predict wellbeing[16]

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Table-5(NSE values of the MLP Network w.r.t input samples and hidden neurons)

Neurons/ Samples	1	2	3	4	5	6	7	8	9	10
10	0.22449	0.019176	0.017409	0.011186	0.010819	0.009982	0.010983	0.012875	0.009982	0.013624
20	0.016912	0.00995	0.009912	0.009992	0.01	0.009957	0.009998	0.009998	0.009922	0.009967
30	0.015836	0.009992	0.009946	0.009971	0.009942	0.009964	0.009986	0.009994	0.009981	0.009997
40	0.013384	0.009933	0.00995	0.009941	0.009958	0.009946	0.009967	0.009984	0.009993	0.00997
50	0.012126	0.009951	0.00996	0.00997	0.009934	0.009967	0.009964	0.00993	0.009955	0.009981
60	0.011987	0.009877	0.009882	0.00989	0.009897	0.009989	0.009952	0.00993	0.009959	0.009958
70	0.012236	0.009987	0.009849	0.009949	0.009903	0.009948	0.009885	0.00994	0.009964	0.009922
80	0.011356	0.009849	0.009899	0.009905	0.009969	0.009934	0.009884	0.009904	0.009893	0.009913
90	0.01075	0.009853	0.009903	0.009951	0.009851	0.009871	0.009866	0.009906	0.009948	0.009938
100	0.011203	0.009762	0.009752	0.009999	0.009991	0.009837	0.009842	0.009976	0.009999	0.009955
110	0.010339	0.010485	0.009812	0.009929	0.009763	0.00987	0.009937	0.009901	0.009882	0.009872
120	0.010355	0.009828	0.009792	0.009936	0.009835	0.009872	0.009942	0.00998	0.009926	0.009957
130	0.010256	0.009981	0.009869	0.009785	0.00996	0.009884	0.009982	0.009932	0.009843	0.009964
140	0.010706	0.00967	0.009782	0.009901	0.009964	0.00985	0.009875	0.009888	0.009812	0.009859
150	0.011901	0.009558	0.009981	0.009831	0.009897	0.009805	0.009974	0.009889	0.00979	0.009861

Table-6:(Accuracy of the MLP Network)

Input1	Input2	Input3	Input4	Input5	Input6	Actual Value	Desired value	%of accuracy
1	0.84	0.19	0.18	0.2	0.94	0.98	1	98
1	0.69	0.38	0.25	0.02	0.00	0.28	0.33	84
1	0.73	0.69	0.16	0.01	0.01	0.61	0.66	92
1	0.78	0.2	0.07	0.1	0.35	0.95	1	95
1	0.83	0.13	0.18	0.13	0.38	0.91	1	91