A Comparative Study of Neural Network and Fuzzy Neural Network for Classification

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Abstract

There are heaps of information discovered identified with sickness on the planet which can't be dealt physically. Data mining is one of the essential ideas which gives pertinent data about dataset and create relationship among the information. In like manner, early finding of sicknesses is imperative in biomedical field. As of now, different Artificial Intelligence systems is across the board, these procedures help doctors as a finding partner. The data mining classification techniques, namely Neural Networks and Fuzzy Neural Network are analyzed on Thoracic data. The performance of these techniques is compared, based on accuracy.

Keywords: Neural Network, Multilayer Perceptron, Fuzzy Neural Network.

Introduction

There are numerous zones in medication in which Classification and acknowledgment of data pattern is imperative . There is generous research work in progress to tackle the classification problems [1]. Artificial Neural networks (ANN) prefer to take care of these issues, because of their parallel processing capabilities, and in addition decision making abilities. ANN have been connected for different medicinal characterization errands as of now. ANNs are utilized as data examination instruments, which give profitable guide to pattern classification. Integrated Fuzzy Neural Network consolidates the learning capacities of neural network and clarification capacities of Fuzzy system . This paper is to show the centrality of cream strategy and exhibits that Fuzzy Neural Network predicts better than Neural Network in Classification.

1. Literature Review:

ANN have been applied for various medical classification such as prognosis predicting and survival rates[2], [3] briefs the application of back propagation method in neural network to the problems in pathology and laboratory, [4] diagnoses myocardial infarction using Artificial Intellegence, diagnosing epilepsy[5], discusses about the comparative study of neural network and other pattern recognition to the diagnosis of low back disorders[6], [7] expalins Pattern Classification for Hybrid Neural Network System which has missing features, In [8] Probe and Prognosis of thyroid disorder using Neuro –Fuzzy System is discussed. [9] artificial neural networks in predicting neonatal disease diagnosis is explained. [10] discusses data mining classification methods in cardiovascular disease prediction.[11] An improved fuzzy min–max neural network for pattern recognition. [12] describes about Fuzzy neural networks in classification problems, [13] details about Fuzzy neural network,[14] method of deformation monitoring prediction based on fuzzy neural network.

3. Artificial Neural Network

Artificial Neural Network (ANN) is one of the important soft computing technique that have attracted more attention in recent years and are mostly used in lots of real world problems such as pattern recognition, classification, forecasting and optimization. There are many methods in ANN among these most used model is Multilayer Perceptron (MLP). The MLP is a three layer architecture which consists of an input-layer(IL), output-layer(OL) and hidden- layers(HL) [15]. In the literature there are few algorithms to train the MLP for instance Ant Colony Optimization [16], Particle Swarm Optimization [17], however the most utilized method is the Back-propagation algorithm (BP) . Training indicates to find the values of all weights to obtain the preferred output for the related input. This minimizes the error which is calculated by difference between desired output and output of network [18]..

3.1 Multilayer Layer Perceptron

A Multilayer Perceptron(MLP) is similar to Original Perceptron model, proposed by Rosenblatt in the 1950 [19],. MLP consists of more than one HLs between ILs and OLs. In the architecture of MLP, neurons associations are always structured from lower layers to upper layers, the neurons in the same layer are not interrelated , figure 1. The choice of layers, number of neurons in each layers and links are called the architecture, choice of neurons in IL and OL always depends on the type of the problem.

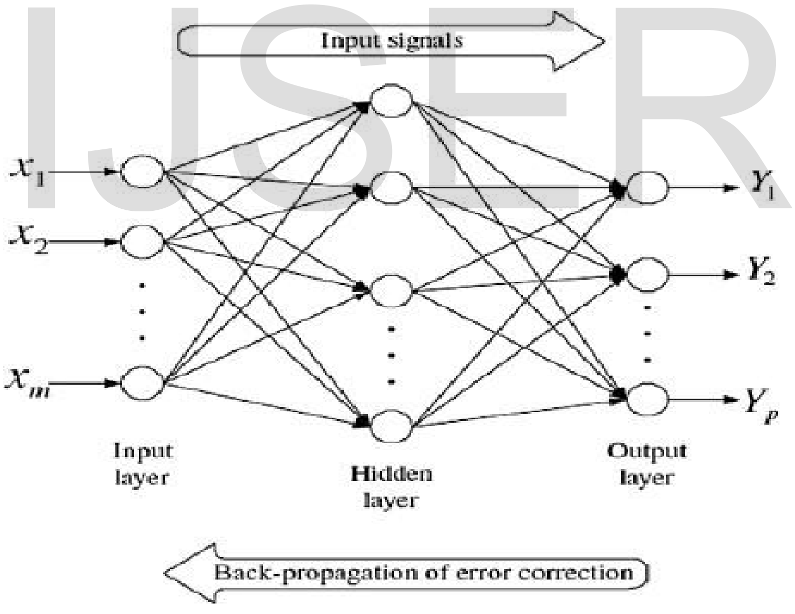


Fig -1 Multilayer Perceptron Neural Network

3.2Back-propagation and learning Method

Learning is the procedure to minimise error by adjusting the weights in connections according to network and desired output [21]. Suppose that IL consists of n_0 neurons as $X = (x_0, x_1, \ldots, x_{n0})$ a sigmoidal activation function $f(x)$ given by [22]

$$f(x) = \frac{1}{1+\exp(-x)} \tag{1}$$

In every layer, output of each unit must be detected to find the network output. Assuming a set of HLs as ($h_1,h_2,\ldots,h_N$) and n_i are the neuron numbers in each HL h_i. The output of first HL is

$$h_1^j = f\left(\sum_{k=1}^{n_0} w_{k,j}^0 \, x_k\right), \; j = 1,\ldots,n_1 \tag{2}$$

HLs neurons output are calculated as:

$$h_i^j = f\left(\sum_{k=1}^{n_{i-1}} w_{k,j}^{i-1} \, h_{i-1}^k\right), \; i=2,\ldots,N \text{ and } j=1,\ldots,n_i \tag{3}$$

Where k^{th} neuron of i^{th} HL is $w_{k,j}^{i-1}$, number of neurons in i^{th} HL is n_i. The output of i^{th} HL is calculated as :

$$h_i = \left(h_i^1, h_i^2, h_i^3 \ldots, h_i^{n_i}\right) \tag{4}$$

The output of network is given by

$$y_i = f\left(\sum_{k=1}^{n_N} w_{k,j}^N \, h_N^k\right)$$

$$Y = \left(y_1,\ldots,y_j,\ldots\ldots,y_{N+1}\right) = F(M,X) \tag{5}$$

Here k^{th} neuron of N^{th} HL and j^{th} neuron on OL is $w_{k,j}^N$, number of neurons in Nth HL is n_N, vector of OL is Y, transfer function is F and weight matrix is M is given by :

$$M = \left(M^0,\ldots,M^j,\ldots\ldots,M^N\right),\; M^i = \left(w_{j,k}^i\right), 0 \le i \le N;\; i \le j \le n_{i+1}; 1 \le k \le n; \text{ where } w_{j,k}^i \in R$$

For simplification let's consider all HLs $n = n_i \; \forall i = 1,\ldots,N$. where X is input , f is activation function, M^i weight matrix which lies between i^{th} and the $(i+1)^{th}$ HL , M^0 weight matrix lies between input and first HL and M^N weight matrix lies between N^{th} HL and OL

4. Fuzzy Neural Network

Many complex domains has different issues, which require diverse kinds of handling techniques. Intelligent hybrid system has enormous growth and is successfully used in many applications in the field of medical diagnosis. Inference mechanism of Fuzzy logic in uncertain conditions and the learning capacity , fault tolerance, adapting to situations and parallelism are advantages of neural networks. Combination of Fuzzy logic and Neural Network is very effective in such a way that Fuzzy systems gains the capacity to work as decision making systems and Neural Networks tune the membership functions.

The classification method used in FMM is hyperbox fuzzy sets . hyperbox fuzzy sets is defined by its maximum and minimum points. The membership function is given by its min-max points that describes the pattern fits . For an n-dimension input pattern is K^n unit cube that allows the membership value to lie in the range between 0 and 1. The membership value in the hyperbox is maintained as 1.

Hyperbox fuzzy set is defined as follows :

$$F_j = \{X, M_j, N_j, f(X, M_j, N_j)\} \quad \forall X \in K^n \tag{6}$$

Where *Mj* and *Nj* are minimum and maximum points. Figure 2 shows the min and max points in a 3-D hyperbox.

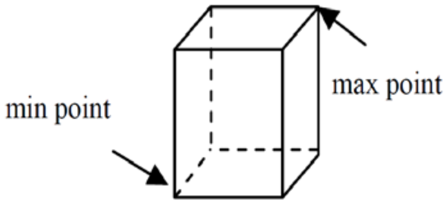


Fig- 2 : min-max points in hyperbox $F_j = \{M_j, N_j\}$ in K^3

Conditions of hyperbosx are applied to get a collective fuzzy sets in order to classify pattern class *P*, L*p*, is

$$L_p = \bigcup_{j \in P} F_j \tag{7}$$

where *P* is the index set related to class *p* in the corresponding hyperbox. Significant feature of this method is the process mainly focuses on fine tuning the boundaries of the classes.

Learning technique is, overlapping of hyperboxes with similar classes is allowed and overlapping with different classes is strictly prohibited. f_j (*Aa*) , $0 \le f_j$ (*Aa*) ≤ 1 is membership function of j^{th} hyperbox , this finds the degree of a^{th} input pattern of Oa lies outside hyperbox *Fj*. This gives a clear view of about each component regarding their measurement whether greater or lesser compared to maximum or minimum points along each dimension which falls outside the min-max bounds of the hyperbox. Further, as *fj* (*Aa*) approaches 1 indicates the point should satisfy hyperbox condition. the sum of two complements is the function that meets all these criteria, that is, violation of average amount of max points and violation of average amount of min point. The membership function is obtained as:

$$f_j(O_a) = \frac{1}{2n} \sum_{1=1}^{n} \left[\max\left(0, 1 - \max\left(0, \gamma \min\left(1, o_{ai} - n_{ji}\right)\right)\right) + \max\left(0, 1 - \max\left(0, \gamma \min\left(1, m_{ji} - o_{ai}\right)\right)\right) \right] \tag{8}$$

where, $O_a = (o_{a1}, o_{a2}, ..., o_{an}) \in K^n$ is the a^{th} input pattern, $M_j = (w_1, w_2, ..., w_{jn})$ is the min point for *Fj*, $N_j = (n_1, n_2, ..., n_{jn})$ is the max point for *Fj*, and γ is the sensitivity parameter that regulates how fast the membership values decrease as the distance between O_a and F_j increases.

As in Figure 3, FMM is a three layer network. First layer is IL which has input nodes, that depends on the dimension of the input pattern of problem. OL has nodes that is equal to number of classes according to the problem . The HL is the hyperbox layer, every node is a fuzzy set hyperbox which are min-max points that connects the IL to HL . the transfer function of hperbox membership function of the HL is given by (8). The min and max points are stored in the form of matrices *M* and *N*. The connections between the HL and OL nodes are binary valued and are also stored in the form of matrix *U*.

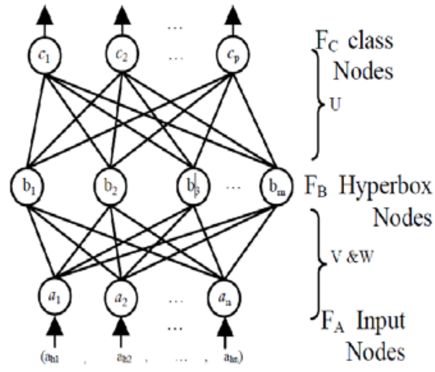


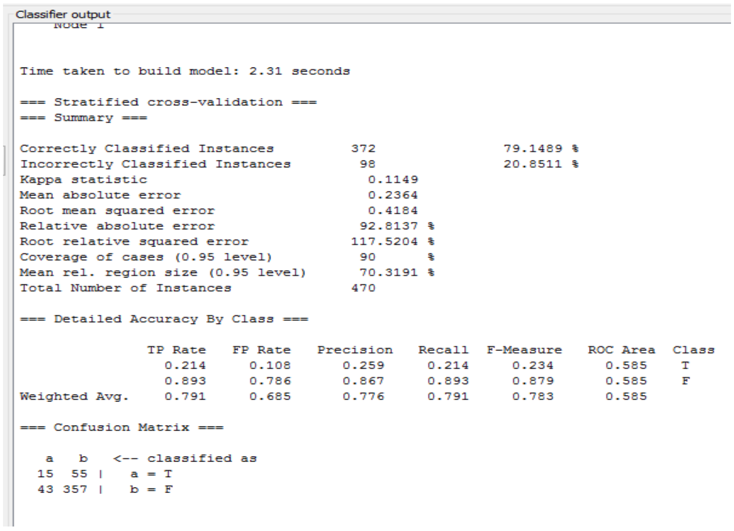
Fig 3 A FMM network

5. Experimental Results and Discussions

For classification, thoracic surgery data set is taken from UCI Machine Learning Repository. The data consists of 470 cases with 17 attributes. In NN Multilayer Perceptron method is used and the learning algorithm is Back propagation method which is used for training the neurons and is based on descent gradient technique. The fuzzy block provides fuzzified values from an input vector to multi-layer neural network. Linguistic statements are used to tune membership functions of fuzzy systems that are employed as decision making for the fuzzy interface . In the neural network block the neural network was constructed with same parameters with epochs of 500 in 1 hidden layer . The network is designed to perform for multidimensional classification that is proposed to design a FNN model for medical data classification. The knowledge used by the model using approximate linguistic terms can be refined through the process of learning from experience. To generalize the performance of the fuzzy neural network model 10-fold cross validation method is used. Results obtained from the experiment are shown in Table-1 and in Figure 3 and 4. FNN performs better than MLP Neural Network.

	Accuracy%
MLP Neural Network	79.1
Fuzzy Neural Network	84.98

Table-1 Classification Rate



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Classifier output
    Node 1

Time taken to build model: 2.31 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         372               79.1489 %
Incorrectly Classified Instances        98               20.8511 %
Kappa statistic                          0.1149
Mean absolute error                      0.2364
Root mean squared error                  0.4184
Relative absolute error                 92.8137 %
Root relative squared error            117.5204 %
Coverage of cases (0.95 level)          90      %
Mean rel. region size (0.95 level)      70.3191 %
Total Number of Instances              470

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0.214     0.108     0.259      0.214     0.234      0.585    T
                 0.893     0.786     0.867      0.893     0.879      0.585    F
Weighted Avg.    0.791     0.685     0.776      0.791     0.783      0.585

=== Confusion Matrix ===

   a   b   <-- classified as
  15  55 |   a = T
  43 357 |   b = F
```

Fig 4 - Classification Result of NN

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Classifier output
using 10 nearest neighbour(s) for classification

Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         399               84.8936 %
Incorrectly Classified Instances        71               15.1064 %
Kappa statistic                         -0.0042
Mean absolute error                      0.1511
Root mean squared error                  0.3887
Relative absolute error                 59.3179 %
Root relative squared error            109.1678 %
Coverage of cases (0.95 level)          84.8936 %
Mean rel. region size (0.95 level)      50      %
Total Number of Instances              470

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall   F-Measure   ROC Area   Class
                 0        0.003      0          0         0          0.499     T
                 0.998    1          0.851      0.998     0.918      0.499     F
Weighted Avg.    0.849    0.851      0.724      0.849     0.782      0.499

=== Confusion Matrix ===

   a   b   <-- classified as
   0  70 |   a = T
   1 399 |   b = F
```

Fig 5 - Classification Result of FNN

From the Table we note that Fuzzy Neural Network based classifier results in 84.98% correct classification compared to 79.10% MLP based Network. Fuzzification improves the accuracy considerably

5. Conclusion

This work gives a relative study on Multilayer Perceptron Neural Network Model and Fuzzy Neural Network for the classification of thoracic data. From the experimental results it is noticed that Fuzzy Neural Network has 85% accuracy and MLP 79 % accuracy. This shows that the hybrid technique could be successfully used to help the diagnosis of thoracic data set. The advantage of Fuzzy Neural Network is capable to perform classification very efficiently and giving high performances to medical data set. Further this work can be extended to other medical data set and the experiment can be carried out in other methods in Neural Network along with Fuzzy Logic.

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