Analysis of Classification Algorithms using Neuro-Fuzzy Approach

[1]Kirti Khedkar, [2]Manisha Mahindrakar

[1]M. Tech Student, [2]Assistant Professor
[1,2]Department of Computer Science and Engineering,
[1]Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded, India

Abstract: The Fuzzy Hypersphere Neural Network classifier uses fuzzy hyperspheres as cluster and classes which are represented as a union of FHS and in Class-specific fuzzy hypersphere neural network clustering is elaborated on inter-class and intra-class fuzzy membership to create fuzzy hyperspheres in the hidden layer. Class-specific FHSNN has two algorithms Rule 1 and Rule 2 for the inclusion of pattern in hypersphere, visualization and to eliminate the overlap between hyperspheres. The performance of class-specific fuzzy hypersphere neural network is analyzed with a fuzzy hypersphere neural network and it found that Class-specific FHSNN is superior with the accuracy of a dataset having a large number of patterns.

***IndexTerms* - Fuzzy Hypersphere Neural Network (FHSNN), Class-specific fuzzy hypersphere neural network (CSFHSNN), fuzzy hypersphere, Supervised and unsupervised learning.**

I. INTRODUCTION

A computer system is like a human brain which is called a neural network. The neural network framework is controlled by its neurons and learning rules. The membership function is used to discover the nature of neurons. The classifier plays an important role in clustering the patterns according to their features. This fuzzy approach is used for various data classification, for example, iris recognition, heart disease breast cancer recognition.

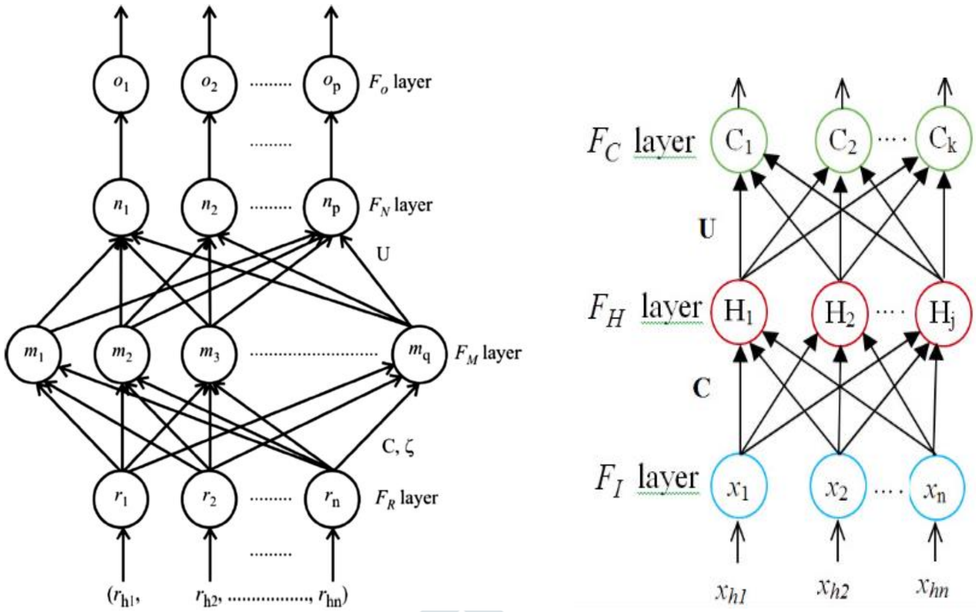
FNN distinguish into supervised and unsupervised learning algorithms. The supervised learning algorithm contains labeled patterns of maps input to output. Dataset is prepared on a predefined set of training which encourages its capacity to achieve exact end when given new information. Unsupervised calculations endeavoring to discover concealed structure in unlabeled information and there is no error. We prefer supervised learning because the algorithm makes predictions on training data and get accurate results. Class-specific fuzzy hypersphere neural network and fuzzy hypersphere neural network classifier these two methodologies we analyze in this paper. The Fuzzy hypersphere neural system which makes the groups with supervised utilizing regulated bunching methods, where each bunch hypersphere is defined by its centroid and radius and described by a fuzzy membership function.

The rest of the paper organized as follows. Next section II analysis of learning algorithms which describes the class-specific FHSNN and FHSNN, later on, it comes with section III represents experimental results. Finally, section IV concludes the paper.

II. ANALYSIS OF LEARNING ALGORITHMS

In this section, we analyzed the architecture of the Class-specific fuzzy hypersphere neural network and Fuzzy hypersphere neural network classifier. In 2001, U. V. Kulkarni, T. R. Sontakke [1] proposed FHSNN has a four-layered structure as shown in Fig.1 (a). The F_R layer takes input having n processing elements. During the training, F_M layer is constructed. Each node in the F_M layer represents the hypersphere. The center points of hypersphere are weights between F_R and F_M layer and the radius of the hypersphere is denoted by ζ_j. Both center points and radius are stored in matrix C. The nodes in F_M and F_O represent the class. Fo is for delivery fuzzy output. In this hyperspheres are formed on the basis of supervised clustering and the pattern of a class is determined by a membership function. If the new pattern falls outside the hypersphere then the radius of the hypersphere is expanded to get the pattern by satisfying expansion criteria. When hypersphere creates overlap then the overlap is removed by restoring the radius of the expanded hypersphere.

In 2018, A. B. Kulkarni, U. V. Kulkarni, S. V. Bonde presented Class-specific fuzzy hypersphere neural network. This reduced the structure up to three-layer as shown in Fig. 1(b) and produces output at hidden layers. Nodes at the F_C layer are also constructed during training. As the hypersphere and classes are created the values of center point radius and matrix U are updated. The hyperspheres created by Class-specific fuzzy hypersphere neural networks are based on interclass and intraclass clustering membership metrics. The interclass metric builds by finding the distance between patterns of one class form pattern of different classes while in interclass metric the distance of patterns in the same class is measured. Rule 1 and Rule 2 are proposed for the order of data visualization to produce identical results and exterminate the overlap between interclass clustering respectively.



(a) **(b)**

Fig. 1 (a) Architecture of FHSNN, (b) Architecture of FHNN

III. EXPERIMENTAL RESULTS

To analyze the performance different UCI datasets along with acquired results have been explored in the following sub-sections. The performance is evaluated using 5 fold cross-validation. In K- fold cross-validation each dataset is divided into K equal size samples. The analysis of FHSNN and CSFHSNN accuracy is done here. The classifiers are implemented using Python 3 and MATLAB 2017a.

3.1 Iris Dataset

Iris dataset is broadly admired data set. In this dataset 150 supervised patterns of plants along with its 3 classes of plants and four features are given. The significance of performance accuracy with k fold is exploited. In each evaluation 120 training and 30 testing samples are considered and it is illustrated in Table 3.1.

Table 3.1. Iris dataset Accuracy

K fold cross-validation	Training samples	Testing Samples	FHSNN Accuracy	CSFHSNN Accuracy
1	120	30	1	0.9
2	120	30	1	1.0
3	120	30	1	1.0
4	120	30	1	1.0
5	120	30	1	0.8

3.2 Glass Dataset

The study of the classification of types of glass was motivated by a criminological investigation. At the scene of the crime, the glass left can be used as evidence. Dataset consists of 214 patterns with its 7 classes. Here the accuracy of the Class-specific fuzzy hypersphere neural network is better than FHSNN as described in table 3.2.

Table 3.2. Glass dataset Accuracy

K fold cross-validation	Training samples	Testing Samples	FHSNN Accuracy	CSFHSNN Accuracy
1	172	42	0.733	0.77
2	172	42	1	1
3	172	42	1	1
4	172	42	1	1
5	172	42	0.72	0.76

3.3 Breast Cancer Dataset

This data set includes 86 instances of classes. The instances are described by 9 attributes, some of which are linear and some are nominal. As less number of patterns, the FHSNN gives better accuracy as shown in table 3.3.

Table 3.3. Breast Cancer dataset Accuracy

K fold cross-validation	Training samples	Testing Samples	FHSNN Accuracy	CSFHSNN Accuracy
1	69	17	0.8	0.47
2	69	17	0.6	0.42
3	69	17	0.8	0.55
4	69	17	0.6	0.38
5	69	17	0.5	0.29

IV. CONCLUSION

This paper proposed the analysis of learning algorithms based on accuracy using K fold cross-validation. The Fuzzy hypersphere neural network has an accuracy of average 1.0, 0.8 and 0.6 on Iris, Glass and Breast Cancer respectively whereas Class-specific fuzzy hypersphere neural network has average accuracy on the same datasets 0.9, 0.906 and 0.4 respectively. Through this result, it shows that the dataset having a large number of patterns Class-specific FHSNN classifier performance gains over accuracy.

REFERENCES

[1] U. V. Kulkarni and T. R. Sontakke, "Fuzzy hyper-sphere neural network classifier," In 10" int. IEEE Conference on Fuzzy Systems, University of Melbourne, Australia, December 2001.

[2] A. B. Kulkarni, U. V. Kulkarni and S. V. Bonde , "Class-Specific Fuzzy Hypersphere Neural Network", India, ICACC 2018.

[3] Mahnaz Mohammadi, Rupali V. Pawar and Priyadarshan S. Dhabe, "Heart Diseases Detection Using Fuzzy Hyper Sphere Neural Network Classifier", India, CiiT 2010.

[4] S. S. Chowhan, U.V. Kulkarni and G. N. Shinde "Iris Recognition Using Modified Fuzzy Hypersphere Neural Network with different Distance Measures ", India, *JACSA* 2011.

[5] U. V. Kulkarni and D. T. Mane, "Modified Fuzzy Hypersphere Neural Network For Pattern Classification using Supervised Clustering", India, ICACC 2018.

[6] P. K Simpson, "Fuzzy min-max neural networks-Part1: Classification," IEEE Trans. on Neural Networks, Vol. 3, No. 5, Sept 1992.

[7] P. K Simpson, "Fuzzy min-max neural networks-Part2: clustering," IEEE Trans. fuzzy systems, Vol. I, No.1, pp. 32-45, 1993.

[8] U. V. Kulkami, T. R. Sontakke, and G. D. Randale, "Fuzzy hyper- line segment neural network for rotation invariant handwritten character recognition, published in int. joint conf: on neural networks: IJChN'OI, held in Washington DC, USA, from 14-19 July, 2001.

[9] D. Wang, X. J. Zeng, J. A. Keane. (2012) "A clustering algorithm for radial basis function neural network initialization."Neuro computing 77(4): 144-155.

[10] U.V. Kulkarni and T.R. Sontakke, "Modified fuzzy neural network classifier for pattern recognition," All India seminar on recent trends in computer communication networks(CCN 2001), I.I.T. Roorkee, pp. 69-75, Nov. 2001.