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Hybrid Approach for Classification using Multilevel Fuzzy Min-Max Neural Network

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ABSTRACT: The neuro-fuzzy classification is the technique in which it uses combination of fuzzy set and neural network. The various fuzzy min-max neural network (FMM) classification models usage hyperbox structure for pattern classification. A multilevel FMM model gives better accuracy than previous model but has drawback of generating large number of hyperboxes. A hybrid approach is developed in which pruning strategy has been used to reduce number of hyperboxes and hence accuracy is improved. Various datasets are used for testing purpose which gives more accuracy andgenerates less number of hyperboxes in classification.

KEYWORDS: Neuro-fuzzy approach, FMM model, hyperbox, pruning, pattern classification

I. INTRODUCTION

Artificial Neural Networks (ANN's) are used in various areas such as medical field, pattern classification, faultdetection and so on. ANN's are similar to human biological nervous system, used for learning. Fuzzy logic proposed by Lotfi A. Zadeh [7] is applied for approximate reasoning instead of only binary values.

There are various pattern classification approaches such as machine learning, statistical approach and neural network. The FMM model is the first model proposed in 1992 for pattern classification, based on neural network and fuzzy set [8].The main purpose of FMM model is to classify pattern by using hyperbox structure. Hyperbox structure is a simple box containing min point and max point. The input sample is checked first for hyperbox of that class is present or not. If there is no such hyperbox then it will generate new hyperbox for that class.Hyperboxes are generated in training phase and according to greatest membership function value input sample is classified in testing phase.The FMM model shown in fig. 1, contains three layers in which first layer is used to denote input sample A_h in h^{th}pattern space, second layer will generate hyperboxes by using V minimum point & W maximum point and calculates membership function. Membership function used here is Simpson's equation [7]. Greatest membership function value is then used to represent output that is actual class of respective input sample.

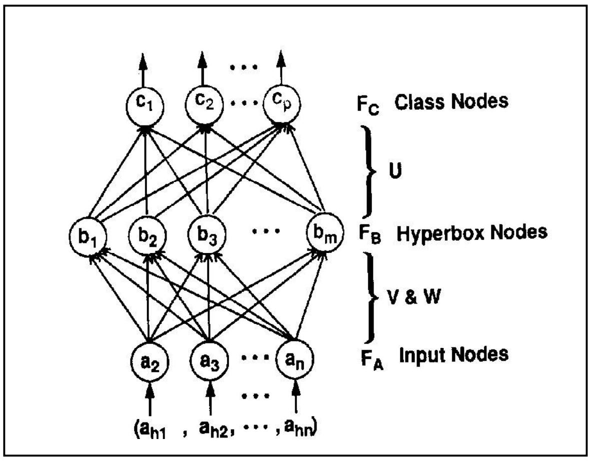

Fig: 1 Examplefor FMM model [8]

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II. LITERATURE SURVEY

In [7] FMM model, the increased expansion parameter (θ) valuecauses to lower precision of the algorithm. This model, gives improved results only when value of (θ) is large.

In [5], developed by Gabrys and Bargiela, introduced some modifications in the basic FMM model toimprove its efficiency. The new membershipfunction was added. The input patterns were in the form of upper bound and lower bound. It alsodescribes some constraint for regulating the maximum size of the hyperbox[20]. Its performance declines when the features of the training and testdata varying.

In [9], contains two types of hyperbox inclusion and exclusion hyperbox. Inclusion belongs to simple hyperbox whereas exclusion hyperbox contains sample belonging to other classes. But, it discards a proportion of patterns that fall into the exclusionhyperbox set.

In [3], compensatory neuron architecture is introduced that is similar to human reflex functioning in emergency situations. This model uses inappropriate membership function for compensatory neuron boxes, andtherefore, it is unable to accurately classify largepercentage of samples that are situated in overlapping regions [20].

In [19], (GNN) Granular Neural Network for granular data classification was developed.Hyperbox fuzzy set is used to describe granulardata [19]. 2n input nodes are used here, therefore,it can handle granules in theform of hyperboxes. It can classifydifferent size granules more accurately thanGFMM method [19]. Its performancegives better results than the previous method. But as thevalue of expansion parameter increases granularity of this method decreases.

In [6], proposed by Zhang, introduced data core and geometry center for pattern classification. The expansion phaseintroduced in this method can reduce the number ofhyperboxes [20]. To handle all types ofoverlaps only one type of overlappingneuron is essential. But, it was unable to correctly classify large percentageof samples that are occurred in the overlappingregions.

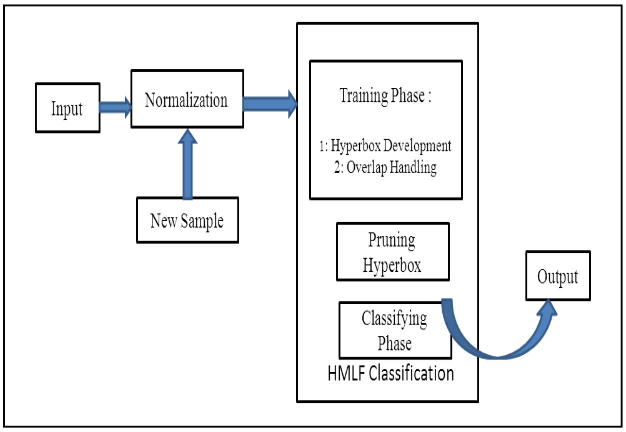
In [1], authors proposed multilevel tree like modelfor pattern classification. The smaller sizes hyperboxes are used with each level. The purpose of this model was to handle overlapping region classification. In each level separate classifier is used. Hyperboxesof the child levels are precise and smallerthan hyperboxes of root levels [1]. Therefore,overlapping regions classified moreprecisely. It generates large number of hyperboxes.

The proposed method contribution is to reduce the large number of hyperboxes which are generated in existing method [1] and also to improve accuracy.Hybrid classification approach using multilevel fuzzy min-max neural network gives better accuracy than previous models.

III. PROPOSED SYSTEM

A. *System Architecture:*

In fig. 2, shows architecture of the proposed system. It takes datasets as input. It includes normalization as pre-processing step. In this input values are converted in between 0 and 1.



There arefollowing phases in HMLF (Hybrid approach for Multilevel Fuzzy Min-Max Neural Network Classification):

- Hyperbox Development: For incoming input sample, firstly a hyperbox is tested within the same class for its presence. A new hyperbox with particular min and max is created if it is not found in their respective test.If

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the input pattern is present in an existinghyperbox with the same class label, no modification of the min and max points is necessary. Otherwise hyperbox is expanded by using hyperbox expansion equation (2).Here, all hyperboxes are stored in hyperbox segment structure.

- Overlap Handling: All overlaps are detected in this phase and stored in overlap boxes segment. The testing cases of overlap are described in [8]. In this phase, the overlapping area of the expanded hyperbox is tested and checked for all other hyperboxes that are absent in the similar class.
- Pruning Hyperbox: Thegenerated hyperboxes are reduced in this phase. The Confidence Factor (CF) is calculated here for pruning strategy. The data set is classified into different chunks such as trained set, prediction set and tested set.
- Classifying Phase: According to membership functionwith greater belongingness is carefully chosen asoutput for the respective input sample.

B. *Proposed Algorithm:*

The main purpose of the proposed algorithm is to reduce the large number of hyperboxes which are generated and to improve the accuracy.

Step 1: Normalization:

The dataset input values are transformedin between value 0 and 1 by normalizationusing equation 1.

$$Zi= Xi\text{-}min(X)/max(X)\text{-}min(X) \quad \text{eq. (1)}$$

Where, x =(x_1, x_2; x_n) and $z_i$is i^{th} normalized data.

Step 2: Hyperbox Expansion:

The hyperboxes is expanded if satisfied the test by using equation 2:

$$q^b_{j} = \min(q^b_j, a^j);\ 1 \le j \le D$$
$$r^b_{j} = \max(r^b_j, a^j);\ 1 \le j \le D \quad \text{eq. (2)}$$

Where, q and r are min point and max point respectively.$a^j$is the input vector in j^{th}pattern space. D is the number of dimensions.

Step 3: Classification:

All hyperboxes are stored in hyperbox segment and overlap boxes are stored in overlap boxes segment. MLF [1] based technique is used for classification. It classifies patterns according to equation 3.

$$g_s^j = \begin{cases} c, \text{if } eo = 1 \\ 0, \text{ Otherwise} \end{cases} \quad \text{eq. (3)}$$

The greatest amount of g_s^j among all theseoutputs is selscted as the output where c is the class, e is the edge connected to overlap box o.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The dataset used for experiments is taken from UCI machine learning repository [18]. Four datasetsare used in the proposed method. The dataset is divided as 60% training and 40% as testing purpose. For testing different threshold values are used in between 0 and 1. In table 1, shows performance comparison of accuracy and number of hyperboxes that are generated in existing and proposed method.The main drawback of existing multilevel fuzzy min-max neural network was to generate large number of hyperboxes during classification. By using pruning strategy less number of hyperboxes are generated in proposed method. The accuracy is improved and less number of hyperboxes are generated with hybrid classification approach.

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Table 1 : Performance comparison for hybrid approach classification

Input Dataset Files	Test Dataset Files	Theta(θ)	ExistingMethod		Proposed Method	
			No. of Hyperboxes	Accuracy (%)	No. of Hyperboxes	Accuracy (%)
Heart.data	heart_test_1.data	0.20	243	23.70	5	55.55
	heart_test_1.data	0.30	218	23.70	7	44.44
	heart_test_1.data	0.40	407	55.55	91	55.55
Haberman.data	haberman_test_1.data	0.20	7	64.37	1	73.52
	haberman_test_1.data	0.30	10	62.09	1	73.52
Tae.data	tae_test_1.data	0.20	25	33.11	23	37.74
	tae_test_1.data	0.30	45	32.45	45	45.69
Diabetes.data	Diabetes_test_1.data	0.70	294	59.01	206	65.87
	Diabetes_test_1.data	0.80	790	53.03	492	56.06

The fig 3, shows comparison of accuracy with different dataset as described in table 1. From four dataset overall 10.34% accuracy is improved as compared to existing method.

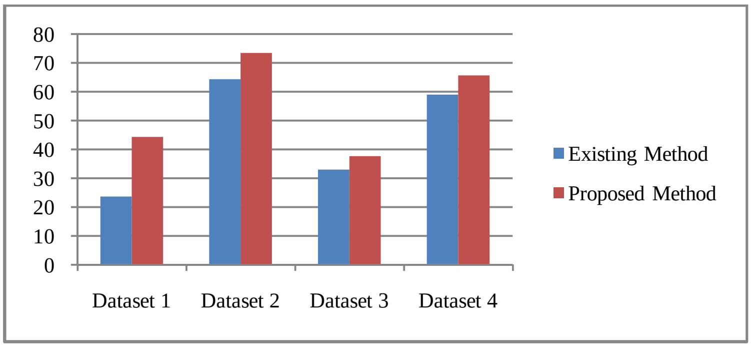

Fig 3. Comparison of accuracy with different datasets

The fig 4, shows comparison of number of hyperboxes with different dataset as described in table 1. Depending on datasets used number of reduction in hyperboxes will vary. By using pruning strategy, overall 46.30% of hyperboxes are reduced in proposed method.

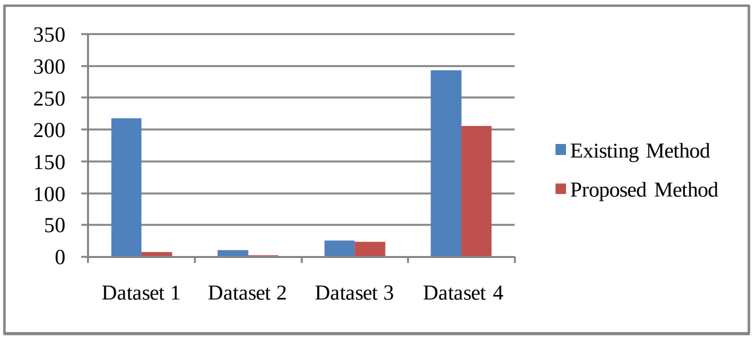

Fig 4. Comparison of number of hyperboxes with different datasets

V. Conclusion and Future Work

Various FMM model have been studied. As the MLF based method generateslarge number of hyperboxes, hybrid approach is proposed. The proposed method uses multilevel based FMM technique which gives better accuracy with

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less number of hyperboxes using pruning strategy. Multi-label classification is possible through this method.This work can be used further for speech classification and text classification.

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