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Object Recognition using Compensatory Fuzzy Min-Max Neural Network Architecture

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Abstract: Object recognition system (ORS) is divided into two parts namely, feature extraction and classification. Feature Extraction part consists rotation, translation and scale (RTS) invariant features. These features are used to train fuzzy min-max neural network with compensatory neuron architecture (FMCN). MPEG7 shape database is used for experimentation. Fuzzy min-max classification neural network (FMN) proposed by Simpson uses the contraction method to eliminate the overlap. FMCN eliminate the contraction method, since it is found to be erroneous. The concept compensatory neurons are inspired from the reflex system of human brain which takes over the control in hazardous condition. Compensatory neurons are getting activated when the testing sample falls in the overlapped regions of different classes. The performance of FMCN is superior than FMN with respect to recognition rate.

Keywords: Object recognition, RTS, Neural network, FMN, FMCN.

I. INTRODUCTION

Object recognition is an important part of computer vision. Humans recognize a large number of objects in images with very trivial effort, despite the fact that the image of the objects may vary somewhat in different point of view, in different sizes/ scale or even when object are translated or rotated. Object recognition system is inspired from the human brain to recognize the object from an image [1].

In past decade there were many existing object recognition methods Liz. Fuzzy min-max classification neural network, General fuzzy min-max neural network for clustering and classification [3], etc. Fuzzy min max classification is made using hyperbox fuzzy set. A hyperbox determines area of the n-dimensional pattern space that is with full class membership. A hyperbox is defined with min point and max point, and a membership function defines with respect to min point and max point of hyperbox. The min points are stored in matrix V and the max points are stored in matrix W. Hyperboxes are created and adjusted during the training phase, and in the test phase these hyperboxes and their membership function are used to assign an input sample to a class and classify them. As the data set become available FMN start creation of hyperbox and expand it up to the max point, FMN checks the overlap among the different classes by overlap test, and if there overlap exists then FMN eliminates the overlap by contraction method. But by using this contraction method hyperbox cannot able to access the full class membership.

An object recognition system finds objects in the real world from an image. Object recognition mainly involves two steps, feature extraction and pattern classification. In the feature extraction part, the features of the object are extracted. Pattern classification extracts the underlying structure of data and then performs recognition.

Remaining part of the paper is organized as follows. Section II describes the feature extraction part. Section III explains the classification part. Compensatory neuron architecture is discussed in section IV. Result and discussion are described in the section V and Section VI explains the conclusion of the work. References are cited at the end.

II. FEATURE EXTRACTION

Feature extraction part extracts the features. Feature can be defined as quantitative description of input. Feature extraction plays an important role in object recognition systems (ORS) since the information related to an object is contained within the extracted features. For the extraction of the features gray scale image is converted into binary image and then centroid is calculated firstly. For an invariant ORS, features must be invariant to translation, rotation and scale [1]. These features includes normalized moment of inertia, max to average ratio, average to max-min difference ratio, radial coding and radial angles.

To extract features, a computation of the centroid for an object is necessary. The centroid (Cx, Cy) for two dimensional object is given by,

$$\text{Cx} = \frac{\sum_{i=1}^{N} xi * f(xi,yi)}{N}, \qquad \text{Cy} = \frac{\sum_{i=1}^{N} yi * f(xi,yi)}{N} \tag{1}$$

$$\text{Where, } f(X_i, Y_i) = \begin{cases} 1 & if\ pixel\ p(X_i, Y_i) \in object \\ 0 & otherwise \end{cases} \tag{2}$$

x_i, y_i : co-ordinates values
N: total number of object pixels.it.

A. *Normalized Moment of Inertia*

Moment of inertia quantifies the inertia of rotating object. The moment of inertia (MI) is figured out by dividing the

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object into N-small pieces of mass $m_1, m_2, .., m_N$, each piece is at distance d_i from the axis of the rotation. MI is given by,

$$I=\sum_{i=1\ldots N} m_i d_i^2 \quad (3)$$

In case of object in binary image, consider each pixel as unit pieces (i.e. m=1). Due to the bounded resolution of digitized image, a rotated object might not conserve the number of pixels. So there may be a chance to variation in moment of inertia but normalized moment of inertia reduces this problem. Normalized Moment of Inertia is invariant to rotation, translation and scale. The normalized moment of inertia (NMI) of an object is calculated by,

$$I_N = \frac{1}{N^2}\sum_{i=1}^{N} d_i^2 = \frac{1}{N^2}\sum_{i=1}^{N}((x_i - C_x)^2 + (y_i - C_y)^2) \quad (4)$$

Where (Cx, Cy) are centroid co-ordinates and xi, yi are object pixel co-ordinates. di is the pixel distance from centroid.

B. Max to Average Length Ratio

Max to average length ratio is a ratio of maximum (dmax) distance of object pixels from centroid to the average pixel distance (davg) from centroid. MAR is,

$$MAR = \frac{d_{max}}{d_{avg}} \quad (5)$$

C. Average to Max-Min Difference Ratio

Average to max-min difference is a ratio of average pixel distance from centroid (d_{avg}) to difference between maximum (d_{max}) and minimum (d_{min}) of pixel distance from centroid.

$$AMMD = \frac{d_{avg}}{(d_{max} - d_{min})} \quad (6)$$

D. Radial Coding and Radial Angles

The radial coding features are based on the fact that circle is the only geometrical shape that naturally and perfectly rotation invariant. Radial coding (RC) is calculated by counting the number of intensity changes on circular boundaries. Radial angles (RA) can be calculated as follow [9][12]:

1) Compute centroid of the object.
2) Generate K equal concentric C_i around the centroid of the object. The spacing is equal to the distance between centroid and furthest pixel of the object divided by K.
3) Count the number of intensity changes for each circular boundary (zero to one or one to zero).
4) Find the largest angles (θ) between the two intensity changes for every circle. This is called Radial Angles. If $\theta > \pi$ then consider θ as $2\pi - \theta$. If there is not at all intensity changes then conceive $\theta = 0$.

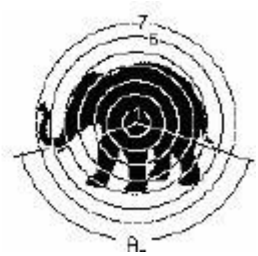

Fig. 1 Radial Coding and Radial Angles

III. CLASSIFICATION

Pattern classification is the key element for extracting the underlying structure of the data [3][4]. Classifier is used to determine the input output relationship. Neural network classifier that creates classes by aggregating several smaller fuzzy sets into a single fuzzy set class. Fuzzy min-max classification neural networks are made up of hyperbox fuzzy sets. A hyperbox defines a region of n-dimensional pattern space that has patterns with full class membership function. A hyperbox is defined by min point and max point, and membership function is defined with respect to hyperbox min-max points. The min-max (hyperbox) membership function combination defines a fuzzy set, hyperbox fuzzy sets are aggregated to form a single fuzzy set class, and the resulting structure fits naturally into a neural network framework; due to this, classification system is called a fuzzy min-max classification neural network.
Fuzzy min max classification algorithm has three steps process, they are as described below.

A. Expansion

In the expansion process, identify the hyperbox that can expand and expand it. If an expandable hyperbox cannot be found any more then add a new hyperbox for that class.

B. Overlap Test

Determines the overlap exists between any hyperboxes that actually belongs to the different classes.

C. Contraction

If there is an overlap exists between two hyperboxes that belongs to the different classes then eliminate the overlap by adjusting the each of the hyperboxes.
FMN retains information regarding the learned hyperboxes by storing their min-max points. Hyperbox min-max points represent the acquired knowledge. It is analyzed that contraction process involved in the learning algorithm modifies these min-max points to remove ambiguity in the overlapped classes. This creates classification errors for the learned data itself. Below figure 2 depicts a hyperbox overlap case [10].

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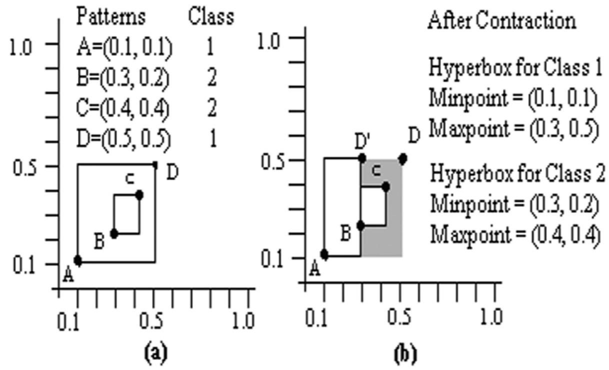

Fig. 2 Full containment problem

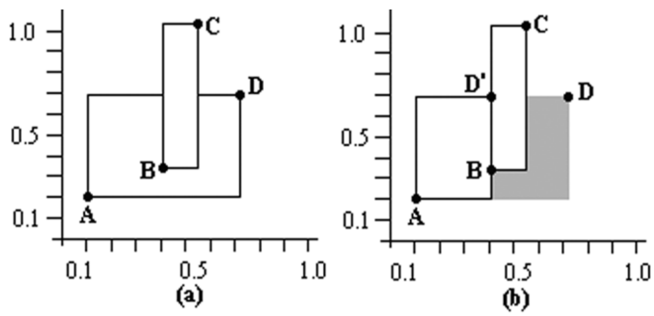

Fig. 3 Partial containment problem

The data shown in figure 4 is used for training FMN classifier; two hyperboxes are created with an overlap. To remove overlap, hyperboxes are contracted. Note that after contraction, training samples B and C are contained in the hyperboxes of classes 1 and 2, respectively. Thus, point C gets full membership of class 2 and partial membership of class 1.

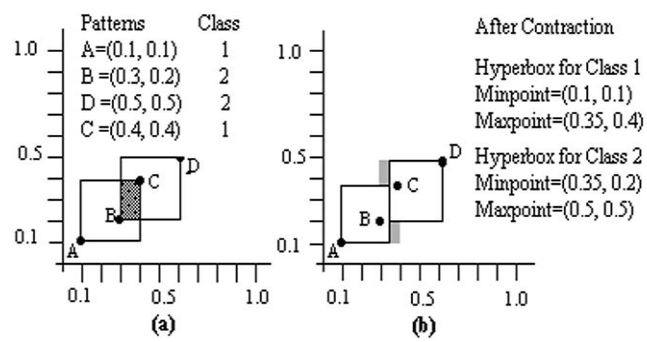

Fig. 4 Overlap removing process

FMCN is capable to approximate the complex topology of data more accurately [2].

IV. COMPENSATORY NEURON ARCHITECTURE

An object recognition system uses the supervised classification technique with Compensatory neuron architecture. The conception of compensatory neuron is inspired from the reflex system of human brain which takes over the control in hazardous situation. Compensatory neurons (CNs) imitate this behavior by getting activated whenever a test sample falls into overlapped regions amongst different classes. Compensatory neurons are capable to handle the hyperbox overlap and containment problem efficiently. Fuzzy min-max neural network classifier with compensatory neurons (FMCNs) uses hyperbox fuzzy sets to represent the pattern classes. FMCN is capable to learn the data online in a single pass through with reduced classification and gradation errors. One of the good features of FMCN, its performance is less dependent on the initialization of expansion coefficient, i.e., maximum hyperbox size [7]. The architecture of the FMCN is as showing in below figure 5,

Number of nodes in the input layer is equal to the dimension of applied input vector Ah, where,

a_{h1} - a_{hn} : Input samples $\epsilon\ I^n$,

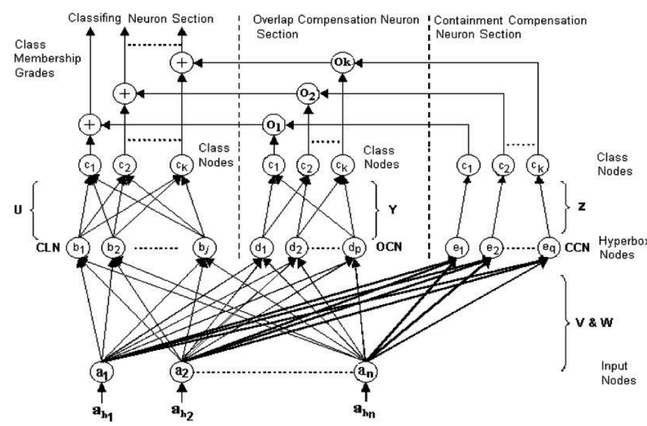

Fig. 5 FMCN architecture

a_1 - a_n : Input nodes,
b_1 - b_j : Classification hyperbox nodes,
c_1 - c_k : Class nodes,
d_1 - d_p : Overlap compensation hyperbox nodes,
e_1- e_q : Containment compensation hyperbox nodes,
o_1 - o_k : Overall compensation nodes.

The middle layer neurons and output layer nodes are divided into three parts: Classifying Neuron (CLN), Overlap Compensation Neurons (OCN), and Containment Compensation Neurons (CCN). The connections between an input node and a hyperbox node in the middle layer represent min-max points (V, W). Hyperbox nodes in OCN and CCN sections represent overlap and containment of hyperboxes in CLN section, respectively. All middle layer neurons are created during the training process.

A. *Classifying Neurons*

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A hyperbox node in classifying neurons (CLN) is produced if training sample belongs to class which has not been encountered previously or existing hyperboxes of that class cannot be expanded any more to adapt it. Matrix U represents the connections between hyperbox and class nodes in CLN section. Node in classifying section is as shown below,

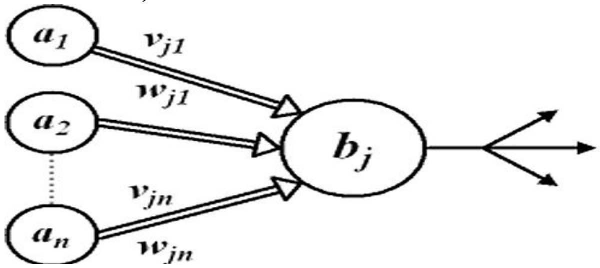

Fig. 6 Node in CLN section

A connection between a hyperbox node b_j to a class node c_i is given by,

$$u_{ij} = \begin{cases} 1, & if \{ b_j \in C_i \} \\ 0, & if \{ b_j \notin C_i \} \end{cases} \quad (7)$$

B. Overlap Compensation Neurons

Hyperbox node in the middle layer of OCN sections is created whenever the overlap has been exists. The OCN section takes care of the overlap problem. Matrix Y represents connections between hyperbox and class nodes in OCN section Node in the OCN section is as shown in below figure.

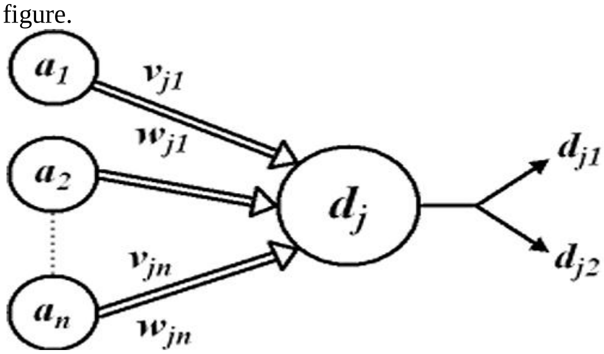

Fig. 7 Node in OCN section

The connection weights from a neuron d_p to i^{th} and j^{th} class nodes in OCN section are given by,

$$y_{ip}\, and\; y_{jp} = \begin{cases} 1, & if \{ d_p \in C_i \cap C_i, i \neq j \} \\ & 0, \quad Otherwise \end{cases} \quad (8)$$

C. Containment Compensation Neurons

A hyperbox node in CCN section is created whenever hyperbox of one class is contained fully or partially within a hyperbox of other class. Matrix Z represents the connection between the hyperbox and class nodes in CCN section. Node in the CCN section is as shown in below figure 8.

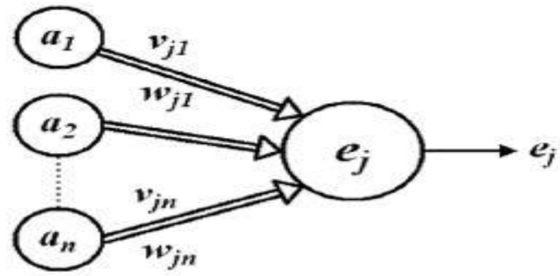

Fig. 8 Node in CCN section

The connection weights from a neuron e_q to a class node c_i in CCN section are given by,

$$z_{iq} = \begin{cases} 1, & if\; c_j\; is\; contained\; fully\; or\; partially\; by\; C_i, i \neq j \\ & 0, \quad Otherwise \end{cases} \quad (9)$$

The number of output layer nodes in CLN section is the same as the number of classes learned. The number of class nodes in OCN and CCN section depends on the nature of the overlap the network faces during the training phase.

V. RESULT AND DISCUSSION

FMCN algorithm is tested on various datasets (MPEG7 and IRIS). The various parameters that have been analyzed like expansion coefficient, sensitivity parameter, rotation, translation and scale invariant features, performance of FMCN, comparative study on FMN, and FMCN.

A. Expansion Coefficient

To understand the effect of expansion coefficient on the hyperbox, various expansion coefficients has been considered and results are carried out. The maximum hyperbox size (θ) is the most important user defined parameter which decides how many hyperboxes will be created. Generally, the larger expansion coefficient (θ), the fewer hyperboxes are created. It is as clearly shown in the below table, as the value of the expansion coefficient increases the less no of hyperboxes are created.

Table 1 Expansion Coefficient for MPEG7 dataset

Expansion Coefficient(θ)	0	0.1	0.2	0.3	0.4	0.5
Hyperbox	691	341	242	86	53	53

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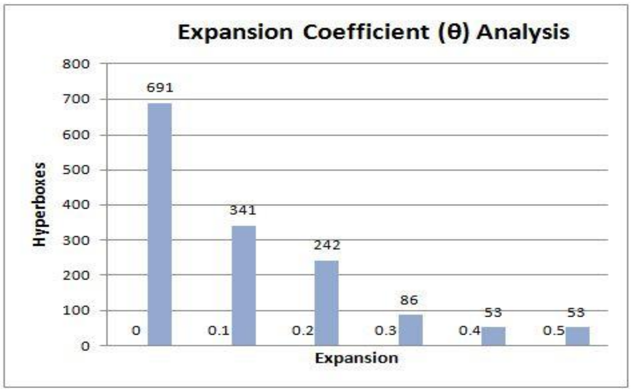

Fig. 9 Expansion Coefficient Analysis on MPEG7 dataset

Table 2 Expansion Coefficient (θ) for IRIS dataset

Expansion Coefficient (θ)	0.1	0.2	0.3	0.4	0.5
Hyperbox	4	3	3	3	3

Table 2 shows the expansion coefficient and hyperbox values for IRIS dataset. It is clear that expansion coefficient and hyperbox are inversely related to each other.

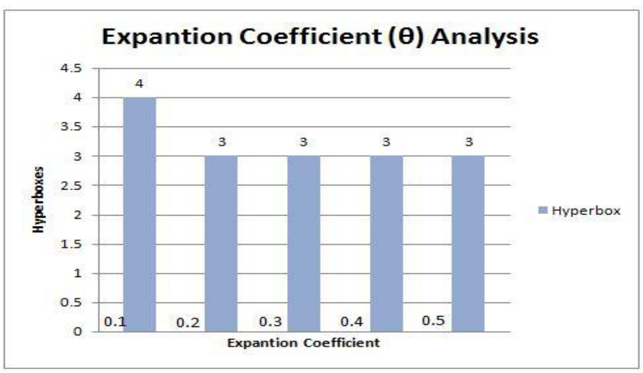

Fig. 10 Expansion Coefficient Analysis on IRIS dataset

It is clear from the above figure 9 and figure 10 as the value of the expansion coefficient increases it directly affects the hyperbox. It is as clearly shown in the graph of hyperbox vs. expansion coefficient.

B. Sensitivity parameter

Sensitivity parameter regulates the how fast the membership values decreases as the distance between Ah & Bj increases. As the value of the sensitivity parameter increases the membership values for the hyperbox gradually decreases. The below table show the membership values for the iris dataset.

Table 3 Sensitivity Parameter (ϒ)

Class	Expansion coefficient	Sensitivity Parameter	Membership
Bat – 18	0.1	1	0.3177
Bat – 18	0.1	5	0.3054
Bat – 18	0.1	10	0.2901
Beetle – 10	0.1	1	0.3196
Beetle – 10	0.1	5	0.3149
Beetle – 10	0.1	10	0.3090

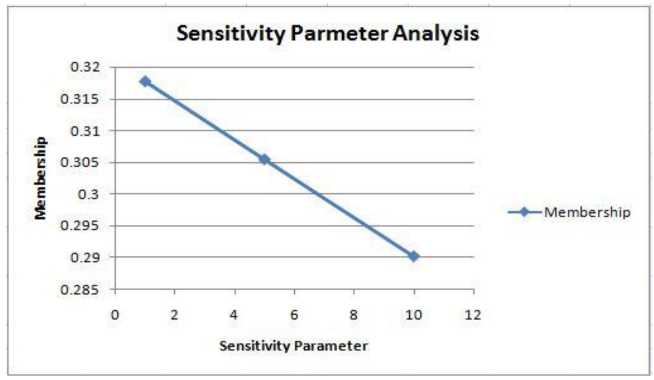

Fig. 11 Sensitivity Parameter Analysis

Figure 11 shows the sensitivity parameter analysis, here as the value of the sensitivity parameter increases the value of the membership gradually decreases. It is as shown in the above figure.

C. Analysis of Rotation, Translation and Scale invariant features

To verify the rotation invariant features, an image has been taken and rotated with the different angles. The below table shows the analysis of NMI, MAR & AMMD features with different rotation.

Table 4 Analysis of Rotation invariant features

Rotation	NMI	MAR	AMMD
0	0.08	1.65	0.60
25	0.08	1.65	0.59
55	0.08	1.65	0.59
85	0.08	1.65	0.59

An image has been rotated with the different angle, it is clear from the above table 4 that features NMI, MAR and AMMD are invariant to rotation.

To check the translation invariant features, different images of the same class has been taken and verified for the translation. The below table shows the analysis of NMI, MAR & AMMD features.

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Table 5 Analysis of Translation invariant features

Image	NMI	MAR	AMMD
Carriage	0.01	1.66	0.6
Carriage	0.01	1.7	0.6
Carriage	0.01	1.7	0.5
Carriage	0.01	1.66	0.5

Different image has been taken and checked for the translation, it is clear from the above table 5 that features NMI, MAR & AMMD are invariant to translation.

To analyze the scale invariant features, different scale for an image has been taken and verified for the scale. The below table shows the analysis of NMI, MAR & AMMD features.

Table 6 Analysis of Scale invariant features

Scale	NMI	MAR	AMMD
0.5	0.01	1.6	0.6
0.6	0.01	1.6	0.6
0.7	0.01	1.6	0.6
0.8	0.01	1.6	0.6

From the above table 6 it is clear that features NMI, MAR & AMMD are invariant to scale.

D. Performance on MPEG7 dataset

To check the performance of the Fuzzy Min-Max Neural Network with Compensatory Neurons (FMCN) and the Fuzzy Min-Max Neural Network (FMN) on MPEG7 dataset, dataset are divided into two parts namely set – I and set – II. Object recognition system is trained with the set – I and tested with the set – II. Set – I indicate the classification result where as set – II indicates recognition result.

1) Complete dataset for training and testing

The complete MPEG7 dataset [15] has been provided for the training and testing. The below table 7 shows the result of complete data for training and testing.

Table 7 Complete data for training and testing

Classifier	Set – I	Set – II
FMN	100%	100%
FMCN	100%	100%

From the above table it is clear that set-I as well as the set-II giving the 100% recognition rate for both the classifier FMN and FMCN.

2) 75% of data for training and 25% of data for testing

Randomly selected 75% of the MPEG7 dataset for the training and remaining 25% for the testing. The below table 8 shows the result for training and the testing.

Table 8 Recognition rate of MPEG7 dataset

Classifier	Set - I	Set - II	Average Recognition Rate
FMN	100%	80%	90%
FMCN	100%	84%	92%

Above table clearly clarifies that FMCN is recognizing the images more efficiently than the FMN classifier. Rate of FMN classifier is 80 while FMCN recognizing the 84 images.

E. Performance on IRIS dataset

To check the performance of the Fuzzy Min-Max Neural Network with Compensatory Neurons (FMCN) and the Fuzzy Min-Max Neural Network (FMN) on IRIS dataset, various data size has been taken and results are carried out.

1) Complete dataset for training and testing

The complete widely available IRIS dataset obtained from the University of California at Irvine (UCI) repository of machine learning database has been provided for the training and testing. Below table shows the result.

Table 9 Complete data for training and testing

Classifier	Set - I	Set - II
FMN	100%	100%
FMCN	100%	100%

From the above table 9 it is clear that set-I as well as the set-II giving the 100% recognition rate for both the classifier FMN and FMCN.

2) 75% of data for training and 25% of data for testing

Randomly selected 75% of the IRIS dataset for the training and remaining 25% for the testing. The below table 10 shows the result for training and the testing.

Table 10 Recognition rate for IRIS dataset

Classifier	Set – I	Set - II	Average Recognition Rate
FMN	100%	97%	98.5%
FMCN	100%	100%	100%

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Above table 10 clearly shows that FMCN is recognizing the more pattern efficiently than the FMN classifier. Rate of FMN classifier is 97 while FMCN is 100.
Result of Fuzzy Min-Max Neural Network classifier with Compensatory Neuron (FMCN) architecture for both the database (MPEG7 and IRIS) is better than the Fuzzy Min-Max Neural Network classifier (FMN).

VI. CONCLUSION

Fuzzy min max neural network with compensatory neuron architecture (FMCN) is based on compensatory neurons (CNs) inspired from the reflex mechanism of human brain, learns data in a single pass through and maintain simplicity in learning. The contraction process in the fuzzy min-max classification neural network (FMN) proposed by Simpson based on the principle of minimal disturbance in the training. FMCN avoids the use of contraction, hence reduces the error caused due to it. In the FMCN hyperbox are not contracted, hence FMCN can retain the knowledge.

FMCN learning algorithm is less computationally demanding, since there is no search of overlap. Here we tested FMCN and FMN on MPEG7 shape database available online and IRIS dataset. Here there are two different parameters, that has been analysed, expansion coefficient and sensitivity parameter. As the value of expansion coefficient increases less no of hyperboxes are created. The sensitivity parameter that directly affects the membership, as the value of sensitivity parameter increases membership value decreases gradually. Here we found the performance of FMCN is superior than FMN with respect to recognition rate.

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