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RESEARCH ARTICLE

A Novel Fuzzy Hypersphere Neural Network Classifier Using Class Specific Clustering for Robust Pattern Classification

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ABSTRACT This paper introduces two novel class-specific fuzzy clustering algorithms: Mean-based Supervised Clustering (MSC) and Density-based Mean Supervised Clustering (DMSC). These algorithms are designed to construct the hidden layer of the Fuzzy Hypersphere Neural Network (FHNN) classifier, which is structured on the framework of the Radial Basis Function Neural Network (RBFNN). The FHNN classifier utilizes fuzzy sets as labeled pattern clusters in its hidden layer, with classes represented in the output layer formed by the aggregation of these fuzzy sets. An important characteristic of this classifier is its independence from tuning parameters. It meticulously determines centroids and radii for labeled clusters, consistently achieving 100% accuracy across any training set. The FHNN classifier effectively handles outliers and is robust to variations in data presentation, ensuring clear data visualization for users. During the creation of labeled clusters in the hidden layer, binary weight values are adjusted concurrently between the hidden and output layers. This study proposes the formation of fuzzy clusters with varying dimensions tailored to the dataset. The classifier architecture, rooted in the radial basis function neural network, achieves 100% training accuracy due to precise fuzzy cluster formation. Experimental comparisons with RBFNN and similar classifiers using sixteen benchmark datasets demonstrate the superiority of the proposed classifier in pattern recognition tasks.

INDEX TERMS Fuzzy neural network, fuzzy set hypersphere, pattern classification, radial basis function neural networks, sep fuzzy membership function.

I. INTRODUCTION

Pattern recognition is a highly favored domain among researchers, with Neural Network classifiers gaining popularity over minimum distance classifiers [1]. In the last few decades, Artificial Neural Networks (ANN) have been widely used in pattern recognition. Error back-propagation and RBFNN are basically used for pattern classification. In RBFNN radial basis function is used to create clusters in the hidden layer [2], [3]. Two heuristic clustering

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algorithms for RBFNN were proposed by Rouhani in the year 2016 [4] while improvements to one of these algorithms were suggested by [5]. Apart from understanding the role of RBFNN, fuzzy neural networks are widely used in pattern recognition. In 1992, there was considerable focus on merging fuzzy logic with neural networks for pattern recognition, leading to the proposal of the fuzzy min–max neural network (FMNN) for classification by [6]. This approach involved creating hyperboxes corresponding to different classes using learning algorithms incorporating expansion and contraction, with hyperboxes described by minimum and maximum points. This concept was further extended by [7] who considered labeled and unlabeled data to create the hyperboxes. In 2004, a new concept of compensatory neuron was introduced [8]. Various new architectures and learning algorithms have been proposed to enhance the performance of FMNN [9], [10], [11], [12].

Various clustering algorithms have been proposed to determine the appropriate centroid and width of the hidden neurons in the hidden layer, alongside Gaussian functions, to enhance performance in terms of recognition rate [4], [13], [14], [15]. Both supervised and unsupervised clustering methods are utilized to ascertain the centers and radii parameters of hidden nodes for Radial Basis Function Neural Networks (RBFNN) [16]. Numerous clustering algorithms incorporate techniques such as K-means clustering [17], subtractive clustering [18], fuzzy clustering [15], [19], [20], [21], ART [22], scatter based clustering [23], input-output clustering [24], artificial fish swarm optimization (AFSO) [25], [26], [27], among others, to illustrate how to create neurons in the hidden layer of RBFNN. Similarly other methods are described in [28], [29], [30], and [31].

The Fuzzy Min-Max Neural Network (FMNN) faces significant disadvantages such as the challenge of altering the hyperbox size, its expansion, contraction, and the overlap test [33]. In contrast, the proposed approach offers several advantages over fuzzy classifiers and Radial Basis Function Neural Networks (RBFNNs) [32]. Firstly, the proposed algorithms, Mean-based Supervised Clustering (MSC) and Density-based Mean Supervised Clustering (DMSC), are utilized to create clusters, known as fuzzy set hyperspheres (FSHs), in the hidden layer without overlap of classes, ensuring 100 % efficiency for the training set. During cluster formation using MSC and DMSC the binary weights are assigned between hidden layer to output layer which is not the case with RBFNN [1]. The training between the hidden layer to output layer which is done by using the LMS algorithm in RBFNN is avoided, and the output is determined by using the fuzzy union operation. Another aspect is that FNN guarantees the training and does not get stuck in local minima which make arise in RBFNN. FMNN describes about the hyperbox creation limited by size stated during initialization. The process of resizing the hyperbox depends on the overlap test. The training process is tedious and takes longer time to form the appropriate number of hyper boxes [6]. RBFNN is a classifier which uses clustering algorithms to create the hidden layer of multilayer network. Different traditional clustering methods where used with constraints like Size of cluster, number of clusters, and cover up of clustered patterns. The training between the hidden layer to output layer which is done by using the LMS algorithm in RBFNN is avoided, and the output is determined by using the fuzzy union operation. Thus FNN reduces the computation time, guarantees 100% accuracy for any training set, and provides superior and comparable recognition accuracy for the datasets with the precise number of FSHs in the hidden layer.

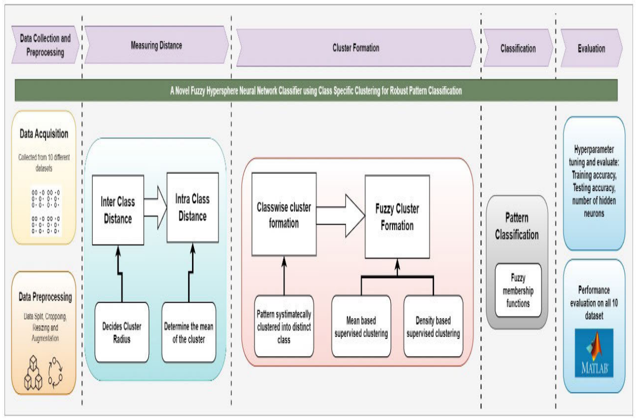


FIGURE 1. Work flow of proposed classifier.

The paper is arranged as follows. The FHNN architecture and two learning algorithms are represented in sections II and III, respectively. Under experimental results, four case studies have been explained in section IV and the conclusion is described in section V.

II. PROPOSED FHNN CLASSIFIER ARCHITECTURE

Here, we proposed the fuzzy cluster formation having different dimensions in accordance with the dataset. The architecture of the classifiers is based on a radial basis function neural network having 100 % training due to precise fuzzy cluster formation. There are no restrictions on fuzzy set hyperspheres (FSHs) size and eliminates the need for overlap tests of clusters, also its robustness extends to any training dataset, leveraging fuzzy membership functions to obscure patterns such that they remain unaffected by neighbouring class patterns which is not the case in traditional clustering methods [34].

Fig. 1 represented the work flow of proposed classifiers. The initial step in the classification process involved determining the inter-class distance between patterns in the dataset, which entailed calculating the distance of one class from the others. This step was essential for deciding the cluster radius. Subsequently, the intra-class distance to the cluster of the same class was computed. Once both inter-class and intra-class distances were determined, clusters were created for each specific class. During this process, the class patterns were systematically clustered until all class patterns were separated into distinct clusters. These clusters were

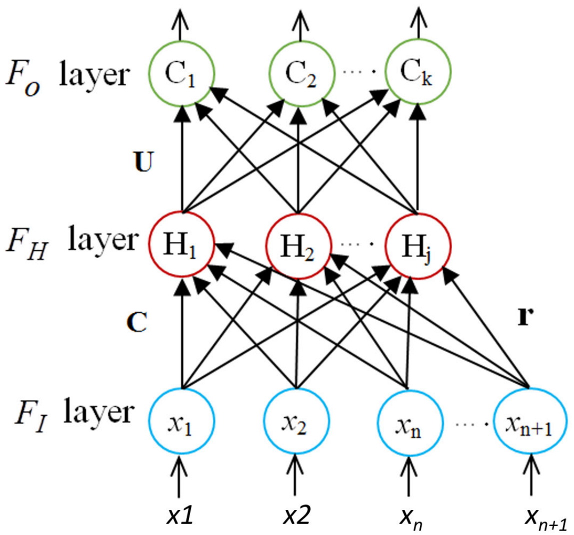


FIGURE 2. Architecture of FHNN.

governed by a fuzzy membership function that determined the output. Ultimately, these clusters formed the hidden layer of the FHSNN for pattern classification. Performance was evaluated using various standard datasets.

This classifier, employing a fuzzy approach, ensures the training of any dataset while providing a clear view of different classes and their outliers. Unlike traditional methods, this classifier does not require parameter adjustments, as it learns autonomously, akin to generative AI [20]. Moreover, this model is well-suited for datasets of any dimensionality and demonstrates improved accuracy for the testing dataset, achieving 100% accuracy for the training dataset.

Fig. 2 represents the proposed FHNN classifier architecture. The input layer is designated as the F_I layer. It consists of $N + 1$ nodes. However, as shown, the N nodes in the F_I layer accept N dimensional pattern. The input to the $(N+1)^{th}$ node is fixed to 1. The nodes in this layer do not perform any processing. Therefore, the transfer function of these nodes is output equal to the input. The next layer is a hidden layer. It is designated as the F_H layer and consists of J nodes. Each node in this layer represents a fuzzy set hypersphere (FSH). There is no need to initialize the parameters. The fuzzy membership function for FSH has been stated in equation 1 and equation 2 and described so as to camouflage the clustered patterns. Two learning algorithms which are described in section III are proposed to construct the FHNN classifier.

In the F_H layer, FSHs are created during learning. The fuzzy membership function, which is defined as:

$$m_j(\mathbf{X}_h, \mathbf{C}_j, r_j) = f(l, r_j) \tag{1}$$

characterizes these FSHs.

where input pattern is represented by $\mathbf{X}_h = (x_{h_1}, x_{h_2}, \ldots, x_{h_N})$, with radius and cenroid of H_j is r_j and $\mathbf{C}_j = (c_{j1}, c_{j2}, \ldots, c_{jN})$.

The function $f()$ is described as:

$$f(len, rad_j) = \begin{cases} 1 & len \leq rad_j \\ rad_j/len & \text{if not} \end{cases} \tag{2}$$

where len is an euclidean distance between $\mathbf{X}_h$ and $\mathbf{C}_j$.

The centroid of FSHs is stored in the matrix $\mathbf{C}$ which are weights between F_I and F_H along with the radii stored in $\mathbf{r}$. The connections between $(N+1)^{th}$ node and FSHs represent respective radii whereas the remaining connections represent centroids. Using MSC or DMSC algorithm the FSH is created in F_H layer with appropriate centroid and radii.

The output layer is designated as the F_O layer. It consists of K nodes which are created during learning representing the class node. The matrix $\mathbf{U}$ contains the binary weights between F_H and F_O.

These weights are assigned as

$$\mathbf{U}(k, j) = \begin{cases} 1 & \text{if } H_j \text{ belongs to class } C_k \\ 0 & \text{if not,} \end{cases} \tag{3}$$

where $k = 1, 2, \ldots.., K$ and $j = 1, 2, \ldots.., J$. The processing of nodes in the F_O layer is defined as

$$C_k = \max_{j=1}^{J} \mathbf{U}(k, j)\, m_j, \quad k = 1, 2, \ldots.., K. \tag{4}$$

The $\mathbf{C}$, $\mathbf{r}$ and $\mathbf{U}$ change during learning as FSH and output class nodes are created

III. LEARNING ALGORITHMS

Two mean-based supervised clustering algorithms have been proposed to construct the FHNN classifier. The detailed description of these two algorithms is given below.

A. MEAN-BASED SUPERVISED CLUSTERING (MSC) ALGORITHM

A training set $\mathbf{Z}$ containing P training pairs is described as $\{\mathbf{X}_j, d_j\}$ for j^{th} input pattern where $d_j \in \{1, 2, \ldots., K\}$ is a desired output for $\mathbf{X}_j$.

Let the k^{th} subset of set $\mathbf{Z}$ contain α_k patterns of class C_k where $k = 1, 2, \ldots, K$. For K classes following steps (1-11) are executed with $t_k = P - \alpha_k$, where t_k is the total number of patterns that do not belong to class C_k.

1) Calculate the inter-class matrix A^k

$$\mathbf{A}^k = \left[\|\mathbf{X}_i - \mathbf{X}_j\|\right]_{\alpha_k \times t_k},$$
$$j = 1, 2, \ldots, t_k \text{ and} i = 1, 2, \ldots, \alpha_k. \tag{5}$$

where $\mathbf{X}_j \notin C_k$, $\mathbf{X}_i \in C_k$.

2) Calculate the intra-class distance matrix B^k as

$$\mathbf{B}^k = \left[\|\mathbf{X}_i - \mathbf{X}_j\|\right]_{\alpha_k \times \alpha_k}, i, j = 1, 2, \ldots, \alpha_k \tag{6}$$

where $\mathbf{X}_i$ and $\mathbf{X}_j \in C_k$.

3) Determine the mean for each pattern using the intra-class distance matrix as

$$\mathtt{M}_i^k = \left(\frac{1}{\alpha_k}\right) * \sum_{j=1}^{\alpha_k} B^k(i,j) \tag{7}$$

in which $i = 1, 2, \ldots, \alpha_k$.

4) Determine the pattern $\mathbf{X}_c^k$ with minimum mean in M^k. Let l_c^k is the location of $\mathbf{X}_c^k$ in the k^{th} subset.

5) Determine minimum inter-class distance d_c^k for this pattern $\mathbf{X}_c^k$ using $\mathbf{A}^k$ as

$$d_c^k = \min_{j=1,2,\ldots,t_k} \mathbf{A}^k(l_c^k, j) \tag{8}$$

6) Create a labeled cluster i.e. FSH with the pattern $\mathbf{X}_c^k$ as a centroid and radius equal to d_c^k in hidden layer of FHNN. Determine the total number of patterns clustered by this FSH using algorithm 1.

7) If $n > 1$ then the revised radius r_c^k is computed as

$$r_c^k = \max_{i=1}^{n} d_i, \tag{9}$$

where Euclidean distance d_i is between i^{th} clustered pattern and centroid $\mathbf{X}_c^k$.
Else If $n = 1$, then to accommodate this outlier, the radius of created FSH is assigned half of d_c^k for good generalization and to minimize the possibility of overlap with clusters belonging to other classes.

8) Create a output node if not created earlier in F_O layer for class C_k and adjust weights linking F_H and F_O layer using (3).

9) Recompute α_k as $\alpha_k \leftarrow \alpha_k - n$, if $\alpha_k \neq 0$. Delete corresponding rows of grouped patterns from $\mathbf{A}^k$ and $\mathbf{B}^k$ and go to step 3. If $k \neq K$ then go to step 1.

10) If $k = K$ then stop.

Algorithm 1 To Determine Patterns Clustered by FSHs

Input: B^k, l_c^k, d_c^k
Output: n
$n \leftarrow 0$
for $j = 1$ **to** α_k **do**
  if $f(\mathbf{B}^k(l_c^k,\ j), d_c^k) <= 1$ **then**
    $n \leftarrow n + 1$
  end if
end for

B. DENSITY-BASED MEAN SUPERVISED CLUSTERING (DMSC) ALGORITHM

Considering the similar data notations from MSC the execution of the following steps is done for K classes.

1) Calculate $\mathbf{A}^k$, $\mathbf{B}^k$ and $\mathbf{M}^k$ as described by steps 1-3 in MSC.

2) Sort mean vector $\mathbf{M}^k$ in ascending order to determine $s = ceiling\ (\sqrt{\alpha_k})$ patterns which have minimum means. Let $\mathbf{X}_1^k, \mathbf{X}_2^k, \ldots\ldots\ldots, \mathbf{X}_s^k$ are these patterns with corresponding locations $l_1^k,\ l_2^k, \ldots\ldots\ldots, l_s^k$.

3) Determine minimum inter-class distance for each pattern using $\mathbf{A}^k$ as

$$\mathbf{d}_i^k = \min_{j=1,2,\ldots\ldots,t_k} (\mathbf{A}^k(l_i^k, j)), \ \text{where } i = 1, 2, \ldots, s. \tag{10}$$

4) Count the number of patterns clustered by s possible clusters i.e. FSHs with $\mathbf{X}_1^k, \mathbf{X}_2^k, \ldots\ldots\ldots, \mathbf{X}_s^k$ as centroids and corresponding radii $d_1^k,\ d_2^k,\ \ldots\ldots\ldots d_s^k$ using algorithm 2.

5) If c^{th} cluster out of s clusters has clustered more patterns then the FSH is created in the hidden layer of FHNN with the centroid $\mathbf{X}_c^k$ and radius d_c^k.

6) Assign $n = \mathbf{n}_c$

7) Steps 7-10, same as MSC.

Algorithm 2 To Determine Patterns Clustered by FSHs

Input: B^k, locations - l_1^k, l_2^k, $\ldots\ldots\ldots l_s^k$ and radii - $d_1^k, d_2^k, \ldots.., d_s^k$
Output: Number of patterns clustered $\mathbf{n} = (n_1, n_2, \ldots., n_s)$

for $i = 1 \rightarrow\ s$ **do**
  $n \leftarrow 0$
  for $j = 1 \rightarrow \alpha_k$ **do**
    if $f(\mathbf{B}^k(l_i^k,\ j), d_i^k) <= 1$ **then**
      $n \leftarrow n + 1$
    end if
  end for
  $\mathbf{n}_i \leftarrow n$
end for

Therefore, the FHNN classifier is constructed with the number of FSHs, which equals the number of clusters created for each class by the above algorithms, forming a hidden layer. Appropriate binary weights are assigned to the links between the hidden layer and the output class neuron. Thus in traditional clustering, the clusters size and number of clusters where restricted by initializing the parameters. Where as in MSC and DMSC, there is no restrictions on fuzzy set hyperspheres (FSHs) that is on cluster size and number of clusters. Even there is no need of overlap tests of clusters as the formed clusters camouflage the clustered patterns. The cluster formation is done based on the appropriate density of patterns which is not the case in the traditional clustering. The MSC and DMSC algorithms are data dependent and to avoid typical traditional clustering no tuning parameter are used because of which there is no restriction of size in cluster formation [1]. Both the MSC and DMSC algorithms do not impose any restriction on number of clusters so no tunning of hyperparameters is required in the hidden layer. Since each FSHs is govern by fuzzy membership functions which obscures cluster patterns such that they remain unaffected by neighboring class patterns so training result for all dataset is 100 %.

TABLE 1. UCI dataset.

Dataset	Total Samples	Features	No. of Classes
Hepatitis	80	19	2
Glass	214	9	7
Heart	297	13	2
Zoo	101	16	7
Segmentation	2310	19	7
Dermatol	150	4	3
Breast	599	9	2
Pima	768	8	2
Ecoli	336	7	8
Liver	345	6	2
Ionosphere	351	34	2
Monks-3	432	6	2
Thyroid	215	5	3
Wine	178	13	3
Iris	150	4	3
sonar	208	60	2

IV. EXPERIMENTAL RESULTS

The performance of the FHNN regarding training accuracy, testing accuracy, and the number of hidden neurons was evaluated [35] using Matlab 2016a and the same system configuration discussed in [36]. The following subsections provide detailed explanations of the experimental results.

A. CASE STUDY I

To gain a proper understanding of the MSC and DMSC learning algorithms, a three-class, two-dimensional example is provided. Twenty-four patterns are included in the training set, with Class 1 consisting of the following patterns:: (1, 5), (1, 7.5), (1.5, 7),(2, 4.5), (0.75, 6), (1.5, 8.5), (1, 9), (0.75, 8). Class 2 has the following patterns: (1, 1), (0.75, 3), (1.5, 2.5), (2, 3.5), (3.25, 4), (4, 1),(2, 1.5), (3, 1.5) and finally class 3 has the following pattern (3.7, 6), (3.75, 8), (3.5, 8.5),(4, 5), (4, 7),(3.75, 9), (3, 9),(3, 8).

1) 2-DIMENSIONAL EXAMPLE USING MSC ALGORITHM

When the FHNN is trained using the MSC algorithm, it constructs seven FSHs in the middle layer. The detailed process of constructing the FHNN classifier using the MSC algorithm is shown in Fig.3(a-f). A scatter plot for the dataset mentioned above is shown in Fig.3(a).

Initially, the training data from class one is used to create the FSHs. After calculating the inter-class and intra-class distance matrices (steps 1 and 2), steps 3 and 4 compute the centroid pattern (1, 7.5) as it has the minimum mean distance with respect to the remaining patterns of class 1. According to step 5, among all the patterns of the other classes (i.e., classes 2 and 3), the pattern (3.5, 8) of class 3 is the nearest to the centroid (1, 7.5), with a distance of 2.6. Step 6 creates the first FSH with this distance as the initial radius and the pattern (1, 7.5) as the centroid. The created FSH as per algorithm 1 clusters the patterns, (.75, 6), (1, 7.5), (1.5, 7), (.75, 8), (1.5, 8.5), (1, 9), of class 1. Since $n > 1$, step 7 assigns the final radius to the created FSH by computing the maximum distance between clustered patterns and centroid which is 1.52. The centroid and final radius of this FSH are stored in **C** and **r**, respectively. As the first FSH of class one is created, according to step nine, the corresponding class node is constructed in the output layer and the matrix **U** is updated accordingly. As per step 10, since $\alpha_k \neq 0$, learning continues further from step 3 and the remaining patterns i.e.(1, 5), (2, 4.5) of class 1 are included in the second FSH with the centroid (1, 5) and radius 1.11. Fig.3(b) shows the class 1 FSHs constructed during learning. Since all patterns of class one are clustered, learning of patterns for class 2 is initiated according to step 10.

Using the same steps, three FSHs were created for class 2 with centroids (1.5, 2.5), (3.25, 4), and (4, 1) with radii 1.0828, 2, and 0.625 respectively as shown in Fig.3(c).

Similarly, for class 3 two FSHs with centroids (3.75, 8) and (4, 5), and with radii 2.0156 and 0.625 respectively, are created as shown in Fig.3(d). The learning also creates the class nodes for these classes and **C**, **r** and **U** are updated accordingly. Since the learning for all 3 classes is over the process stops as per step 11.

So overall created seven FSHs i.e. 02 for class one, 03 for class two, and 02 for class three are shown in Fig.3(e). The architecture of the FHNN classifier with these seven FSHs and 3 class nodes, is shown in Fig.3(f). The Fig.3(f) also depicts the final status of **C**, **r** and **U**.

2) 2-DIMENSIONAL EXAMPLE USING DMSC ALGORITHM

The implementation of the DMSC algorithm using above-mentioned data, constructed five FSHs i.e. 02 FSHs for class one, 01 FSH for class two, and 02 FSHs for class three. The radii and centroids of class one FSHs were the same as the MSC learning algorithm. The centroid of class 2 FSH is (2, 1.5) with a radius of 2.79 and the centroid of class three FSHs are (3.75, 8), (4, 5) with radii 2.01 and 0.625, respectively.

Fig.4(a-f) shows the whole process of construction of the FHNN classifier using the DMSC algorithm. With the same scatter plot as shown in Fig.3(a), Fig.4(a) shows the created first FSH with centroid (1, 7.5) and radius equal to 1.52 for class 1 which clusters the six patterns. Fig.4(b) shows both FSHs of class 1. The second FSH with centroid (1, 5) and radius equal to 1.11 clusters the remaining patterns.

For class 2, there are eight patterns to be clustered. According to the DMSC algorithm, three patterns (1.5, 2.5), (3, 1.5), and (2, 1.5) with the minimum means in ascending order are selected as the initial centroids in step 2. After performing steps 3, 4, and 5, the pattern (2, 1.5) is selected as the centroid instead of the first two patterns, even though their mean values are lower. Fig. 4(c) shows the FSH created for class 2 with centroid (2, 1.5) and a radius of 2.79.

Fig. 4(d) shows the formation of two clusters for class 3 with centroids at (3.75, 8.00) and (4.00, 5.00) and respective radii of 2.01 and 0.62. The overall FSHs created for all three classes are shown in Fig. 4(e).

A class node is created whenever the first FSH for that class is created and accordingly upadation of **r**, **C**, and **U** is done.

The architecture of FHNN classifier with centroids in **C**, radius in **r** for FSHs and the weight matrix **U** for 2-D problem using DMSC algorithm is shown in Fig.4(f).

TABLE 2. Comparison of average % test accuracy with 5-fold validation with existing algorithms.

Dataset	**MSC**	**DMSC**	RBF-R	RBF-N	RBF-WTA	DKP	MLP	KNN	PNN	RBF
Hepatitis	**92.9**	**94.1**	81.9	81.1	82.1	72.0	61.0	56	62.0	65.0
Zoo	93.3	93.3	95.2	94.3	96.2	89.6	99.4	93.5	92.0	83.8
wine	65.0	70.6	95.5	94,4	93.5	93.3	82.7	67.3	68	94
Glass	**76.3**	**79.0**	66.1	66.3	69.1	70.4	52.8	62.4	70.2	38.7
Ecoli	**82.4**	**81.4**	78.5	79.3	81.0	92.9	88.9	92.7	94.4	69.5
Liver	**66.9**	66.1	62.2	62.8	61.0	65.5	64.2	66.6	65.3	53.8.
Ionosphere	**96.3**	92.3	95.5	95.2	94.3	90.3	87.8	85.8	85.8	81.5
Monks-3	85.9	88.1	99.0	95.8	68.6	89.6	94.9	97.1	96.8	97.5
Dermatol	74.9	80.6	92.8	92.1	92.7	90.3	95.9	94.7	94.9	70.2
Breast	96.0	96.6	96.3	96.4	97.0	96.1	94.5	95.7	95.9	94.1
Pima	71.0	**78.0**	75.3	72.1	73.8	74.7	67.5	73.2	70.5	71

TABLE 3. Comparison of % recognition error.

Dataset	MSC	DMSC	Complex-valued	Real-valued	RBF-R	RBF-N	RBF-WTA	RBF	SVM	LIBSVM	SMOSVM
Thyroid	8.4	6.05	2.95	3.78	4.4	5.3	3.7	9.8	/	4.18	/
Heart	21.5	18.2	17.08	19.68	18.1	19.5	19.4	21.1	16.4	16.67	18.1
Ionosphere	3.7	7.7	7.14	6.13	4,5	4.8	5.7	12.9	10.5	6.25	6.3
Breast	4.0	3.4	2.9	1.1	3.7	3.6	3.0	6.7	3.3	3.3	3.1
Segmentation	10.7	11	3.53	4.54	6.4	5.7	5.4	35.1	OM	6.2	/

TABLE 4. Average number of hidden neurons.

Dataset	MSC	DMSC	Complex-valued	Real-valued	RBF-R	RBF-N	RBF-WTA	RBF	SVM	LIBSVM	SMOSVM
Thyroid	26.8	21.2	19.65	20.78	15.1	18.7	14.6	43	/	58.8	/
Heart	91.6	79.4	44.12	46.15	24	27	46	54	216	124/	88.8
Ionosphere	74.2	97	117.12	116.45	65	48	66.6	70	280.8	105.2	58
Breast	76.2	49.4	28.12	29.48	40	35	40	140	527.9	90.2	46.1
Segmentation	274	252	39.52	41.58	200	241	200	462	/	632.8	/

The comparison shows that the DMSC algorithm constructs fewer FSHs than MSC.

B. CASE STUDY II

To evaluate the performance of FHNN, it was compared with other algorithms using sixteen UCI datasets [37], as shown in Table 1. During experimentation, the selected data was divided into 5-fold sequences to facilitate researchers in comparing their results with the FHNN classifier. Table 2 presents the average percentages of 5-fold validation test accuracies of the FHNN classifier and other specified classifiers [4]. Proposed MSC and DMSC experiment results are compared with existing state of the art method like RBF-R, RBF-N, RBF-WTA in Table 2. For dataset Hepatitis, Glass, Ecoli, Liver, ionosphere and Pima are better than existing state of the art methods, while results for other datasets are comparable.

C. CASE STUDY III

The primary concern with the RBFNN lies in the number of hidden neurons formed within its hidden layer [38]. The FHNN classifier's performance, in terms of both the average number of FSHs and relative recognition error, is compared with various classifiers. Tables 3 and 4 present the comparison of FHNN with other classifiers as detailed in [5]. Despite potentially having a greater total number of FSHs for certain datasets compared to other algorithms, the computation time for FHNN is generally lower. Table 4 indicates that FHNN is a swift pattern classifier in terms of retrieval.

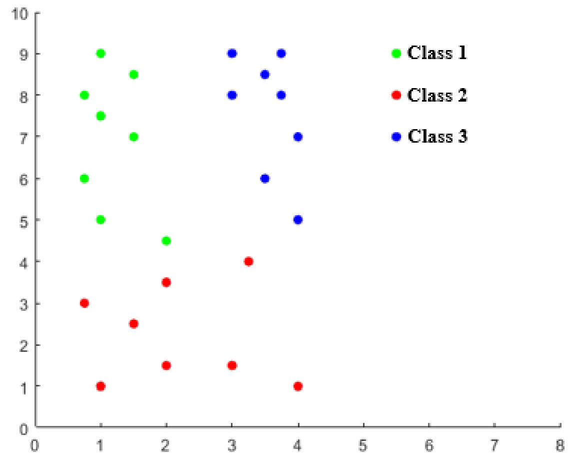
TABLE 5. Comparison table for accuracy in training and testing.

	AP-ELM		ELM		**MSC**		**DMSC**	
Dataset	Train	Test	Train	Test	Train	Test	Train	Test
Hepatitis	.92	.87	.98	.83	1	.93	1	.94
Heart	.83	.84	.86	.79	1	.79	1	.82
Sonar	.99	.83	.78	.70	1	.56	1	.51
Wine	1.0	.98	.98	.95	1	.65	1	.71
Zoo	.92	.94	1	.74	1	.94	1	.93
Iris	.97	.98	1	.94	1	.94	1	.93

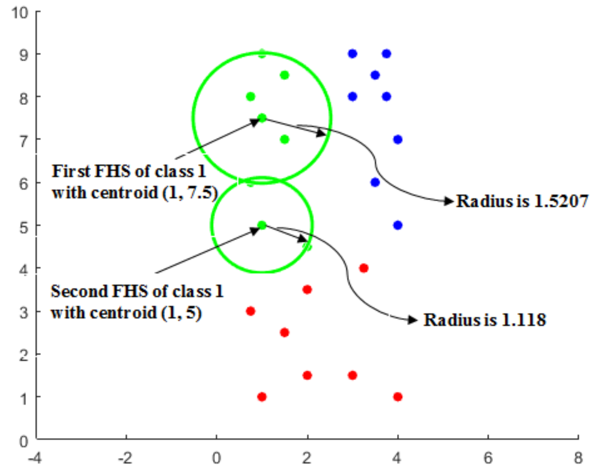
D. CASE STUDY IV

The FSHs in FHNN are characterized by membership functions that accommodate clustered patterns, providing 100% accuracy for any training dataset. In this case study, the performance of the FHNN classifier is compared with the fuzzy neural network proposed by [39] in terms of training and testing accuracy. Table 5 presents the training and testing results. As shown in the comparison table, the training results of the FHNN classifier are 100% for all datasets, whereas the testing results are superior for three datasets and comparable for others. However, averaging the training and testing results reveals that FHNN performs better across all datasets, except for the wine dataset.

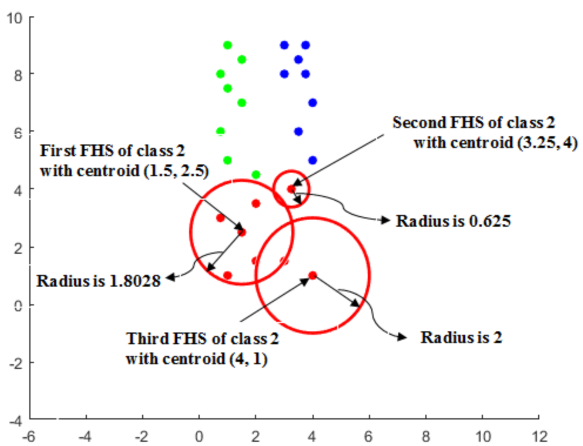
In summary, the simulation results clearly indicate that the FHNN classifier outperforms other algorithms in terms of 5-fold validation test accuracy, number of neurons with recognition rate, and training with testing accuracy, both in superiority and comparability. Additionally, it is observed that the FHNN classifier learns faster and requires less retrieval time compared to other algorithms. The FHNN classifier can be trained on any training dataset without falling



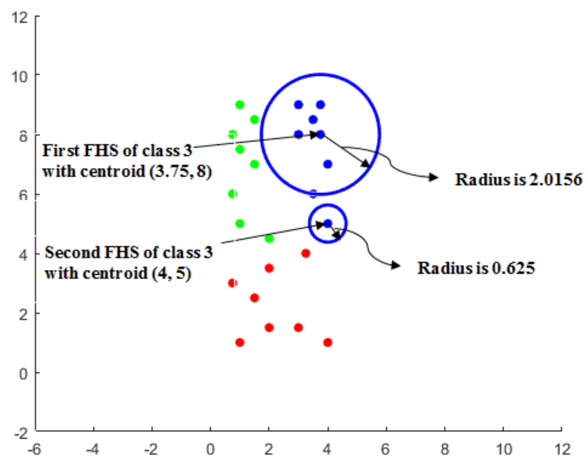
(a) Scatter plot of patterns in 2D space



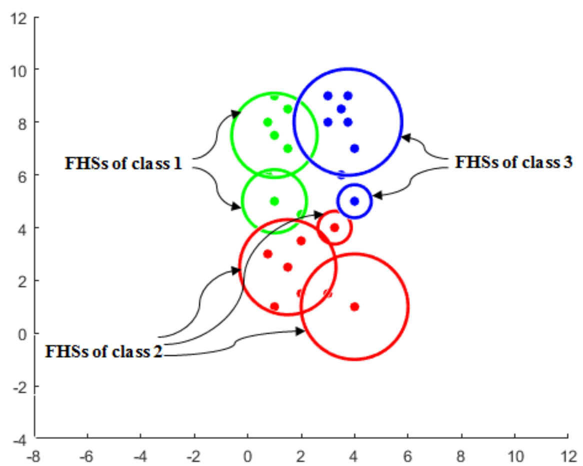
(b) Class 1 FSHs



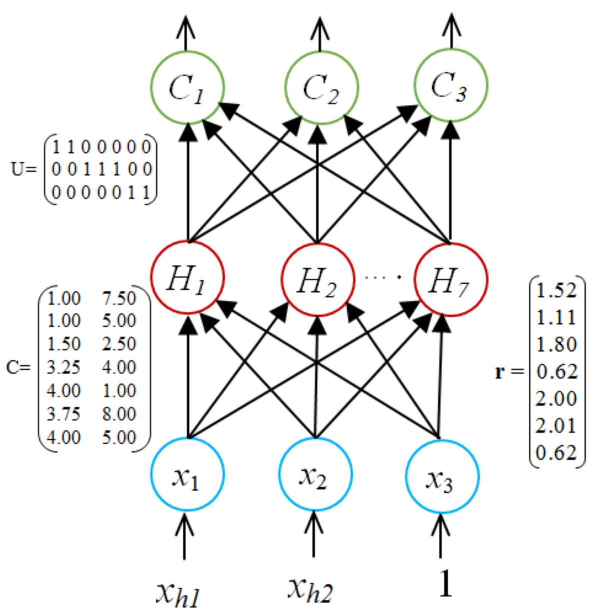
(c) Class 2 FSHs



(d) Class 3 FSHs



(e) FSHs for all classes



(f) FHNN classifier using MSC algorithm

FIGURE 3. **Process in creation of FHNN classifier using MSC algorithm.**

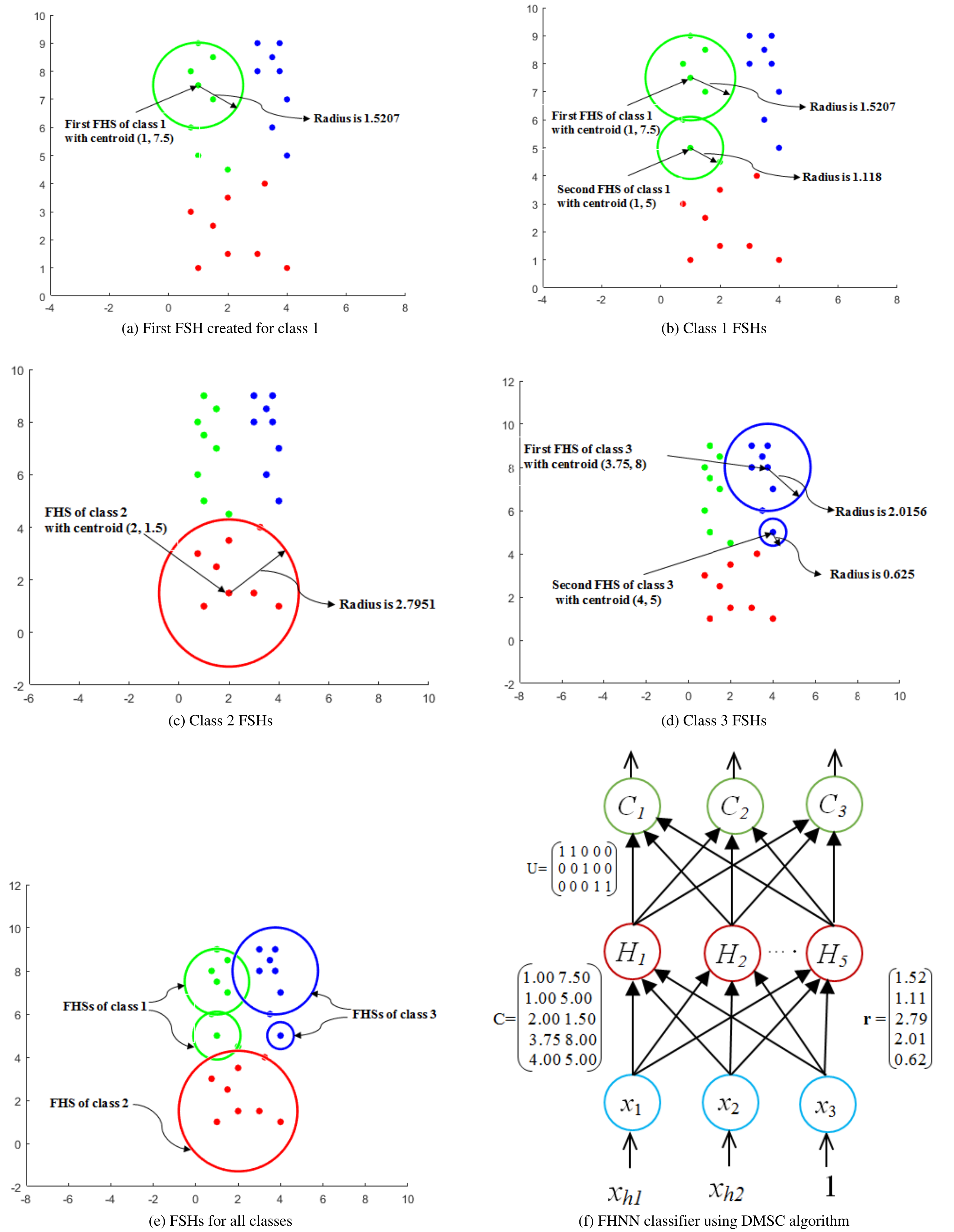


FIGURE 4. **Process in creation of FHNN classifier using DMSC algoritham.**

into local minima. Therefore, the FHNN classifier is highly efficient for pattern recognition, as previously discussed in [40].

V. DISCUSSION

The cluster formation in the hidden layer of the FHNN classifier is refined by the MSC and DMSC algorithms. These algorithms utilize density-based clustering [41] and measure inter-class and intra-class distances [42]. Average percentage test accuracy with five-fold validation for various datasets was reported in recent research papers. Table 2 shows that the test accuracy is higher for Hepatitis, Glass, E. coli, Liver, Ionosphere, and Pima compared to other classifiers. For the remaining datasets, results are comparable. Table 3 indicates that the recognition error for these five datasets is also comparable.

Table 4 demonstrates that both proposed algorithms, MSC and DMSC, exhibit robustness in terms of training and testing time complexity. Table 5 reveals that both algorithms achieve 100% training and testing accuracy for Hepatitis, Zoo, and Iris datasets, outperforming other algorithms. The primary goal of developing these algorithms was to achieve 100% training accuracy with minimal cluster overlap to enhance testing accuracy.

Figure 3 illustrates that for a 2D dataset, seven clusters are formed in the hidden layer due to centroid selection based on cluster density. In contrast, Figure 4 shows that for the same 2D dataset, five clusters are formed in the hidden layer due to centroid selection based on both cluster density and inter-class distance. Comparing Figure 3 and Figure 4, for class 2, MSC creates three clusters while DMSC creates only one cluster. The proposed classifier based on the MSC and DMSC algorithms presents several compelling advantages over traditional classifiers, positioning it as a robust choice in the field of pattern recognition. One of its primary strengths lies in its parameter independence, requiring no tuning parameters yet consistently achieving 100% training accuracy across diverse datasets. This feature not only simplifies implementation but also enhances the algorithm's adaptability to various training scenarios. By employing strategies that circumvent the local minima problem, the algorithms effectively determine an optimal number of clusters suited to each dataset's unique characteristics, thereby ensuring efficient and thorough training.

Furthermore, the algorithms' insensitivity to the order of data presentation ensures stability in clustering outcomes, fostering reliable and reproducible results crucial for data visualization and interpretation. This attribute is particularly advantageous in exploratory data analysis and understanding complex dataset structures. In terms of computational efficiency, the MSC and DMSC algorithms demonstrate competitive performance, achieving minimal training and testing times, especially beneficial for smaller datasets where rapid processing is pivotal.

A distinctive feature of the proposed approach is the incorporation of fuzzy neurons in the hidden layer, characterized by fuzzy membership functions. This design choice enhances the classifier's ability to accurately model and categorize complex patterns within data, contributing to its high training accuracy.

In summary, the MSC and DMSC algorithms represent a significant advancement in pattern recognition due to their robust performance across various metrics including accuracy, computational efficiency, and flexibility in handling different dataset characteristics. These attributes make them well-suited for applications requiring precise and reliable classification, contributing to advancements in fields ranging from biomedical research to industrial automation. Future research could involve optimizing these methods for the number of clusters. Large datasets with a higher prevalence of outliers may result in a larger number of clusters, thus increasing the processing overhead during training, hence a strategy for removing outliers must be formed. The next goal should be to increase dataset accuracy by avoiding overfitting, and experimentation should encompass use of parameters for cluster size and cluster number. Finally, an approach would be to change the fuzzy membership function.

VI. CONCLUSION

The proposed FHNN classifier, utilizing the MSC and DMSC algorithms, constructs FSHs in the hidden layer based on intra-class and inter-class metrics, incorporating fuzzy membership functions within the framework of RBFNN. Unlike traditional RBFNNs that use Gaussian neurons, the FHNN achieves 100% training efficiency across all datasets by employing FSHs. The weights between the hidden and output layers are binary and adapt in real-time during node construction, reducing both training and retrieval time complexities. The MSC and DMSC algorithms effectively select centroids, minimizing the influence of outliers and optimizing cluster width. DMSC, specifically, generates fewer FSHs compared to MSC.

The FHNN classifier imposes no restrictions on FSH size and eliminates the need for overlap tests typical in FMNN classifiers. Its robustness extends to any training dataset, leveraging fuzzy membership functions to obscure patterns such that they remain unaffected by neighboring class patterns. Future research directions could explore limiting FSH size and altering the order of classwise data to further enhance performance. Simulation results using standard datasets demonstrate that the FHNN classifier excels in pattern recognition tasks, affirming its suitability and effectiveness in practical applications.

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