Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 46 (2025), No. 2, pp. 383–401
DOI : 10.47974/JIOS-1922

DOFCM- PSO : A novel hybridized fuzzy clustering technique for segmentation of noisy mammogram images

Kanika Bhalla *
Anjana Gosain †
University School of Information, Communication and Technology
Guru Gobind Singh Indraprastha University
Dwarka 110078
New Delhi
India

Abstract

Fuzzy clustering techniques are commonly applied to manage intricate data patterns using fuzzy partitioning methods. However, their performance deteriorates in presence of noise/outliers and higher-dimensional spaces. To address these limitations, we propose a hybrid algorithm DOFCM-PSO which hybridizes the Density-Oriented Fuzzy C Means clustering technique with metaheuristic algorithm, Particle Swarm Optimization to leverage their respective strengths. The proposed algorithm addresses the challenges of noisy datasets in higher dimensional spaces and provides a promising solution. We evaluate and compare the performance of DOFCM-PSO with existing algorithms on three benchmark datasets (Iris, Wine, and Glass), four real-world digital images, and three breast cancer image datasets. The experimental results demonstrate that DOFCM-PSO consistently outperforms all other algorithms. By effectively integrating DOFCM and PSO, our algorithm achieves improved accuracy, robustness, and stability in various applications. The findings highlight the potential of DOFCM-PSO as a valuable tool for real-world applications.

Subject Classification: *Primary 93A30, Secondary 49K15.*

Keywords: *Fuzzy Clustering, Metaheuristic Algorithms, Optimization.*

1. Introduction

Fuzzy C-Means, developed by Bezdek et al. [1] performs well with noise-free data but struggles with distinguishing between data points and outliers. To address this, various algorithms like Possibilistic C-Means and

* *E-mail:* **kanikabhalla88@gmail.com (Corresponding Author)**
† *E-mail:* **anjana_gosain@yahoo.com**

Noise Clustering [2] have been proposed. However, these methods often face difficulties when dealing with clusters of varying sizes [3].

To handle the problem of clusters with unequal sizes, Zang and Chen [4] introduced the Kernelized Fuzzy C Means Algorithm (KFCM) which utilizes a radial basis kernel function. In 2011, Chaira [5] introduced the Intuitionistic Fuzzy C Means (IFCM) algorithm which enhances the convergence of cluster centers by integrating a hesitation degree [6], [7].

Kernelized Intuitionistic Fuzzy C Means (KIFCM) algorithm proposed by Lin [8] effectively handles non-linearly separable data which utilizes a radial basis kernel function. But all these algorithms fail to handle noisy data. To handle the noisy data Kaur et al [9] introduced the Density Oriented Fuzzy C Means Clustering (DOFCM) algorithm by using density and neighborhood membership for noise detection and removal. However, these algorithms often struggle in high-dimensional spaces [10].

To address the difficulties fuzzy clustering algorithms encounter in high-dimensional spaces, researchers have created hybrid approaches that combine global optimization techniques with fuzzy clustering methods [11], [12]. These approaches treat the FCM clustering task as an optimization problem, seeking to enhance results by optimizing the objective function [13].

Reddy and Khare [14] integrated the firefly-bat method with FCM, utilizing the resulting clusters as input for an artificial neural network to diagnose diabetes. Jansi and Subashini [15] developed a hybrid algorithm that combines FCM with Genetic Algorithm (GA) for segmenting brain Magnetic Resonance Imaging (MRI) scans.

To overcome the problem of global search, researchers [11], [16]–[19] have hybridized fuzzy clustering algorithm with PSO which is an efficient heuristic algorithm known for its effectiveness in solving global optimization problems [12]. This hybrid approach provides more stable and accurate clustering results. However, these algorithms tend to be vulnerable to noise and outliers, which can interfere with the clustering process and undermine the reliability and precision of the results.

To tackle the challenge of noise/outliers, we introduce DOFCM-PSO, a novel algorithm that combines the DOFCM fuzzy clustering method with the PSO optimization algorithm. DOFCM detects noisy points by analyzing neighborhood density, isolating them into a separate cluster, while PSO, known for its efficiency in solving complex global optimization problems, enhances the clustering process. This paper focuses on applying DOFCM-PSO for breast cancer detection. Radiologists analyze mammogram images to identify abnormalities such as cell masses and microcalcifications, which can suggest the presence of cancer [20]–[22].

The primary contribution of our study in this paper can be outlined as follows:

- Hybridized DOFCM-PSO: In this study, we propose an innovative hybrid algorithm that synergizes the strengths of DOFCM and PSO, enhancing both clustering accuracy and noise handling capabilities. This integration allows us to enhance DOFCM's noise elimination capabilities, with the fitness function in DOFCM-PSO being derived from DOFCM's objective function. By utilizing PSO's global optimization abilities, our approach significantly improves clustering outcomes.
- Evaluation on Real-time Data Sets and Medical Images: To assess our algorithm's effectiveness, we conduct extensive experiments using three real-time datasets, four real-world digital images, and three mammogram images. We specifically focus on mammogram segmentation for early tumor detection and compare our algorithm's performance with existing hybrid methods, including FCM-PSO, IFCM-PSO, KFCM-PSO, and KIFCM-PSO.

The structure of this paper is outlined as follows:

Section II: Review of Hybridized Fuzzy Clustering Algorithms

Section III: Methods and Materials

Section IV: Proposed Algorithm - Hybridized DOFCM with PSO

Section V: Experimental Analysis and Results

Section VI: Conclusion

2. Related Work

This section offers a concise review of various hybrid fuzzy clustering algorithms, such as FCM-PSO, KFCM-PSO, IFCM-PSO, and KIFCM-PSO. The analysis and comparison of these algorithms are conducted with respect to the chosen datasets T= {t1, t2, t3……… tn}

Where, n: number of points in two-dimensional spaces, ε: Minimum improvement: 1^{-5}, cen_k: centroid of kth cluster, and tc: count of clusters, that ranges from [1, tc], OJ: objective function, mb_{ik}: degree of membership with respect to t_i in k cluster, dis_{ji}: Euclidian distance between given point t_i and cen_i center point of i^{th} cluster [19].

2.1 *Hybridized FCM with PSO*

Input Given: Dataset T, population size SP, cognitive and social coefficients sc1 and sc2, maximum iteration matrix MaxIt, inertia weight w.

Step 1: Form a population of swarms with SP number of particles and initialize the values x_i and vel_i

Step 2: Find the fitness evaluation function by calculating the membership function mb

$$mb_{ik} = \frac{1}{\sum_{i=1}^{tc}\left(\frac{dis_{ki}}{dis_{ji}}\right)^{\frac{2}{m-1}}} \quad (1)$$

Step 3: Find the objective function OJ_{FCM}

$$OJ_{FCM}=\sum_{k=1}^{tc}\sum_{i=1}^{n} mb_{ik}^{m}\, dis_{ik}^{2} \quad (2)$$

$$dis_{ik} = ||x_i - cen_k|| \quad (3)$$

Step 4: Calculate the P_b for every particle and P_g for the population.

Step 5: Modify the velocity vel_i for each particle

$$vel(u+1) = wvel_i(u) + sc_1r_1\,[P_b(u) - x_i(u)] + sc_2r_2[P_g(u) - x_i(u)] \quad (4)$$

Step 6: Update the velocity x_i for each particle

$$x_i(u+1) = x_i(u) + vel_i(u+1) \quad (5)$$

Step 7: If iteration < MaxIt, go to step 2.

Output: Get the accuracy as output.

2.2 *Hybridized KFCM with PSO*

Input Given: Dataset T, population size SP, cognitive and social coefficients sc1 and sc2, maximum iteration matrix MaxIt, inertia weight w.

Step 1: Form a population of swarms with SP number of particles and initialize the values x_i and vel_i

Step 2: Find the fitness evaluation function by calculating the membership function mb

$$mb_{ik} = \frac{1}{\sum_{i=1}^{tc}\left(\frac{dis_{ki}}{dis_{ji}}\right)} \quad (6)$$

Step 3: Find the objective function OJ_{FCM}

$$OJ_{KFCM} = \sum_{k=1}^{tc}\sum_{i=1}^{n} mb_{ik}^{m}\, ||\emptyset(x_i) - \emptyset(cen_k)||^2 \quad (7)$$

$$||\emptyset(x_i) - \emptyset(cen_k)||^2 = K(x_i, x_i) + K(vel_k, vel_k) - 2K(x_i + vel_k) \quad (8)$$

Step 4: Calculate the P_b for every particle and P_g for the population.

Step 5: Modify the velocity vel_i for each particle

$$vel(u+1) = wvel_i(u) + sc_1r_1\,[P_b(u) - x_i(u)] + sc_2r_2[P_g(u) - x_i(u)] \quad (9)$$

Step 6: Update the velocity x_i for each particle

$$x_i(u+1) = x_i(u) + vel_i(u+1) \quad (10)$$

Step 7: If iteration < MaxIt, go to step 2.

Output: Get the accuracy as output.

2.3 *Hybridized IFCM with PSO*

Input Given: Dataset T, population size SP, cognitive and social coefficients sc1 and sc2, maximum iteration matrix MaxIt, inertia weight w.

Step 1: Form a population of swarms with SP number of particles and initialize the values x_i and vel_i
Step 2: Find the fitness evaluation function by calculating the membership function mb and hesitation degree η_{ik}

$$\eta_{ik} = 1 - mb_{ik} - (1 - mb_{ik}^{\alpha})^{1/\alpha} \text{ where } \alpha>0 \quad (11)$$

$$mb_{ik}new = mb_{ik} + \eta_{ik} \quad (12)$$

Step 3: Find the objective function OJ_{FCM}

$$OJ_{IFCM} = \sum_{i=1}^{tc} \sum_{k=1}^{n} mb_{ik}^{*m} dis_{ik}^2 + \sum_{i=1}^{c} \eta_i^* e^{1-\eta_i^*} \quad (13)$$

Step 4: Calculate the P_b for every particle and P_g for the population.
Step 5: Modify the velocity v_i for each particle

$$vel(u+1) = wvel_i(u) + sc_1 r_1 [P_b(u) - x_i(u)] + sc_2 r_2 [P_g(u) - x_i(u)] \quad (14)$$

Step 6: Update the velocity x_i for each particle

$$x_i(u+1) = x_i(u) + vel_i(u+1) \quad (15)$$

Step 7: If iteration < MaxIt, go to step 2.

Output: Get the accuracy as output.

2.4 *Hybridized KIFCM with PSO*

Input Given: Dataset T, population size SP, cognitive and social coefficients sc1 and sc2, maximum iteration matrix MaxIt, inertia weight w, threshold value α.

Step 1: Form a population of swarms with SP number of particles and initialize the values x_i and vel_i
Step 2: Find the fitness evaluation function by calculating the membership function mb and hesitation degree η_{ik}

$$\eta_{ik} = 1 - mb_{ik} - (1 - mb_{ik}^{\alpha})^{1/\alpha} \text{ where } \alpha>0 \quad (16)$$

$$mb_{ik}new = mb_{ik} + \eta_{ik} \quad (17)$$

Step 3: Find the objective function OJ_{FCM}

$$OJ_{KIFCM} = \sum_{i=1}^{tc} \sum_{k=1}^{n} mb_{ik}^{*m} dis_{ik}' + \sum_{i=1}^{c} \eta_i^* e^{1-\eta_i^*} \quad (18)$$

$$dis_{ik}' = \sqrt{2(1 - K(x,y)} \quad (19)$$

$$K(x,y) = \exp\left(-\left||x-y|\right|^2/\sigma^2\right. \quad (20)$$

Step 4: Calculate the P_b for every particle and P_g for the population.
Step 5: Modify the velocity v_i for each particle

$$vel(u+1) = wvel_i(u) + sc_1 r_1 [P_b(u) - x_i(u)] + sc_2 r_2 [P_g(u) - x_i(u)] \quad (21)$$

Step 6: Update the velocity x_i for each particle

$$x_i(u+1) = x_i(u) + vel_i(u+1) \quad (22)$$

Step 7: If iteration < MaxIt, go to step 2.

Output: Get the accuracy as output.

3. Materials and Method

This section provides an overview of the DOFCM algorithm and PSO method utilized in this research.

3.1 *Density Oriented Fuzzy C Means (DOFCM) Clustering Algorithm*

DOFCM seeks to detect noise within a dataset by analyzing the density of data points. It distinguishes noisy points by assessing the number of neighboring data points in their vicinity. The calculation of the neighborhood membership for a given point "*i*" in the dataset *T* is defined as follows:

$$M^{i}_{neighborhood}(X) = \frac{\eta^{i}_{neighborhood}}{\eta_{max}} \tag{23}$$

Where $\eta^{i}_{neighborhood}$ = Neighborhood count of data points and η_{max} = maximum neighborhood points

If point 'j' is part of the neighborhood of point 'i', then 'j' will fulfill the following condition:

$$j \in T \mid dis(i, j) \le rad_{neighborhood} \tag{24}$$

Objective function, OJ_{DOFCM} is calculated as:

$$OJ_{DOFCM} = \sum_{k=1}^{tc} \sum_{i=1}^{n} mb_{ik}^{m} dis_{ik}^{2} \tag{25}$$

Where $$dis_{ik} = \| t_i - cen_k \| \tag{26}$$

3.2 *Particle Swarm Optimization (PSO)*

This is an optimization approach grounded in the concept of swarm intelligence. In an *M* dimensional space, the total number of particles is represented by t. $I_i = [I_{i_1}, I_{i_2}, I_{i_3}, \ldots, I_{i_M}]$ is the position of particle p with velocity represented by, $Vel_i = [Vel_{i_1}, Vel_{i_2}, Vel_{i_3}, \ldots, Vel_{i_M}]$, its best position is $P_b = [P_{i_1}, P_{i_2}, P_{i_3}, \ldots, P_{i_M}]$. The optimal position among all particles is $P_g = [P_{i_1}, P_{i_2}, P_{i_3}, \ldots, P_{i_n}]$. Each particle's velocity is adjusted using the following equation.

$$Vel_i^{n+1} = Vel_i^{n} + sc_1 r_1 (P_b - I_i^{n}) + sc_2 r_2 (P_g - I_i^{n}) \tag{27}$$

Each particle's position is adjusted using the following equation.

$$I_i^{n+1} = I_i^{n} + Vel_i^{n} \tag{28}$$

Here i=1, 2, 3… t represents different particles. sc_1 and sc_2 are known as the accelerated constants; the values of r_1 and r_2 fall within the range of [0,1] while 'n' denotes the evolutionary epochs.

4. Proposed Algorithm DOFCM-PSO

The DOFCM algorithm[23], has garnered attention for its effectiveness in outlier detection and removal. However, while DOFCM excels in handling outliers, it may encounter challenges to solve global optimization

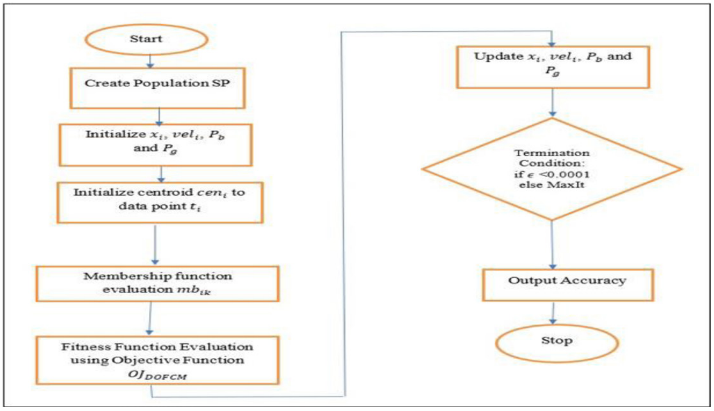

Figure 1

DOFCM-PSO Framework

problem in higher dimensional space. To overcome this constraint, we introduce a novel hybrid algorithm by hybridizing the distinctive features of DOFCM and PSO. By incorporating the global optimization capabilities of PSO, our hybrid approach further optimizes the results obtained from DOFCM, leading to improved clustering outcomes. The structure of the proposed method is illustrated in Figure 1

The algorithm is shown below:

Input Given: Dataset T, population size SP, cognitive and social coefficients sc1 and sc2, maximum iteration matrix MaxIt, inertia weight w, threshold value α, fuzziness index m.

Step 1: Form a population with SP number of particles and initialize the values x_i, α and vel_i

Step 2: Find the fitness evaluation function by calculating the membership function mb.

$$mb_{ik} = \begin{cases} \dfrac{1}{\sum_{i=1}^{tc}\left(\frac{dis_{ki}}{dis_{ji}}\right)^{\frac{2}{m-1}}}, & if\ M^{i}neighborhood \geq \propto \\ 0\ (zero), & if\ M^{i}neighborhood < \propto \end{cases} \tag{29}$$

Step 3: Find the objective function OJ_{FCM}

$$OJ_{FCM}=\sum_{k=1}^{tc}\sum_{i=1}^{n} mb_{ik}^{m}\, dis_{ik}^{2} \tag{30}$$

$$dis_{ik} = ||t_i - cen_k|| \tag{31}$$

Step 4: Calculate the P_b for every particle and P_g for the population.

Step 5: Modify the velocity vel_i for each particle

$$vel(u+1) = wvel_i(u) + sc_1 r_1 [P_b(u) - x_i(u)] + sc_2 r_2 [P_g(u) - x_i(u)] \tag{32}$$

Step 6: Update the velocity x_i for each particle

$$x_i(u+1) = x_i(u) + vel_i(u+1) \tag{33}$$

Step 7: If iteration < MaxIt, go to step 2.

Output: Get the accuracy as output.

5. Experimental Results and Analysis

In this study, we assessed our proposed algorithm's performance across three benchmark datasets- Iris, Wine, and Glass-along with four real-world digital images and three medical image datasets. Section 5.1 compares our DOFCM-PSO algorithm with other hybrid methods, including FCM-PSO, IFCM-PSO, KFCM-PSO, and KIFCM-PSO, using established datasets. Sections 5.2 and 5.3 evaluate the algorithm's performance on real-world digital and medical image datasets, respectively.

5.1 *Real Data Sets*

To evaluate the effectiveness of the proposed method, we utilized three benchmark datasets: Iris, Wine, and Glass, sourced from the UCI Machine Learning Repository. Table 1 presents the characteristics of these real time datasets.

Table 1

Properties of datasets

S. No	Name	Number of Data points	Dimensions	Cluster Count
1	Iris	150	4	3
2	Wine	178	13	3
3	Glass	214	9	2

Figures 2-4 present scatter plots of the optimized fuzzy clustering results for the Glass, Iris, and Wine datasets. Figures 5-8 and Table 2 show the performance metrics of the algorithms, including accuracy, F1 score, MCC, and Kappa coefficient.

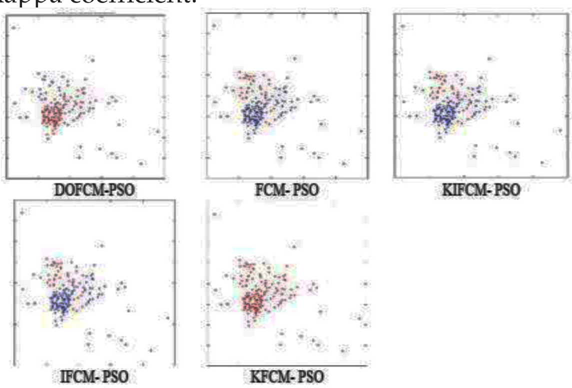

Figure 2

Optimized clustering results for Glass Dataset

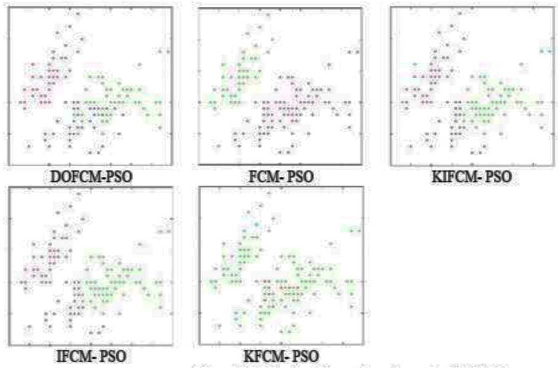

Figure 3

Optimized fuzzy clustering results for Iris Dataset

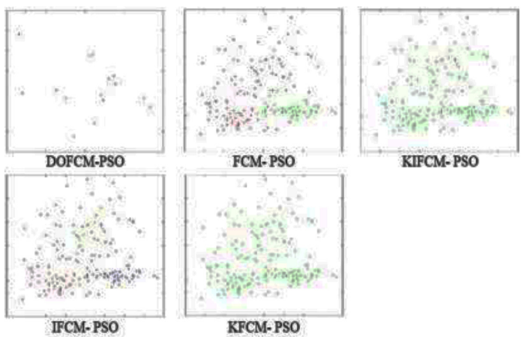

Figure 4

Optimized fuzzy clustering results for Wine Dataset

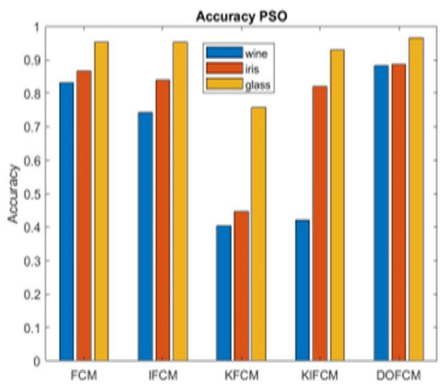

Figure 5

Performance of algorithms baed on Accuracy

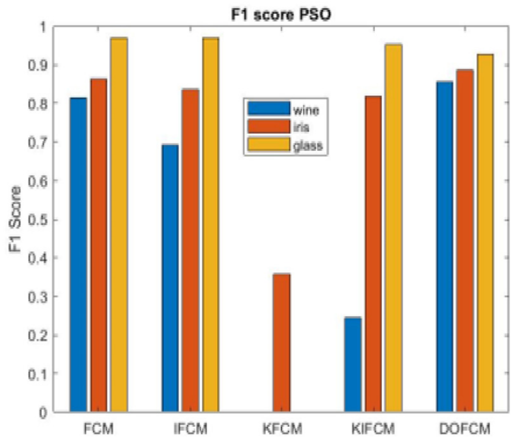

Figure 6

Performance of algorithms baed on F1 score

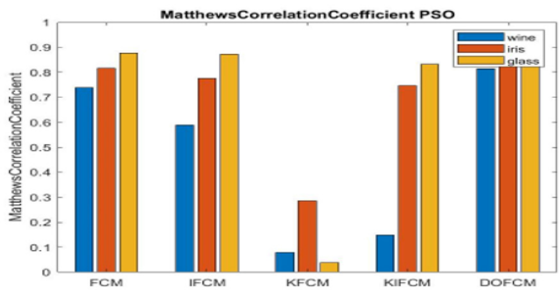

Figure 7

Performance of algoritms based on MCC

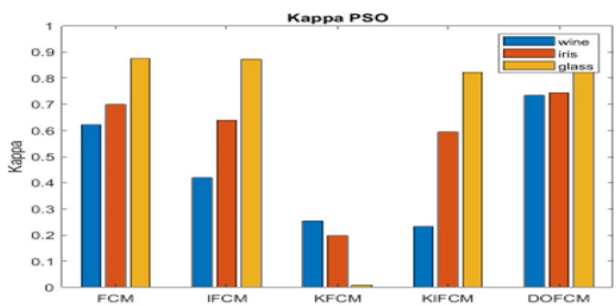

Figure 8

Performance of algorithms based on Kappa coefficient

Table 2
Results of performance criterial for hybridized fuzzy clustering algorithms

Algorithm	Performance Metrics	Wine	Iris	Glass
FCM- PSO	Accuracy	0.8315	0.8667	0.9533
	F1-Score	0.8139	0.8622	0.9689
	Error	0.1685	0.1333	0.0467
	Matthews	0.7389	0.8167	0.8758
	Kappa	0.6208	0.7000	0.8747
IFCM- PSO	Accuracy	0.7416	0.8400	0.9533
	F1-Score	0.6916	0.8346	0.9691
	Error	0.2584	0.1600	0.0467
	Matthews	0.5879	0.7747	0.8733
	Kappa	0.4185	0.6400	0.8730
KFCM- PSO	Accuracy	0.4045	0.4467	0.7570
	F1-Score	0.3426	0.3568	0.9780
	Error	0.5955	0.5533	0.2430
	Matthews	0.0798	0.2858	0.0383
	Kappa	0.2537	0.1968	0.0092
KIFCM- PSO	Accuracy	0.4213	0.8200	0.9299
	F1-Score	0.2435	0.8172	0.9521
	Error	0.5787	0.1800	0.0701
	Matthews	0.1486	0.7458	0.8324
	Kappa	0.2319	0.5950	0.8225
DOFCM- PSO	Accuracy	**0.8824**	**0.8867**	**0.9653**
	F1-Score	0.8556	0.8861	0.9278
	Error	0.1176	0.1133	0.0347
	Matthews	0.8139	0.8326	0.9072
	Kappa	0.7353	0.7450	0.9051

Table 2 showcases the comparative performance of various optimized fuzzy clustering methods, including the DOFCM-PSO algorithm proposed in this study. According to the results, the DOFCM-PSO algorithm achieves the highest accuracy among all the optimized fuzzy clustering methods. For the glass dataset, the DOFCM-PSO algorithm achieves an accuracy of approximately 96%. Similarly, for the Iris and Wine datasets, the DOFCM-PSO algorithm demonstrates an accuracy rate of 88% in both scenarios.

5.2 *Real-World Digital Images*

This section presents an assessment of the algorithms' performance using authentic digital images sourced from real-world scenarios, presented in RGB formats. The images used for experimentation include a bacteria image, a fruits image, a hand image, and a Lena image, as shown in Figure 9 (a-d). Figures 10a, 11a,12a and 13a show the corresponding noisy images, where Gaussian noise with a variance of 0.05 is added to evaluate the algorithm's performance. We analyze the segmentation results of these images using different algorithms, and the corresponding validity measures partition entropy (CV_{PC}), partition coefficient (CV_{PE}) and Fukuyama-Sugeno function (CV_{FS}) are presented in Tables 4-6. For the bacteria image, Figure 10 and related tables show that DOFCM-PSO excels in accurately segmenting bacteria regions without noise. KFCM-PSO also detects bacteria, but its results are noisy, as are the outputs of other algorithms. In the fruits image (Figure 11), DOFCM-PSO effectively reduces noise but slightly blurs the fruits. FCM-PSO offers clearer segmentation with less noise, while other algorithms struggle with clarity. For the hand image (Figure 12), DOFCM-PSO is the only algorithm that segments without noise. KFCM-PSO, IFCM-PSO, and FCM-PSO also perform well with minimal noise, but KIFCM-PSO shows the worst performance. In the Lena image (Figure 13), DOFCM-PSO again leads, accurately segmenting all regions without noise. FCM-PSO follows, but other algorithms suffer from varying levels of noise interference. Overall, DOFCM-PSO consistently outperforms others with minimal noise.

Figure 9

Real World digital images

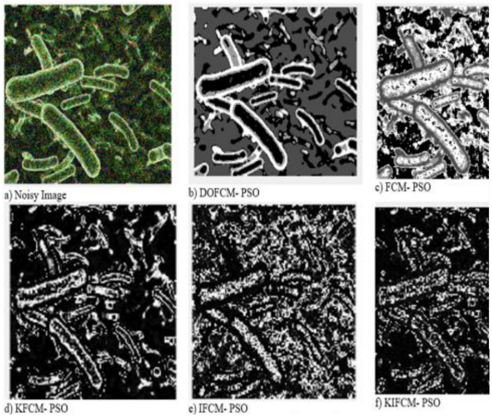

Figure 10

Segmented Outcomes for Bacteria Image

Figure 11

Segmented Outcomes for Fruits Image

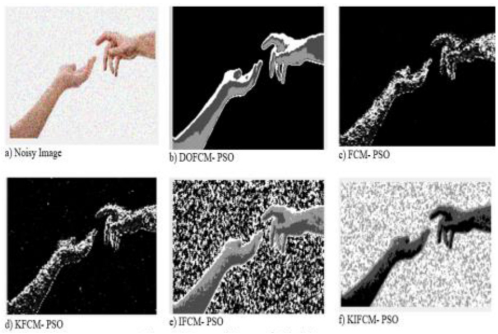

Figure 12

Segmented Outcomes for Hands Image

Figure 13

Segmented Outcomes for Lena Image

5.3 *Mammogram Image Segmentation*

This section evaluates various algorithms on mammogram images from the MIAS database, with segmentation results and validity measures detailed in Tables 4-6. Figures 14a, 15a, and 16a show mammograms labeled as mdb001, mdb005, and mdb132. In mdb001, a single lump is highlighted (Figure 14b), while mdb005 has two lumps and ducts (Figure 15b), and mdb132 has two small lumps (Figure 16b). Gaussian noise (variance 0.005) is added to these images (Figures 14c, 15c, 16c) to test noise-handling. KIFCM-PSO struggles with noise and lump detection in mdb001, while IFCM-PSO slightly improves but remains inadequate.

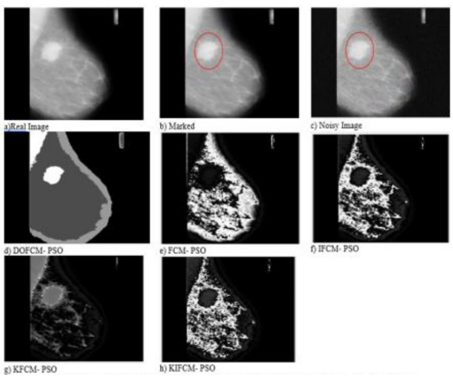

Figure 14

a)Real Image-mdb001, b) Marked Image, c) Noisy Image d) Segmented outcome using DOFCM-PSO, e) Segmented outcome using FCM-PSO, f) Sebmented outcome using KFCM-PSO g) Segmented outcome using IFCM-PSO, h) Segmented outcome using KIFCM-PSO

FCM-PSO and KFCM-PSO perform better, but DOFCM-PSO excels in all scenarios. In mdb005, KIFCM-PSO fails to detect both lumps, while FCM-PSO, IFCM-PSO, and KFCM-PSO detect only one. DOFCM-PSO successfully identifies both lumps. In mdb132, KIFCM-PSO only identifies the breast region. IFCM-PSO and KFCM-PSO also perform poorly, while FCM-PSO detects just one lump. DOFCM-PSO consistently outperforms other methods, accurately identifying lumps in shape and size.

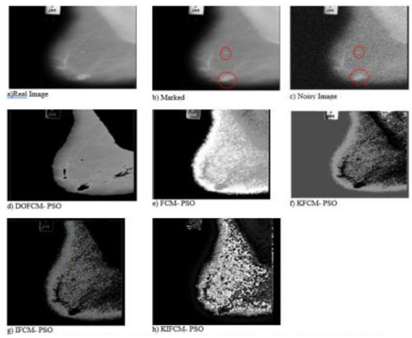

Figure 15

a)Real Image-mdb005, b) Marked Image, c) Noisy Image d) Segmented outcome using DOFCM-PSO, e) Segmented outcome using FCM-PSO, f) Sebmented outcome using KFCM-PSO g) Segmented outcome using IFCM-PSO, h) Segmented outcome using KIFCM-PSO

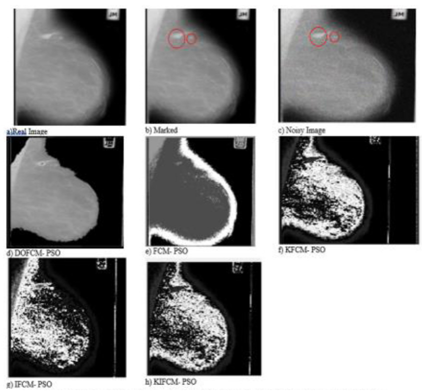

Figure 16

a) Real image-mdb132, b) Marked Image, c) Noisy Image d) Segmentd outcome using DOFCM-PSO, e) Segmented outcome using FCM-PSO, f) Sebmented outcome using KFCM-PSO g) Sebmented outcome using IFCM-PSO, h) Segmented outcome using KIFCM-PSO

Table 4

Results of peformance criteria based on CV_{PC} for all the techniques

Images	FCM- PSO	KFCM- PSO	IFCM- PSO	KIFCM- PSO	DOFCM- PSO
Bacteria	0.8765	0.7865	0.6168	0.5068	0.9974
Fruits	0.7124	0.7289	0.6975	0.5144	0.9548
Hands	0.5673	0.4155	0.5811	0.3933	0.9332
Lena	0.6845	0.6671	0.7034	0.3820	0.9827
Mdb001	0.9243	0.9055	0.8356	0.8041	0.9563
Mdb005	0.9271	0.8212	0.8148	0.7754	0.9512
Mdb025	0.8876	0.8648	0.7312	0.6799	0.9165
Average CV_{PC}	0.783867	0.741357	0.711486	0.588057	0.95601429

Table 5

Results of peformance criteria based on CV_{PE} for all the techniques

Images	FCM- PSO	KFCM- PSO	IFCM- PSO	KIFCM- PSO	DOFCM- PSO
Bacteria	0.6845	0.3671	0.6947	0.6186	0.1361
Fruits	0.5321	0.5719	0.5172	0.7981	0.0263
Hands	0.257	0.8712	0.6576	1.1831	0.0517
Lena	0.3543	0.6148	0.6100	1.0276	0.0461
Mdb001	0.2874	0.2636	0.2444	0.3941	0.1549
Mdb005	0.3815	0.3751	0.2949	0.2651	0.1428
Mdb025	0.3394	0.3193	0.3383	0.6433	0.1230
Average CV_{PE}	0.40 517	0.48 328	0.47 958	0.70 427	0.09 727

Table 6

Results of peformance criteria based on CV_{FS} for all the techniques

Images	FCM- PSO	KFCM- PSO	IFCM- PSO	KIFCM- PSO	DOFCM- PSO
Bacteria	-14107	-14162	-14162	-10714	-31404
Fruits	-14283	-14255	-13265	-11438	-20137
Hands	-13124	-13381	-13103	-9862	-36528
Lena	-17340	-15786	-15428	-13186	-59184
Mdb001	-82491	-82392	-80418	-32731	-91177
Mdb005	-73353	-71391	-70387	-14492	-80276
Mdb132	-76265	-68247	-72362	-16001	-83576
Average CV_{FS}	-41566.1429	-39944.9	-39875	-15489.1	-57468.8571

6. Conclusion

In this study, we present the DOFCM-PSO algorithm as an innovative solution for managing noisy data. We evaluated its performance against four existing optimized fuzzy clustering algorithms using a range of datasets, including benchmarks, digital images, and mammograms. The assessment was based on several validity measures, including accuracy, MCC, F1 score, Kappa coefficient (κ), and cluster validity functions for image segmentation. Our findings demonstrate that DOFCM-PSO outperforms all other methods, achieving an outstanding accuracy of

99.74%. FCM-PSO ranked second, while KIFCM-PSO showed the weakest performance with 60.68% accuracy. This research underscores the importance of noise reduction preprocessing, leading to significant improvements in segmentation accuracy. The results confirm the efficiency of DOFCM-PSO, positioning it as a superior choice for fuzzy clustering tasks.

References

[1] J. C. Bezdek, R. Ehrlich, and W. Full, "FCM: The fuzzy c-means clustering algorithm," *Computers & geosciences*, vol. 10, no. 2–3, pp. 191–203 (1984).

[2] A. Anitha, J. Jayakumari, V. Kumutha, S. Palaniammal, A. S. Ohamad, A. T. Kalaivani, B. I. Mamun, F. H. Fazida, M. D. Sawal Hamid, H. Suprayitno, and B. M. Indrasurya, "Performance analysis of WLAN under variable number of nodes using the adjustable parameters in EDCA," *Journal of Theoretical and Applied Information Technology,* vol. 62, no. 1, Apr. 10 (2014).

[3] H. Izakian and A. Abraham, "Fuzzy C-means and fuzzy swarm for fuzzy clustering problem," *Expert Systems with Applications* vol. 38, no. 3, pp. 1835–1838 (2011).

[4] D. Z. S. Chen, "Fuzzy clustering using kernel method," *IEEE, Nanjing, China* (2002).

[5] T. Chaira, "A novel intuitionistic fuzzy C means clustering algorithm and its application to medical images," *Applied soft computing*, vol. 11, no. 2, pp. 1711–1717 (2011).

[6] P. Kaur, A. K. Soni, and A. Gosain, "Robust Intuitionistic Fuzzy C-means clustering for linearly and nonlinearly separable data," in *2011 international conference on image information processing*, pp. 1–6 (2011).

[7] P. Kaur, A. K. Soni, A. Gosain, and I. I. India, "Novel intuitionistic fuzzy c-means clustering for linearly and nonlinearly separable data," *WSEAS Transactions Computing*, vol. 11, no. 3, pp. 65–76 (2012).

[8] K. P. Lin, "A novel evolutionary kernel intuitionistic fuzzy c -means clustering algorithm," *IEEE Transactions on Fuzzy systems*, vol. 22, no. 5, pp. 1074–1087 (2013).

[9] K. Prabhjot, I. M. S. Lamba, and G. Anjana, "DOFCM: a robust clustering technique based upon density," *International Journal of Engineering and Technology*, vol. 3, no. 3, p. 297 (2011).

[10] K. Bhalla and A. Gosain, "Performance Analysis of Hybridized Fuzzy Clustering Algorithms Using Metaheuristic Algorithms," in *International Conference on Innovations in Computational Intelligence and Computer Vision*, pp. 445–461 (2022).

[11] A. Mekhmoukh and K. Mokrani, "Improved Fuzzy C-Means based Particle Swarm Optimization (PSO) initialization and outlier rejection with level set methods for MR brain image segmentation," *Computer methods and programs in biomedicine*, vol. 122, no. 2, pp. 266–281 (2015).

[12] K. Bhalla and A. Gosain, "Optimization in Fuzzy Clustering: A Review," in *International Conference on Information and Communication Technology for Intelligent Systems*, pp. 321–337 (2023).

[13] D. Binu, "Cluster analysis using optimization algorithms with newly designed objective functions," *Expert Systems with Applications*, vol. 42, no. 14, pp. 5848–5859 (2015).

[14] G. T. Reddy and N. Khare, "An efficient system for heart disease prediction using hybrid OFBAT with rule-based fuzzy logic model," *Journal of Circuits, Systems and Computers*, vol. 26, no. 04, p. 1750061 (2017).

[15] S. Jansi and P. Subashini, "Modified FCM using genetic algorithm for segmentation of MRI brain images," in *2014 IEEE International Conference on Computational Intelligence and Computing Research*, pp. 1–5 (2014).

[16] R. K. Brouwer and A. Groenwold, "Modified fuzzy c-means for ordinal valued attributes with particle swarm for optimization," *Fuzzy sets Systems*, vol. 161, no. 13, pp. 1774–1789 (2010).

[17] S. Chen, Z. Xu, and Y. Tang, "A hybrid clustering algorithm based on fuzzy c-means and improved particle swarm optimization," *Arabian Journal for Science and Engineering*, vol. 39, pp. 8875–8887 (2014).

[18] V. Kachitvichyanukul, "Comparison of three evolutionary algorithms: GA, PSO, and DE," *Industrial Engineering and Management Systems*, vol. 11, no. 3, pp. 215–223 (2012).

[19] J. Zhang, Z. Ma, X. Li, Y. Wang, and L. Zhang, "Hybrid fuzzy clustering method based on FCM and enhanced logarithmical PSO (ELPSO)," *Comput. Intell. Neurosci.*, vol. 2020 (2020).

[20] N. Al-Najdawi, M. Biltawi, and S. Tedmori, "Mammogram image visual enhancement, mass segmentation and classification," *Applied Soft Computing*, vol. 35, pp. 175–185 (2015).

[21] B. Hela, M. Hela, H. Kamel, B. Sana, and M. Najla, "Breast cancer detection: A review on mammograms analysis techniques," in *10th International Multi-Conferences on Systems, Signals \& Devices 2013 (SSD13)*, pp. 1–6 (2013).

[22] S. Dahiya and A. Gosain, "A novel type-II intuitionistic fuzzy clustering algorithm for mammograms segmentation," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 4, pp. 3793–3808 (2023).

[23] P. Kaur and A. Gosain, "Density-oriented approach to identify outliers and get noiseless clusters in Fuzzy C—Means," in *International Conference on Fuzzy Systems*, pp. 1–8 (2010).

Received November, 2024