Fuzzy clustering optimization based artificial bee colony algorithm for brain magnetic resonance imaging image segmentation

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ABSTRACT

In brain magnetic resonance imaging (MRI) analysis, image clustering is regarded as one of the most crucial tasks. It is frequently employed to estimate and visualize brain anatomical structures, identify pathological regions, and assist in guiding surgical procedures. Fuzzy c-means algorithm (FCM) is widely used in the MRI image segmentation process. However, it has been several weaknesses such as noise sensitivity, stuck in local optimum and issues with parameters initialization. To address these FCM problems, this paper presents a novel fuzzy optimization method that enhances brain MRI image segmentation by integrating the artificial bee colony (ABC) algorithm with FCM clustering techniques. The proposed method seeks to optimize multiple FCM parameters simultaneously, including the objective function, number of clusters, and cluster center values. The method was evaluated on both simulated and clinical brain MR images, with an emphasis on segmenting white matter, grey matter, and cerebrospinal fluid regions. Experimental results demonstrate significant improvements in segmentation accuracy, achieving a Jaccard similarity (JS) of nearly 1, a partition coefficient index (PCI) of 0.92, and a Davies-Bouldin index (DBI) of 0.41, outperforming other stats of the arts methods.

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ABBREVIATIONS

Abbrev.	Description	Abbrev.	Description
ABC	Artificial bee colony	GMM	Gaussian mixture models
AFCM	Adaptive fuzzy c-means	GWA	Gray wolf algorithm
CNN	Convolutional neural networks	LDCFCM	Local density clustering fuzzy c-means
CSF	Cerebrospinal fluid	ML	Machine learning
DBI	Davies-Bouldin index	MRI	Magnetic resonance imaging
DL	Deep learning	PCI	Partition coefficient index
DPSO	Dynamic particle swarm optimization	PSO	Particle swarm optimization
FCM	Fuzzy c-means algorithm	RDO	Raindrop optimizer
FPSOFCM	Fuzzy PSO for FCM	SVM	Support vector machines
GA	Genetic algorithm	WM	White matter
GM	Gray matter	WOA	Whale optimization algorithm

1. INTRODUCTION

Brain MRI image segmentation is a critical task in medical imaging, enabling the delineation and analysis of anatomical structures, pathological regions, and functional areas within the brain. It plays a pivotal role in diagnosing neurological disorders, planning treatments, and monitoring disease progression. Over the past few decades, significant advancements have been made in segmentation techniques, driven by the increasing availability of high-resolution MRI data and the development of sophisticated computational methods [1]. However, despite these advancements, brain MRI segmentation remains a challenging problem due to the inherent complexity of brain structures, variability across individuals, and limitations in imaging technology [2], [3]. The current state of brain MRI segmentation is characterized by a diverse array of methods, ranging from traditional approaches to modern deep learning-based techniques [4].

Traditional methods for brain MRI segmentation rely on intensity values, spatial information, and anatomical priors to differentiate structures. Techniques include thresholding, region-based methods (*e.g.*, region growing and watershed algorithm), edge detection (*e.g.*, Sobel and Canny), active contours, atlas-based methods, and morphological operations. While these methods have contributed to segmentation, they face challenges such as intensity inhomogeneities, and anatomical variability, as well as reliance on manual intervention and local information, which limits their accuracy and generalizability. These limitations have spurred the development of advanced techniques like machine learning and deep learning, which automate complex pattern recognition. However, traditional methods remain relevant for specific applications and as preprocessing steps in modern segmentation pipelines [5], [6].

Machine learning, including supervised and unsupervised techniques, has significantly advanced brain MRI segmentation by offering more robust, data-driven approaches compared to traditional methods. Supervised methods like support vector machines and random forests use labeled datasets to learn complex patterns, improving segmentation accuracy. However, their success depends on high-quality annotated data, which is costly and time-consuming to produce, and they often struggle to generalize across different imaging protocols or populations. Unsupervised methods, such as k-means clustering, Gaussian mixture models, and fuzzy c-means, group pixels based on similarity without labeled data, making them useful for exploratory analysis. However, they lack precision for clinical applications due to reliance on low-level features and sensitivity to noise and artifacts. Both approaches face challenges like intensity inhomogeneities, noise, class imbalance, and high computational costs, which can degrade performance and limit scalability. While machine learning remains relevant in specific applications and hybrid pipelines, its challenges highlight the need for continued innovation in brain MRI segmentation [7].

The rise of deep learning, particularly convolutional neural networks, revolutionized brain MRI segmentation by enabling automatic learning of hierarchical features from raw data. Architectures like U-Net, with its contracting and expansive paths connected by skip connections, excelled in capturing fine details and achieving state-of-the-art results. Fully convolutional networks (FCNs) further advanced the field by enabling end-to-end, pixel-wise segmentation without handcrafted features. However, deep learning methods face challenges, including the need for large, high-quality annotated datasets, which are costly and time-consuming to produce. Limited dataset diversity can hinder model performance and generalization, even with data augmentation. Additionally, the high computational cost of training, especially for 3D volumetric data, poses scalability and accessibility issues, particularly in resource-constrained settings. Despite these limitations, deep learning remains a transformative approach in brain MRI segmentation [2], [8], [9].

In this article, we advocate for the hybridization of the fuzzy c-means method [10] applied to brain MRI image segmentation, positioning it as a compelling alternative to purely machine learning and deep learning approaches. While ML and DL methods have revolutionized medical image segmentation with their ability to learn complex patterns and achieve state-of-the-art results, they come with significant challenges, including the need for large annotated datasets, high computational costs, and limited interpretability. In contrast, fuzzy c-means, a well-established unsupervised clustering technique, offers several unique advantages that can be enhanced through hybridization, making it a viable and efficient solution for brain MRI segmentation.

FCM is particularly well-suited for medical imaging due to its ability to handle the inherent ambiguity and uncertainty in tissue boundaries. Unlike traditional hard clustering methods, FCM allows pixels to belong to multiple clusters with varying degrees of membership, reflecting the partial volume effect often observed in MRI data. This flexibility makes FCM highly effective for segmenting brain tissues such as GM, WM, and CSF, where intensity distributions often overlap. However, traditional FCM presents serious limitations which can degrade its performance in complex MRI datasets.

- Firstly, it needs the right number of clusters which is not available in all cases.
- Secondly, it is very sensitive to initialization, deferent cluster centers initialization can lead to deferent clustering results.

– Thirdly, due to the principle of the iterative optimization of a cost function, it is strongly sensitive to the problems of local minima. These challenges can lead to suboptimal segmentation results, particularly in complex MRI datasets with intensity inhomogeneities or overlapping tissue distributions.

To address these limitations, we propose a hybrid approach that integrates FCM with ABC optimization [11]. This hybrid approach, referred to as FCM-ABC optimizer, leverages the strengths of both methods to address the limitations of traditional FCM while enhancing its accuracy, robustness, and efficiency. The integration of ABC with FCM is particularly justified in the context of brain MRI segmentation due to the unique challenges posed by medical imaging data. Brain MRI images often exhibit high variability in intensity, and anatomical structures, making it difficult for traditional methods to achieve consistent and accurate results. ABC-FCM optimizer addresses these challenges by combining the flexibility of FCM in handling uncertainty with the global optimization capabilities of ABC.

Moreover, the hybrid ABC-FCM approach aligns with the need for interpretable and clinically relevant segmentation methods. Unlike deep learning models, which often operate as “black boxes,” ABC-FCM provides transparent and intuitive results, making it easier for clinicians to understand and trust the segmentation outcomes. This is particularly important in medical applications, where interpretability and explainability are critical for clinical decision-making.

The integration of ABC with FCM addresses several key challenges in brain MRI segmentation:

– Improved initialization: ABC's global search capabilities optimize initial cluster centers, reducing the risk of poor initialization and enhancing segmentation accuracy.
– Escape from local optima: ABC helps FCM avoid local optima by exploring new regions of the solution space, ensuring that cluster centers converge closer to the global optimum.
– Computational efficiency: Although ABC adds complexity, its efficient search mechanism often leads to faster convergence, balancing accuracy and computational cost.
– Adaptability to complex brain structures: ABC's adaptive refinement of cluster centers makes it effective for segmenting complex brain structures (*e.g.*, gray matter, white matter, cerebrospinal fluid) and pathological regions (*e.g.*, tumors), handling the variability and intricacy of brain MRI data.

Our goal is to enhance segmentation accuracy by optimizing the FCM algorithm through the simultaneous optimization of its key parameters, including the objective function, the number of clusters, and the cluster center values, using the ABC algorithm. Once the optimal number of clusters and cluster center values are determined, the classification of all pixels is performed using the membership degree matrix. Our approach leverages the ABC algorithm's strong optimization capabilities, which ensure the discovery of the global optimum and allow for individuals of varying sizes in the initial population. These properties significantly improve the FCM algorithm, leading to more effective clustering. By integrating ABC with FCM, our proposed method addresses critical challenges in fuzzy clustering, such as determining the appropriate number of clusters, identifying optimal cluster centers, and achieving the optimal value of the objective function, all in a unified and simultaneous manner.

The remainder of the paper is organized as follows: section 1 introduces the paper. Section 2 reviews relevant studies on optimizing brain MRI image segmentation using fuzzy techniques. Section 3 presents the proposed clustering method based on the FCM-ABC optimizer. Section 4 discusses the experimentation and results, followed by the conclusion in section 5.

2. RELATED WORK

FCM method as unsupervised approach is widely studied and used as a powerful tool in a wide range of applications and successfully applied in medical image segmentation. In the field of brain MRI image segmentation, FCM algorithm is extensively utilized due to its ability to handle the uncertainty and complexity of medical images [12]–[15]. One of its main advantages is its ability to produce smooth and accurate segmentations, making it a valuable tool for medical diagnosis and treatment planning. However, the algorithm has some limitations, such as its sensitivity to noise and intensity inhomogeneity, which can lead to misclassification. Moreover, FCM requires prior knowledge of the number of clusters, and its computational cost can be high, especially for large medical datasets.

In recent years, researchers often integrate FCM with preprocessing techniques, hybrid models and optimization methods, such as particle swarm optimization, genetic algorithms, artificial bee colony, and gray wolf algorithm, to improve clustering accuracy, enhance robustness, and reduce computational complexity in brain MRI segmentation. Song *et al.* [16] proposed a fuzzy c-means clustering model with spatial constraint for unsupervised segmentation of brain magnetic resonance images. They incorporate the spatial distance and the gray level information between the local neighborhood pixels, combined with the non-linear weighting form in the similarity measure of the fuzzy clustering. In the proposed method [17] fuzzy kernel seed selection technique is used to define the complete brain MRI image into different groups of similar intensity. Among these groups the most accurate kernels are selected empirically that show highest resemblance with the tumor. The concept of fuzziness helps making the selection even at the boundary regions.

Genetic algorithms have been applied to fuzzy clustering for MRI segmentation. In study [18] an innovative approach to brain MRI image segmentation was presented. The researchers enhanced the traditional FCM algorithm by using GA for parameter optimization, which significantly improved segmentation accuracy. They integrate fuzzy set theory, fuzzy metrics, and Sugeno negation principles. When tested on the BraTS2018 dataset, their modified approach outperforming the conventional FCM method. This advancement is particularly significant for medical imaging analysis, as it better handles the challenges of uncertainty, noise, and ambiguity in MRI images.

Particle swarm optimization has been extensively utilized to enhance FCM by optimizing its cluster centers. For instance, PSO-FCM algorithms aim to reduce the impact of local minima and improve segmentation robustness by globally searching for better cluster configurations. These methods have shown promise in improving segmentation accuracy and computational efficiency. Dhanachandra and Chanu [19] combine dynamic particle swarm optimization (DPSO) with the FCM algorithm, addressing FCM's limitations such as sensitivity to initial values and noise. The proposed method dynamically adjusts inertia weight and learning parameters, enhancing global search capabilities while incorporating a noise reduction mechanism based on surrounding pixel attributes. The method shows improved robustness and accuracy in segmentation, making it a significant advancement in image processing. Mahesa and Wibowo [20] present an optimization method for brain tumor image segmentation using fuzzy c-means enhanced by PSO. The research addresses the inefficiencies of manual tumor segmentation, which delays patient treatment. By optimizing the objective function of FCM, the proposed FCM-PSO method achieved lower objective function values across six MRI T2 images, demonstrating improved segmentation accuracy compared to the original FCM. The findings suggest that integrating PSO with FCM can significantly enhance the reliability of automated brain tumor segmentation, facilitating timely medical decisions. Kavitha and Prabakaran [21] present an approach for brain tumor detection using a hybrid method combining assured convergence particle swarm optimization (ACPSO) and FCM clustering. It emphasizes the importance of pre-processing techniques, particularly the adaptive bilateral filter. The study compares various segmentation techniques, concluding that the proposed method significantly enhances tumor detection accuracy. Semchedine and Moussaoui [22] proposed a novel initialization approach for the fuzzy c-means algorithm based on fuzzy particle swarm optimization (FPSO) applied to brain MR image segmentation. The proposed method uses the FPSO algorithm to get the initial cluster centers of FCM according to a new fitness function which combines fuzzy cluster validity indices.

Gray wolf optimization (GWO) has been effectively used to optimize FCM by searching for the best cluster centroids, leading to improved clustering accuracy and robustness. By integrating GWO with FCM, the optimization process avoids local minima and enhances clustering performance, making it particularly useful in complex image segmentation and data clustering tasks [23]. Singh *et al.* [24] introduce a novel image segmentation method combining spatial fuzzy c-means (SFCM) clustering with the GWO, termed SFCMGWO, to enhance the accuracy of MRI image segmentation. The study demonstrates that SFCMGWO outperforms traditional SFCM and GA-based SFCM (GASFCM) in segmentation tasks, as evidenced by improved clustering validity functions. The effectiveness of the proposed method is validated through comparative analysis on two brain MRI images, where it achieves superior performance. Nayak *et al.* [25] a novel objective function called fuzzy entropy clustering with local spatial information and bias correction (FECSB) was proposed to enhance the accuracy of MRI brain image segmentation. The proposed hybrid approach maximizes the efficiency of FECSB in MRI brain image segmentation by combining PSO with GWO. The PSO-GWO clustering method outperforms the conventional FCM method, as shown by the experimental findings.

ABC has been employed to optimize FCM for MRI brain segmentation. These methods focus on improving convergence speed and segmentation accuracy in complex MRI datasets. For instance, the study in [26] introduces a new method for MRI brain tumor segmentation that combines the ABC algorithm with FCM clustering. It addresses the challenges of segmenting similar texture fields in MRI images by employing a fitness function based on two-dimensional grey entropy, derived from discrete wavelet transforms. The ABC algorithm optimizes threshold estimation, resulting in efficient segmentation with minimized noise. Experimental results demonstrate clear tumor delineation in segmented images, enhancing tumor intensity visibility. Alomoush *et al.* [27] a spatial information of fuzzy clustering-based mean best artificial bee colony algorithm (SFCM-MeanABC) is presented. This algorithm aims to enhance medical image segmentation, particularly for Phantom MRI brain images. SFCM-MeanABC integrates spatial information to mitigate noise effects and employs the MeanABC algorithm to balance exploration and exploitation, improving cluster center optimization. The method proved particularly effective at reducing noise sensitivity while maintaining accurate segmentation results compared to ground truth image. Authors in [28] combine the concept of the FCM and four-chain quantum bee colony optimization (FQABC). The FQABC algorithm overcomes the drawbacks of FCM which is sensitive to initial clustering centers. Performance evaluation experiments with FCM, FABC and FQABC have been done on real and magnetic resonance images. The experimental results show that the FQABC algorithm is more effective.

Other studies have employed the whale optimization algorithm (WOA) to enhance FCM for MRI brain image segmentation. By refining cluster centroids and enhancing the global search capability, WOA-FCM improves segmentation accuracy, speeds up convergence, and enhances robustness against noise and intensity variations, making it a promising approach for MRI brain analysis. A novel image segmentation method combining FCM with the WOA to enhance segmentation accuracy and noise reduction was presented in [29]. The proposed approach addresses FCM's limitations, such as sensitivity to initial values and noise, by utilizing WOA's global optimization capabilities. Experimental evaluations on synthetic and MRI images with various noise types show that the approach surpasses existing techniques, such as FCM and standalone WOA, by achieving lower mean square error (MSE) and higher peak signal-to-noise ratio (PSNR). A study in [29] introduces a new approach for image segmentation based on the WOA and FCM algorithm. Since exploration and exploitation phases are performed in nearly equal numbers of iterations separately, the WOA simultaneously shows better avoidance from local optima and superior convergence speed. To validate the performance of the proposed system, experiments are conducted on synthetic and MRI Images by taking various types of noise and the findings indicate that the proposed method is more efficient and effective.

Recent studies have also explored raindrop optimizer for FCM in MRI brain segmentation. In study [30] an improved FCM clustering method optimized with the raindrop algorithm (FCM-RO) for brain MRI segmentation was introduced. The proposed method incorporates a hybrid filter for noise reduction, achieving a well partition coefficient (PC) and partition entropy (PE) values across five MRI images, significantly outperforming traditional FCM. The study demonstrates that FCM-RO effectively extracts lesions, thereby improving diagnostic accuracy in medical imaging.

3. PROPOSED METHOD

In this section, prior to delving into the details of the proposed FCM-ABC optimizer method, we will first review the FCM and ABC algorithms. This foundational overview is essential for understanding how these two methodologies are integrated to address the limitations of traditional FCM, particularly in terms of parameter initialization, cluster center optimization, and the challenge of local minima. By revisiting the core principles and mechanisms of both algorithms, we aim to provide a comprehensive context for the development of our hybrid approach, highlighting the synergistic benefits that arise from their combination. Additionally, this background will facilitate a clearer understanding of how the proposed optimizer enhances the robustness and accuracy of brain image segmentation tasks, setting the stage for its application in complex real-world scenarios.

3.1. Fuzzy c-means algorithm

The FCM algorithm belongs to the family of clustering algorithms based on fuzzy function optimization. The standard version is firstly introduced by Dunn and generalized by Bezdek [10]. It has undergone many interventions leading to a lot of algorithms. All these algorithms are considered as soft clustering in the way that each element of the data to be clustered may belong to more than one cluster with deferent degrees of membership. The objective function is optimized in an iterative way and at the end of the process; each element is assigned to the cluster in which it has the highest membership.

Let $I = (x_1,\ x_2, \dots, x_N)$ an image of N pixels to be clustered into K $(2 < K \leq N)$ clusters, where x_i represents data features. The standard FCM objective function [10] is formulated as (1):

$$J(U, C) = \sum_{i=1}^{K} \sum_{j=1}^{N} u_{i,j}^{m} d^2(x_j, c_i) \tag{1}$$

U and $C = (c_1, c_2, \dots, c_K)$ are the memberships degrees matrix and a vector of clusters centers respectively. $m \in [1, \infty[$ is to control fuzziness, $d^2(x_j, c_i)$ is the grayscale Euclidean distance and $u_{i,j}$ is the membership degree of the pixel j in the i^{th} cluster c_i which must check the following constraints:
$\forall i \in [1, K], j \in [1, N]$:

$$\sum_{i=1}^{K} u_{i,j} = 1,\ u_{ij} \in\ [0, 1], \quad 0 \leq \sum_{j=1}^{N} u_{i,j} \leq N \tag{2}$$

An alternate optimization is applied on the membership function $u_{i,j}$ and clusters centers using (3) and (4):

$$u_{i,j} = \frac{(d^2(x_j,c_i))^{\frac{1}{1-m}}}{\sum_{l=1}^{K}(d^2(x_j,c_l))^{\frac{1}{1-m}}} \tag{3}$$

and

$$C_i = \frac{\sum_{j=1}^{N} {u_{i,j}}^m x_j}{\sum_{j=1}^{N} {u_{i,j}}^m} \tag{4}$$

The FCM algorithm begins with a random initialization of cluster centers and iteratively updates them using formulas (3) and (4) until no further improvement in their positions is observed. Once the cluster centers are stabilized, each pixel j in the image is assigned to the cluster for which it has the maximum fuzzy membership degree. This process ensures that every pixel is associated with the most relevant cluster based on its degree of belongingness, as determined by the algorithm's iterative optimization.

As discussed in section 2, formulating a global solution that effectively accounts for all parameters of FCM algorithm presents significant challenges. In fact, to address these challenges and solve the complex optimization problem posed by the FCM algorithm, we propose in this work an evolutionary algorithm (EA) based on the ABC algorithm. By integrating the ABC algorithm into the FCM framework, our proposed method seeks to simultaneously optimize multiple parameters, including the number of clusters, their initialization, and the overall objective function. The strengths of the ABC algorithm such as its strong global search capability, simplicity, and ease of implementation are leveraged to ensure that the FCM algorithm operates at its full potential, delivering more accurate and reliable results.

3.2. Artificial bee colony algorithm

ABC algorithm is an evolutionary algorithm bio-inspired [11]. It imitates the honey bee swarms in food foraging and successfully applied in various optimization problems**.** It operates through the collaboration of three types of bees: employed bees, onlooker bees, and scout bees, each with distinct roles in the search for nectar (or optimal solutions).

The employed bees are responsible for exploiting known food sources. Each employed bee represents a potential solution and assesses its quality based on a fitness function. They search in the vicinity of their assigned food source and can adjust their position to improve the solution. If a bee finds a better solution, it shares this information with the onlooker bees. The later monitor the quality of food sources shared by employed bees. They utilize a probability-based selection mechanism to choose which food source to explore based on its fitness. By concentrating on the most promising sources, onlooker bees contribute to the exploitation phase of the algorithm called also local search, further refining the search for optimal solutions. The scout bees present the explorative phase and they are responsible for exploring new areas of the search space to discover new food sources. Their random search helps maintain diversity in the population and prevents the algorithm from getting trapped in local optima. Through the coordinated efforts of these three types of bees, the ABC algorithm efficiently explores and exploits the solution space. The ABC algorithm begins food foraging (solution search) by producing randomly an initial population of *NS* bees in search space according to (5):

$$b_i = b_{min} + rand(0,1) * (b_{max} - b_{min}) \qquad i = 1, \dots, NS \tag{5}$$

where b_i is a bee, b_{min} and b_{max} are the upper and the lower values of the search space respectively.

After the initialization phase, the ABC algorithm evaluates the initial population and performs the three following steps until convergence to the optimal global solution (satisfactory fitness) or maximum iterations.

Step 1: Employed bee phase

- Each employed bee generates a new solution in the neighborhood using expression (6):

$$b_i^{k+1} = b_i^k + \varphi_q\left(b_i^k - b_B^k\right) \qquad i = 1, \dots, NS \tag{6}$$

  where φ_q is a random number in the range $[-1,1]$, b_i^k and b_B^k are the *i^th^* solution and the best solution of *k^th^* iteration respectively and b_i^{k+1} represents the updated solution.
- Evaluate the new solution's fitness.
- If the new solution is better, update the current solution and memorize the new one.

Step 2: Onlooker bee phase
- Each onlooker bee selects a source food b_i with a probability proportionally to the quality of the nectar (the solution). The probability $P_i$of selecting the source food b_i is calculated according to (7):

$$P_i = \frac{f(b_i)}{\sum_{j=1}^{NS} f(b_j)} \qquad i = 1, \dots, NS \tag{7}$$

  where $f(b_i)$ is the fitness of the solution b_i.
- Generate new solution for the selected food source using (6)
- Update solutions if improvements are found.

Step 3: Scout bee phase
- If any food source presents no improvements for a number of cycles, it is abandoned.
- If so, replace it with a new random food source using (5).
- Return to the employed bee phase.

Step 4: Termination
- If the stopping criterion is met or the maximal iteration number is reached, return the best bee (optimal solution).

To reach the global optimum, the ABC Algorithm balance between exploitative search and exploratory search and the both in random manner.

3.3. Proposed FCM-ABC optimizer method

In this work, a new enhancement of FCM called FCM-ABC optimizer is introduced; it is based on the ABC algorithm. Although the FCM has advantages like efficacy, simplicity and computational efficiency, it nonetheless has major drawbacks such as number of clusters, cluster centers values and is easily trapped in local optima. So, the main objective is to overcome these major drawbacks that will affect the clustering in term of precision. For this purpose, we improve the FCM clustering by exploiting ABC algorithm in order to find simultaneously the right number of clusters and the optimal clusters centers for a given image *I* of *N* pixels. ABC algorithm combines between exploitation and exploration to find the optimal values of FCM parameters. It ensures the searching in all directions in the solution space.

To achieve this objective, first, each bee b_i consists of a vector comprising two parts. The first part maintains the number of clusters while the second maintains the values of the centers of these clusters in Figure 1.

Nbc_i	Val_1^i	Val_2^i	………….	Val_{Nbc}^i

Figure 1. Structure of a bee

where Nbc_i is the number of clusters of the image to be segmented. This number is between 2 and maximum number of clusters ($MaxNbc$). Val_j^i is the value of the center c_j of the bee b_i which is the grey levels of the input image *I*.

Second, we develop a new objective function *F* in order to evaluate solutions fitness. This function ensures the optimal values of the cluster's centers and the right number of clusters. It exploits the objective function of the FCM algorithm and a validity index. It is defined as:

$$F(b_i) = W_1 F1(b_i) + W_2 F2(b_i) \qquad i = 1, \dots, NS \tag{8}$$

where $F1(bi)$ corresponds to the standard FCM objective function, which minimizes the weighted sum of squared distances between data points and cluster centers. The second term, $F2(bi)$, represents a clustering validity index that evaluates the quality of the resulting partitions in terms of compactness and separation. The weights W_1 and W_2 control the relative importance of each component in the overall optimization process.

The motivation behind this hybrid formulation lies in addressing the limitations of using FCM alone. While FCM effectively minimizes intra-cluster variance, it does not inherently ensure well-separated or meaningful clusters, especially when the optimal number of clusters is unknown or the data contains overlapping structures. Incorporating a validity index as an additional criterion enhances the ability of the algorithm to identify more compact and distinct clusters, thereby improving overall segmentation quality.

By combining both objectives, the proposed function enables a balanced trade-off between minimizing within-cluster distortion (via FCM) and maximizing cluster validity (via the index). This dual-objective approach proves particularly beneficial in complex applications such as brain MRI segmentation, where accurate and interpretable clustering is essential for diagnostic reliability.

Both weights W_1 and W_2 can be adjusted depending on the specific requirements of the application or based on prior knowledge about the data structure. According to the structure of bee b_i, $F1$ is defined as (9):

$$F1(b_i) = \sum_{k=1}^{Nbc_i} \sum_{j=1}^{N} u_{k,j}^{m} d^2(x_j, Val_k^i) \tag{9}$$

x_j are the image pixels and d are the Euclidean distance.

$F2$ is a cluster validity index, known as the IMbalanced index (IMI Index), proposed by Liu *et al.* [31] to identify the optimal number of clusters. It is formally defined in (10).

$$F2(b_i) = \frac{\sum_{k=1}^{Nbc_i} \frac{\sum_{j=1}^{N} u_{k,j}^{m} d^2(x_j, Val_k^i)}{\sum_{j=1}^{N} u_{k,j}^{2}}}{\min_{l \neq k} \delta_{l,k} d^2(Val_l^i, Val_k^i) + \underset{l \neq k}{median}\, \delta_{l,i} d^2(Val_l^i, Val_k^i)} \tag{10}$$

where $\delta_{l,k} = \frac{\sum_{j=1}^{N} u_{l,j}}{\sum_{j=1}^{N} u_{k,j}}$.

3.3.1. General steps of the FCM-ABC optimizer

The general steps of the FCM-ABC optimizer method are outlined as follows, integrating the strengths of the FCM algorithm and the ABC optimization technique to achieve robust and accurate segmentation results:

Step 1: Initialization: we set the maximum number of clusters $MaxNbc$, and the number of cycle $NBcycle$, then an initial population of NS bees is generated in which each bee b_i, in its first part ought to be assigned a random value in the range $[2, MaxNbc]$,while each value Val_j^i in second part is initialized randomly using (5) according to the grey levels of the image *I*. For each bee b_i, we set the counter *"no-improvement-cycle"* to 0.

Step 2: Fitness evaluation: after calculating the membership value $u_{k,j}^i$ for each cluster centers c_k^i of the bee b_i $(i = 1, \dots, NS)$ using (3), we evaluate the fitness of all the bees in the population, $F(b_i)$ according to the (8). The bee with the best configuration is stored.

Step 3: Employed bee phase: in this step, each employed bee generates a new solution in the neighborhood according to (6). It consists of modifying each center c_k^i of each bee b_i slightly to find a better position through local exploration without affecting the number of clusters Nbc_i. Then, the new solution's fitness is evaluated. If the new solution is better, update the current solution. Otherwise increase the counter "*no-improvement-cycle*".

Step 4: Onlooker bee phase: based on the fitness values, we assign probability to each solution b_i using (7). According to these probabilities, each onlooker bee chooses a solution and applies modifications using (6) to further refine the clusters centers.

Step 5: Scout bee phase: to enhance the capability to exploit the global search, we sort the bees according to (10) and we abandon all bees that the "*no-improvement-cycle*" exceeds $NBcycle$. If any abandoned bee belongs to the L highest bees, we replace the abandoned bees with new configurations, a random number of clusters and new cluster centers using (5), else we keep the number of clusters and we reset randomly only the cluster centers.

Step 6: Loop: steps from 2 to 5 are repeated until the objective function F became less than a threshold or maximum number of iterations is reached.

Step 7: Termination: finally, we use the best configuration stored of the number of clusters and their centers to perform a last calculation of pixel memberships $u_{i,j}$ according to FCM. We assign each pixel of the image I to center for which the memberships $u_{i,j}$ is higher for the purpose to generate the segmented image.

3.3.2. FCM-ABC optimizer algorithm

Our proposed method is summarized in the pseudocode presented in Figure 2. The pseudocode outlines the key steps and logic of the FCM-ABC optimizer, highlighting how the ABC algorithm is integrated with the FCM framework to achieve robust and accurate segmentation results. Each step in the pseudocode corresponds to a specific phase of the optimization process, ensuring clarity and reproducibility of the method.

FCM-ABC optimizer algorithm

```
Input: original image I
1.  fix the parameters MaxNbc, NS, e, NBcycle, L lowest bees, MaxIteration.
2.  generate randomly an initial population of bees b_i (i = 1,2,…,NS).
3.  it=0
4.  for each bee b_i, fix "no-improvement-cycle" to 0.
5.  repeat
6.  it=it+1
7.  for each bee b_i
    calculate the membership value u_{i,j} using (3)
    calculate the fitness function F(b_i) according to (8).
8.  endfor
9.  select the lowest fitness Fl, memorize the best solution Bbest.
10. for each bee b_i
    generate a new solution bnew according to (6).
    evaluate the bnew's fitness.
    If bnew is better, b_i=bnew.
    else "no-improvement-cycle"++.
    calculate the solution probability using (7).
11. endfor
12. applied greedy algorithm to update solutions that have the highest probabilities
    using (6).
13. evaluate their fitness according to (10).
14. ElitBee =L lowest bees
15. for each bee b_i
    if "no-improvement-cycle">NBcycle
    if b_i ∈ ElitBee, replace b_i with new clusters centers without affecting the number of
    clusters Nbc_i
    else generate a new solution for b_i according to (5).
16. endfor
17. until (Fl < e or it >= MaxIteration)
18. Calculate the membership value u_{i,j} according to Bbest.
```

Figure 2. Pseudo code of FCM-ABC optimizer

4. EXPERIMENTAL RESULTS

The performance of the FCM-ABC optimizer algorithm depends on several key parameters. These parameters are selected to balance exploration, exploitation, and computational efficiency. The population size refers to the total number of bees, including employed, onlooker, and scout bees, typically set between 50 and 100. This range balances exploration and computational efficiency: a larger population enhances solution diversity and search space exploration, helping avoid local optima, while a smaller size reduces computational overhead. For brain MRI segmentation, a population size of 50 is chosen as it effectively explores the high-dimensional search space of cluster centers without incurring excessive computational costs.

In our implementation, the maximum number of iterations is set to 300. Typically, values between 100 and 500 iterations are recommended in optimization tasks, including medical image segmentation. The number of iterations plays a crucial role in balancing exploration and computational efficiency, the higher the number, the more thoroughly the algorithm can explore the search space and refine potential solutions. However, this also results in increased computation time. In the context of brain MRI segmentation, where convergence is often achieved within this range, 300 iterations provide a reasonable trade-off between accuracy and performance, allowing the algorithm to converge effectively without unnecessary resource consumption.

To avoid stagnation in a local minimum, we set maximum number of cycles ($MaxNbc$) to 10, which limits the number of consecutive cycles without improvement and helps maintain a balance between exploration and exploitation during the optimization process. In the objective function, the weights W_1 and W_2 are both set to 0.5, ensuring a balanced contribution of the individual components in the optimization process.

4.1. Metrics used for segmentation evaluation

The evaluation of brain MRI segmentation performance relies on several metrics to quantify accuracy, robustness, and consistency [32]. In cases where the ground truth is available, we use Jaccard Similarity Metric. In cases where the ground truth is unavailable, it becomes necessary to rely on internal validation indices to evaluate the quality of the clustering results. By utilizing these indices in combination, we can obtain a comprehensive evaluation of the clustering outcomes, ensuring that the proposed method achieves optimal performance even in the absence of ground truth information. This approach not only enhances the reliability of the segmentation process but also enables meaningful comparisons with other clustering techniques under similar conditions.

4.1.1. Jaccard similarity metric

The Jaccard similarity (or Jaccard Index) measures the overlap between two sets, in this case, the segmented region and the ground truth. It is defined as (11):

$$JS_k = \frac{|A_k \cap B_k|}{|A_k \cup B_k|} \tag{11}$$

where A_i and B_i are the total number of pixels labeled into the cluster k identified by the clustering algorithm and the ground truth respectively. The cluster k is well detected when the value of JS_k is near 1.

4.1.2. Partition coefficient index

The partition coefficient index (PCI) measures the fuzziness of the clustering result. It is defined as (12):

$$PCI = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^2 \tag{12}$$

4.1.3. Partition entropy index

The partition entropy index (PEI) measures the uncertainty or randomness in the clustering result. It is defined as (13):

$$PEI = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}\, log\left(u_{ij}\right) \tag{13}$$

4.1.4. Davies-Bouldin index

The Davies-Bouldin index (DBI) measures the compactness and separation of clusters. It is defined as (14):

$$DBI = \frac{1}{K}\sum_{i=1}^{K} \underset{i \neq j}{max} \left(\frac{S_i + S_j}{D_{i,j}}\right) \tag{14}$$

where S_i is the mean distance between the center of the cluster *I* and all the points belonging to this cluster and $D_{i,j}$ denotes the distance between the centroids of the clusters *I* and *J*.

4.2. Experimental results on simulated brain MR images

The following experiments were conducted using simulated brain database (SBD) [33]. The SBD provides synthetic MRI brain images with known ground truth segmentations, making it ideal for validating segmentation algorithms. The images simulate different intensity inhomogeneities, and slice thicknesses, mimicking real-world MRI challenges. This database includes ground truth information for tissue of WM, GM, and CSF. It offers a controlled setting to assess the algorithm's accuracy and its ability to handle intensity inhomogeneity effectively.

The proposed FCM-ABC optimizer method was initially tested on a T1-weighted brain MR image with dimensions of 217×181 pixels, which includes 20% grayscale non-uniformity to simulate real-world imaging challenges. The primary objective of this application was to accurately segment and identify critical brain regions, namely WM, GM, and CSF. These tissue types are fundamental for radiologists in their analysis and diagnosis of various neurological disorders and diseases.

Figure 3 provides a visual representation of the segmentation results, allowing for a direct comparison of the performance of four different algorithms: FCM, GA-FCM, FCMA-ES, and the proposed FCM-ABC optimizer method. To provide context, the original brain image is shown in Figure 3(a), while its corresponding ground truths for WM, GM, and CSF are displayed in Figure 3(b). The segmented images produced by the FCM, GA-FCM, FCMA-ES, and FCM-ABC optimizer methods are presented in Figures 3(c), 3(d), 3(e), and 3(f), respectively.

From Figure 3, it is clear that the proposed FCM-ABC optimizer method outperforms the other methods in terms of accurately extracting brain tissues. A closer examination reveals that the FCM-ABC optimizer method effectively maintains regional homogeneity, ensuring that the segmented regions are consistent and uniform. Additionally, the algorithm preserves more detailed information from the original MR image, which is crucial for maintaining the integrity of the anatomical structures being analyzed. This ability to retain fine details is particularly advantageous in medical imaging applications, where subtle variations in tissue types can have significant diagnostic implications. Furthermore, the FCM-ABC optimizer method demonstrates superior performance in delineating the boundaries between different tissue types. It accurately marks out the WM and GM regions, ensuring that these critical structures are well-defined and distinct achieving a level of precision that surpasses the other methods.

(a)

(b)

(c)

(d)

(e)

(f)

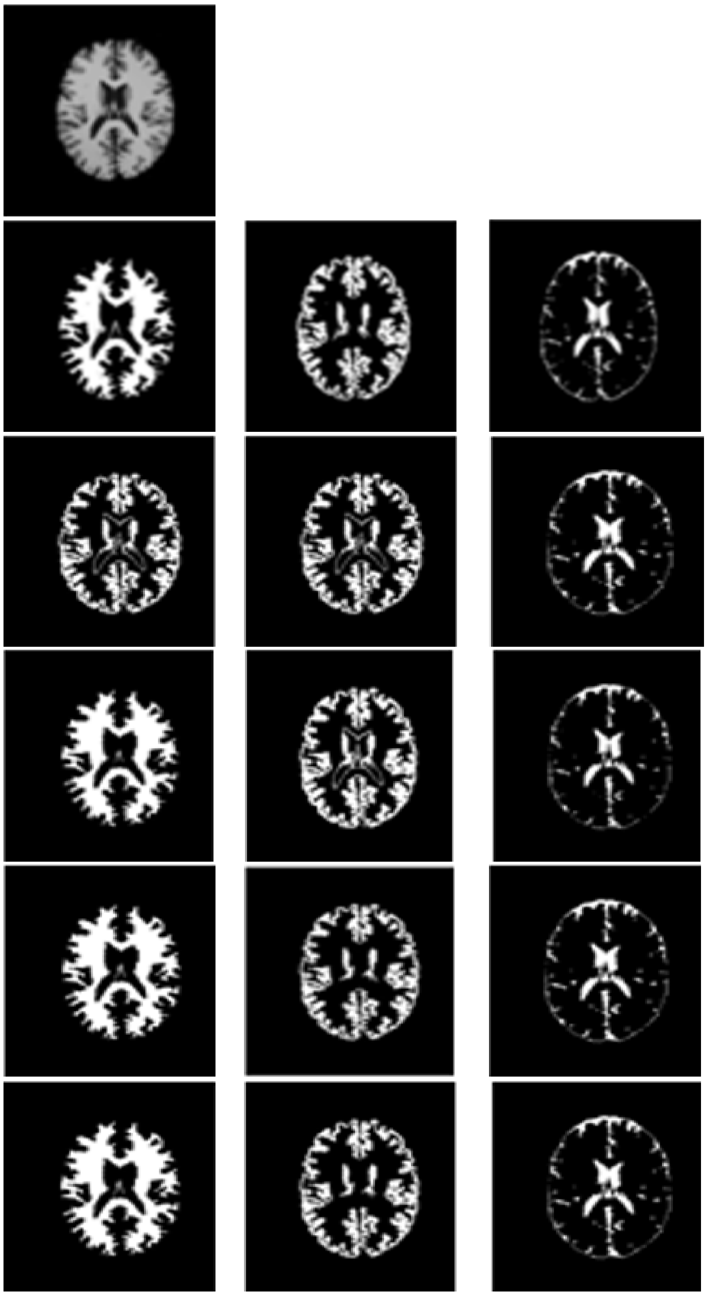

Figure 3. Segmentation results of the four methods on the simulated MRI image (a) original image, (b) ground truth image (WM, GM, CSF), (c) FCM, (d) GA-FCM, (e) FCMA-ES, and (f) FCM-ABC optimizer

4.3. Experimental results on clinical brain MR images

To further evaluate the performance of the algorithm, real clinical MRI images were selected from the open access series of imaging studies (OASIS) dataset [34]. OASIS is a publicly available dataset containing real brain MRI scans from healthy and Alzheimer's disease patients. It includes T1-weighted images with diverse anatomical variations and pathologies. It ensures the algorithm's applicability to real-world clinical data, including pathological cases, enhancing its practical utility.

Experiments were conducted on multiple images from this database. The performance of the proposed FCM-ABC optimizer method was compared with the FCM and FCMA-ES methods. The effectiveness of the three methods was evaluated using the DBI, PCI and PEI metrics where the results are shown in Table 1.

Table 1. Performance results with DBI, PCI, and PEI metrics on the clinical brain MR images

Original image	Index	FCM	FCMA-ES	FCM-ABC optimizer
Image1	DBI	0.42	0.41	0.36
	PCI	0.90	0.92	0.96
	PEI	0.19	0.15	0.12
Image 2	DBI	0.44	0.42	0.43
	PCI	0.89	0.93	0.91
	PEI	0.21	0.19	0.14
Image 3	DBI	0.52	0.47	0.42
	PCI	0.87	0.89	0.92
	PEI	0.23	0.22	0.16
Image 4	DBI	0.46	0.45	0.46
	PCI	0.88	0.89	0.88
	PEI	0.21	0.21	0.21
Image 5	DBI	0.61	0.38	0.41
	PCI	0.85	0.95	0.91
	PEI	0.31	0.13	0.18
Image 6	DBI	0.46	0.39	0.37
	PCI	0.89	0.94	0.96
	PEI	0.22	0.15	0.12
Image 7	DBI	0.45	0.49	0.42
	PCI	0.89	0.88	0.91
	PEI	0.23	0.24	0.21
Image 8	DBI	0.51	0.46	0.43
	PCI	0.86	0.89	0.91
	PEI	0.25	0.21	0.19
Image 9	DBI	0.44	0.41	0.42
	PCI	0.88	0.93	0.93
	PEI	0.21	0.19	0.19
Image 10	DBI	0.46	0.41	0.41
	PCI	0.87	0.93	0.93
	PEI	0.22	0.18	0.19
Mean result	DBI	0.47	0.43	**0.41**
	PCI	0.87	0.91	**0.92**
	PEI	0.23	0.19	**0.17**

Figure 4 illustrates the segmentation results obtained from processing 10 brain images using three different methods: FCM, FCMA-ES, and the proposed FCM-ABC optimizer method. The figure is organized into four columns for ease of comparison. The first column displays the original images, providing a reference for the subsequent segmentation outcomes. The second column shows the results produced by the traditional FCM algorithm, while the third column presents the segmentations generated by the FCMA-ES method. Finally, the fourth column highlights the segmentations achieved using the proposed FCM-ABC optimizer approach.

By visually comparing the segmented images across the three methods, it becomes evident that the FCM-ABC optimizer method offers superior performance in terms of clarity, detail preservation, and accurate delineation of tissue boundaries. This visual comparison aligns with the quantitative evaluations presented in Table 1, reinforcing the conclusion that the proposed FCM-ABC optimizer method represents a significant advancement in brain MRI image segmentation.

From the results presented in Table 1, a detailed comparison between the proposed method and the traditional FCM and FCMA-ES algorithms reveals that our algorithm consistently achieves superior performance across various evaluation metrics. These metrics provide a comprehensive assessment of the clustering quality, highlighting the strengths of the proposed approach in terms of both compactness and separation of clusters, as well as the clarity and certainty of cluster assignments.

Firstly, when considering the DBI, which evaluates the quality of clustering by simultaneously assessing the compactness of individual clusters and their separation from one another, our algorithm demonstrates a significant advantage. In this regard, our algorithm achieved an average DBI value of 0.41, which is notably lower than those obtained by the FCM and FCMA-ES methods. This result strongly suggests that the proposed method is more effective at ensuring that the final clusters in the image are well-defined and distinctly separated, thereby improving the overall segmentation quality.

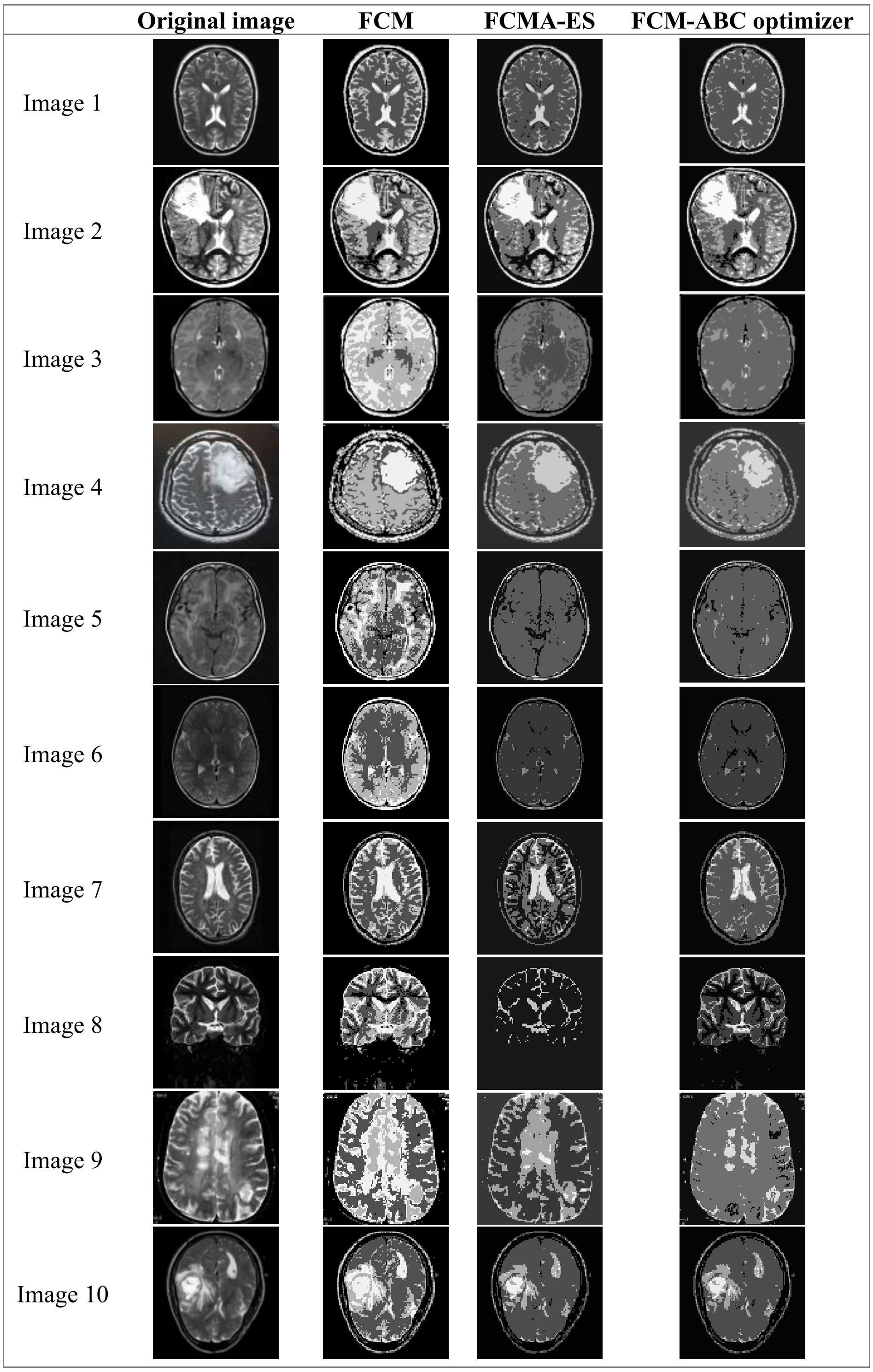

Figure 4. Segmentation results on the clinical brain MR images with FCM, FCMA-ES and FCM-ABC optimizer

Secondly, the PCI further corroborates the superiority of our algorithm. The PCI measures the degree of fuzziness in the clustering process, with higher values indicating clearer partitioning and less overlap between clusters. Our algorithm achieved an impressive average PCI value of 0.92, surpassing the results of the other methods. This high PCI value, which remains consistent across all test images, indicates that the cluster memberships are predominantly closer to 0 or 1. In other words, the data points are assigned to clusters with greater certainty, resulting in reduced fuzziness and a more definitive partitioning of the image.

Lastly, the PEI provides additional evidence of the robustness of our algorithm. The PEI quantifies the uncertainty or randomness in the membership assignments, with lower values reflecting more certain and well-defined clusters. Our algorithm achieved an exceptionally low average PEI value of 0.17, significantly outperforming the other methods. This low PEI value underscores the minimal overlap between clusters and highlights the algorithm's ability to assign data points to clusters with greater confidence and precision. In order to evaluate the effectiveness of our proposal FCM-ABC optimizer, its performance is compared with other related works using simulated and real brain MRI.

The Jaccard similarity scores presented in Table 2 provide a comprehensive comparison of various fuzzy clustering methods for segmenting WM and GM in brain MRI images. The proposed FCM-ABC optimizer demonstrates superior performance, achieving the highest Jaccard scores for both WM (0.91) and GM (0.83) segmentation. This indicates that our method better captures the complex tissue boundaries and spatial distributions compared to existing approaches. The improved performance of our method can be attributed to several factors. First, the ABC optimization helps escape local minima during clustering, leading to more accurate segmentation. Second, the adaptive parameter tuning in our approach better handles the intensity inhomogeneity common in brain MRI, particularly in GM regions. Third, the method demonstrates robust performance across both tissue types, unlike some approaches that excel in one but falter in the other.

Table 2. Jaccard similarity scores for WM and GM segmentation across different fuzzy clustering methods

Method	WM	GM
GA-FCM [12]	0.89	0.83
FCMA-ES [12]	0.91	0.82
FSMIB [15]	0.85	0.79
AFCM [16]	0.82	0.71
LDCFCM [17]	0.83	0.74
FCM [35]	0.88	0.80
FCM-ABC optimizer (Proposed)	0.91	0.83

The PCI and PEI scores in Table 3 provide crucial insights into the effectiveness of different fuzzy clustering algorithms. Our proposed FCM-ABC optimizer demonstrates superior performance, achieving the highest PCI score (0.92) and one of the lowest PEI scores (0.17), indicating excellent clustering quality with minimal uncertainty. The proposed method's PCI score of 0.92 surpasses all other approaches, including FQABC (0.90) and FPSOFCM/DPSO (both 0.89). This significant improvement suggests our proposed FCM-ABC optimizer produces more distinct and well-separated partitions. The standard FCM [35] shows the weakest PCI performance (0.70), highlighting the limitations of conventional fuzzy clustering without optimization. Notably, while FABC [28] incorporates ABC principles, its PCI (0.81) is substantially lower than our method, emphasizing the importance of our specific implementation improvements. Our method's PEI score of 0.17 is only slightly better than DPSO (0.18) and significantly lower than FABC (0.36) and standard FCM (0.42). This indicates our clusters have less ambiguity and overlap compared to these methods. Interestingly, FQABC (0.18) and FPSOFCM (0.21) show competitive PEI scores, but our method maintains an advantage while also achieving superior PCI performance. The high PEI of FABC (0.36) suggests that while basic ABC integration helps, our enhanced approach better manages partition uncertainty.

Table 3. PCI and PEI scores for various fuzzy clustering algorithms

Method	PCI	PEI
AFCM [16]	0.86	0.07
FPSOFCM [22]	0.89	0.21
FABC [28]	0.81	0.36
FQABC [28]	0.90	0.18
FCM [35]	0.70	0.42
DPSO [36]	0.89	0.18
FCM-ABC optimizer (Proposed)	0.92	0.17

The experimental results presented in this study demonstrate the effectiveness and superiority of the proposed FCM-ABC optimizer for brain MRI image segmentation. By integrating the ABC algorithm with the FCM framework, our method addresses several key limitations of traditional FCM, including sensitivity to initialization, local minima, and the need for prior knowledge of the number of clusters. The results highlight the robustness, accuracy, and adaptability of the FCM-ABC optimizer, making it a promising tool for medical image analysis. The implication of the results is summarized as follows:

a. Improved segmentation accuracy:
   - The FCM-ABC optimizer consistently outperformed traditional FCM, GA-FCM, and FCMA-ES methods across both simulated and clinical datasets. This is evidenced by higher JS values for critical brain tissues such as WM, GM, and CSF. For example, on the simulated dataset, the FCM-ABC optimizer achieved an average JS score of 0.8917, surpassing the scores of FCM (0.86), GA-FCM (0.87), and FCMA-ES (0.88).
   - The improved accuracy is particularly significant in clinical applications, where precise segmentation of brain tissues is crucial for diagnosing and monitoring neurological disorders such as Alzheimer's disease, brain tumors, and ischemic strokes. The ability of the FCM-ABC optimizer to maintain region homogeneity while preserving fine details ensures that subtle anatomical structures are accurately delineated, which is essential for reliable diagnosis and treatment planning.

b. Superior clustering quality:
   - The evaluation using internal validation indices such as the DBI, PCI, and PEI further underscores the superiority of the FCM-ABC optimizer. The method achieved an average DBI of 0.41, indicating well-defined and distinctly separated clusters. Additionally, the high PCI value of 0.92 and low PEI value of 0.17 suggest that the clustering results are less fuzzy and more certain, with minimal overlap between clusters.
   - These results are particularly significant in the context of brain MRI segmentation, where overlapping intensity distributions between tissues (e.g., GM and WM) often lead to ambiguous clustering results. The FCM-ABC optimizer's ability to produce clear and definitive clusters ensures more accurate and interpretable segmentation outcomes.

5. CONCLUSION

In this work, we have successfully introduced a novel FCM-ABC optimizer method that addresses a significant limitation in traditional FCM-based brain MRI image segmentation. By integrating the strengths of the ABC algorithm with the FCM framework, the proposed method enhances the performance, robustness, and adaptability of the segmentation process. A key innovation of our approach lies in its ability to simultaneously optimize multiple critical parameters of the FCM algorithm, including the objective function, the number of clusters, and the initial cluster center values. This capability significantly improves the flexibility and accuracy of the segmentation process, enabling it to better handle the complexities inherent in medical imaging data.

Our experimental results, conducted on both simulated (SBD) and clinical (OASIS) brain MRI datasets, demonstrate the effectiveness and superiority of the proposed FCM-ABC optimizer compared to conventional approaches such as standard FCM, GA-based FCM, and fuzzy covariance matrix adaptation evolution strategy. The proposed method consistently achieved higher accuracy, as measured by metrics such as JS, PCI, PEI, and DBI, across diverse imaging conditions, including varying intensity inhomogeneity. One of the standouts features of the proposed method is its ability to maintain region homogeneity while preserving detailed information from the original MR images. This is essential for accurately segmenting critical brain regions, such as gray matter, white matter, and cerebrospinal fluid, which are often challenging due to their subtle intensity variations and spatial overlaps. The FCM-ABC optimizer's robustness to noise and its ability to handle pathological cases further highlight its potential for real-world clinical applications.

Future research directions for the proposed method include extending it to multi-modal MRI data (*e.g.*, T1-weighted, T2-weighted, FLAIR) to enhance segmentation accuracy and robustness, optimizing the FCM-ABC optimizer for real-time applications such as surgical planning and intraoperative imaging, and generalizing its use to other imaging modalities like CT and PET for broader applicability.

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