Medical Image Processing by Swarm-Based Methods

María-Luisa Pérez-Delgado and Jesús-Ángel Román-Gallego

1 Introduction

There are several techniques to obtain medical images, such as x-ray, magnetic resonance (MR) imaging, computed tomography (CT), positron emission tomography (PET), ultrasound (US) or single-photon emission computed tomography (SPECT). In general, each technique is applied to specific parts of the body and generates a different type of image (Fig. 1).

The images obtained by all these methods provide very useful information to help experts in making medical decisions. For this, it is necessary to process the images to extract useful information. Currently, there are several different methods available to apply each processing. It must be taken into account that many image processings have a high computational cost due to the dimensionality of the data. This makes it necessary to use rapid techniques that allow obtaining good results. Among such techniques, swarm-based algorithms have been successfully applied in various image processing operations. This chapter shows the application of swarm-based methods for medical imaging. In general, these methods are combined with others to define a system that addresses various aspects of image processing. Although there are many articles related to the subject, the description focuses on analyzing recent works that present interesting proposals.

Many image processing operations are closely related and are often applied sequentially to an image. For example, feature extraction and feature selection are two operations that are usually applied to an image consecutively. The first operation extracts a set of features from the image, which allow representing the image and at the same time reducing the dimensionality of the data to be treated. Subsequently,

M.-L. Pérez-Delgado (✉) · J.-Á. Román-Gallego
University of Salamanca, Escuela Politécnica Superior de Zamora, Zamora, Spain
e-mail: mlperez@usal.es; zjarg@usal.es

S. Pandey et al. (eds.), *Role of Data-Intensive Distributed Computing Systems in Designing Data Solutions*, EAI/Springer Innovations in Communication and Computing, https://doi.org/10.1007/978-3-031-15542-0_14

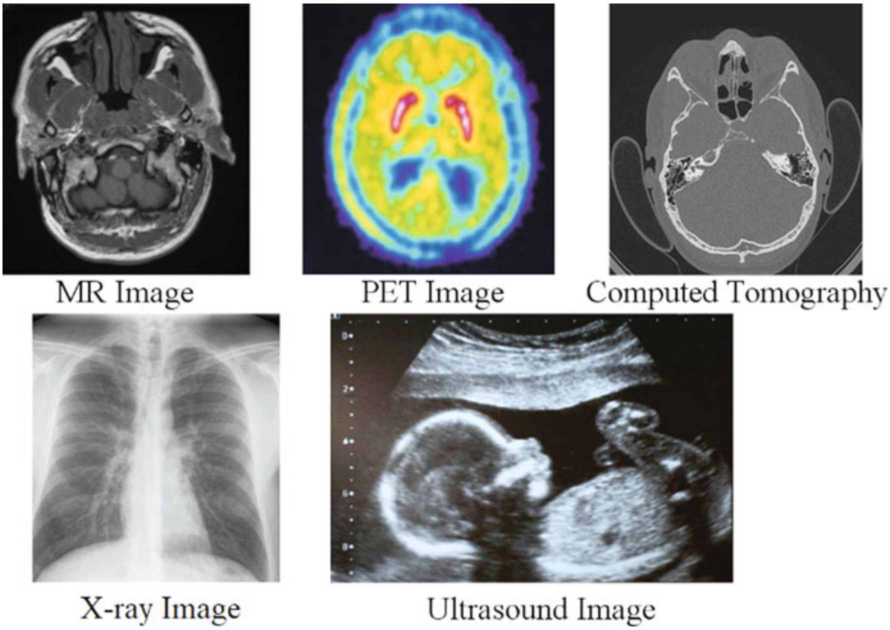

Fig. 1 Medical images obtained by different techniques

a subset is selected that includes only the most interesting features for the next processing that must be applied to the image.

Among the operations applied to medical images, the chapter focuses on four interesting cases: feature selection, segmentation, classification, and registration. A section is included to describe interesting works that use swarm algorithms to apply each of these processings. As already indicated, the processing of an image includes several operations that are carried out by applying different methods. For example, it is necessary to perform feature selection before applying a classification operation. Therefore, although all the operations described in the subsequent sections are related, it is easier to analyze them separately.

2 Swarm-Based Methods

Swarm-based methods apply a bioinspired approach to solve complex problems [1]. These algorithms try to imitate the intelligent behavior observed in several natural systems formed by a set of individuals that cooperate to face problems. Although everyone in the population can only perform simple tasks, the cooperation established among all individuals enables the population to perform complex tasks.

Swarm-based algorithms simulate this collective behavior and apply it to solve optimization problems. These methods have been applied to solve a variety of complex problems, generating good results compared to other existing methods [2–4].

Although there are various swarm-based algorithms, they all share the same basic structure. A population of individuals that represent solutions to the problem is considered, and an iterative process is applied in which the population shares information to move toward better positions in the search space. The initial solution represented by each individual is defined in the initialization step. This step generally associates each individual with a random solution of the search space. Then, an iterative process improves the current solutions associated with the individuals (some or all). To perform this improvement, it is necessary to compute the quality or fitness of the solutions. This value is computed by applying the objective function of the problem (or a modification of said function) to the solution represented by each individual. The solution with the best fitness of the current iteration represents the solution to the problem in that iteration, while the final solution of the problem is the best found throughout the iterations. Once the fitness of the solutions has been determined, the population shares information to try to move the individuals to better areas of the search space. The computations applied to perform this operation are different for each swarm-based method. Nevertheless, in all cases, some or all the individuals move to new positions (generally more promising positions) in the search space. The iterative process continues for a predefined number of iterations or until the solution converges.

The first swarm-based method proposed in the literature mimics the foraging behavior of ants. Several ant-based algorithms have been proposed over the years, [5]. The first one, called ant system, was applied to solve the well-known traveling salesman problem. To solve this optimization problem, the associated weighted graph is considered, and the algorithm looks for a minimum cost path on the graph. With this purpose, a set of ants is used that move on the graph. The ants share information through the pheromone that they deposit on the connections of the graph that they traverse. Each ant traverses the graph to define a path that passes through all the nodes once, choosing more likely connections that have low cost and large amounts of pheromone. When an ant has built its solution, it shares information with other ants by updating the pheromone of the graph's connections. The amount of pheromone that an ant contributes is proportional to the cost or quality of the solution it has found. As a result of this update, the connections that are part of the best solutions become more desirable to the ants in the next iteration of the algorithm. The solution to the problem is the lowest cost path found throughout the iterations. Algorithm 1 shows the basic steps that have been described above.

Algorithm 1: Ant-Based Algorithm
Initialize the pheromone of the graph connections
REPEAT
  Define a closed path for each ant
  Compute the cost of the solution defined by each ant
  Update the pheromone of the graph connections
  Update the best solution to the problem
UNTIL stop criterion is met

The particle swarm optimization (PSO) algorithm proposes a different approach to that proposed by the ant-based algorithm [6]. PSO is applied to solve an optimization problem that has an associated objective function. The solution to the problem is a vector whose size is equal to the number of dimensions of the solution space. To solve this problem, a set or swarm of particles is considered, and the position of each particle is a feasible solution to the problem. In addition to a position, each particle has a velocity and remembers the best position it has found throughout the iterations of the algorithm. The quality or fitness of a solution is calculated by applying the objective function of the problem. The algorithm begins by giving initial values to the particles in the swarm. Then, it applies an iterative process that allows the particles to move within the search space, to find a good solution to the problem. Each particle adjusts its position, based on both the best position reached by itself and the best position reached by the swarm. The best position found by the swarm throughout the iterations will be the solution to the problem. Algorithm 2 shows the basic steps of PSO.

Algorithm 2: PSO
Initialize the particles in the population
REPEAT
  Update the velocity of each particle
  Update the position of each particle
  Update the personal best position of each particle
  Update the best solution of the swarm
UNTIL stop criterion is met

The length of this chapter precludes detailing the operations of other swarm algorithms. However, the description given for PSO shows a general scheme followed by many of these algorithms. For example, this can be seen in the steps of the firefly algorithm (FA) [7] and the shuffled-frog leaping algorithm (SFLA) [8], shown in Algorithms 3 and 4, respectively. To complete the information associated with the algorithms that appear in this section, this chapter includes an appendix that shows the flowchart of each method along with the equations associated with the basic operations.

Algorithm 3: FA
Initialize the population of fireflies
REPEAT
  Sort the fireflies by brightness (fitness)
  Update all fireflies except the brightest one
  Update the brightest firefly
  Update the best solution to the problem
UNTIL stop criterion is met

The following sections of this chapter refer to some other swarm-based methods that cannot be described in this section due to space limitations. However, they are listed below, and a reference is cited where they are clearly described. The indicated methods are as follows: artificial bee colony (ABC) [9], bacterial foraging optimization (BFO) [10], bat algorithm (BA) [11], cat swarm optimization (CSO) [12], crow search (CRS) [13], cuckoo search (CUS) [14], flower pollination algorithm (FPA) [15], and gray wolf optimization (GWO) [16].

Algorithm 4: SFLA
Initialize the population of frogs
REPEAT
  Sort the frogs by fitness
  Create the memeplexes
  FOR each memeplex
    Improve the worst frog in the memeplex
  END-FOR
  Recombine the frogs of all memeplexes
  Update the best solution of the population
UNTIL stop criterion is met

3 Feature Selection

An image can be represented by a set of features drawn from it. They are obtained as a result of a feature extraction procedure, which is usually applied before other image processing operations, such as classification. Once the set of features that represent the image has been extracted, different operations can be applied to said image. In general, these operations do not use the entire feature set, but only the most suitable subset for the task to be performed. Therefore, a feature selection operation is applied to the initial feature set. The objective of feature selection is to reduce the initial set of features to a small subset, by selecting those that are the most relevant for the processing to be applied to the image and reducing the redundancy.

The proposal of Jona and Nagaveni defines a feature selection method that is applied to mammograms to detect breast cancer [17]. This method applies an ant-based algorithm called ant colony optimization (ACO) and uses the CUS algorithm to perform the local search of ACO. The method considers an initial set with 78 features. When the first iteration of ACO is applied, each ant randomly selects a subset of features. However, in subsequent iterations, the ants can only select features from the subsets used in the previous iteration to update the pheromone. CUS is used at each iteration to select the best features.

Sudha and Selvarajan described a feature selection method for breast cancer classification based on mammograms that uses a modification of the CUS algorithm [18]. The image is first segmented to extract the region of interest that contains the suspicious mass. The mass is then represented by a set of 123 features, and the CUS method is applied to select the most suitable subset of features to classify the image. Since the final objective of the feature selection process is to classify the images, the fitness function used for CUS is computed based on the classification accuracy of the nearest neighbor classifier.

Jothi combined FA with tolerance rough set to define a feature selection method for MR brain images in which the features are used for the detection of brain tumors [19]. The tolerance rough set is a feature selection method that can operate on real values [20]. The method described by Jothi first performs image segmentation. Then, feature extraction is applied to obtain 28 features (including shape, intensity-based features, and texture-based features). After this, the feature selection operation is applied by executing FA. This algorithm uses the similarity measures defined in the tolerance rough set to compute the similarity among fireflies.

The research reported in [21] describes a system for brain tumor grade identification based on the analysis of MR images. The system applies successive methods for image segmentation, tumor isolation, feature extraction, feature selection, and classification. The feature extraction operation obtains textural, non-textural, shape, and intensity-based features. Then, SFLA is applied to said features in order to select the best subset of features to perform the classification.

Sahoo and Chandra describe a system for classifying cervix lesions as benign and malignant [22]. This system applies a modified version of GWO to perform the feature selection operation. Since the original GWO was defined to solve single objective optimization problems, this article describes two variants for applying GWO to the multi-objective problem associated with feature selection.

Shankar et al. described a system for Alzheimer detection from MI brain images [23]. After identifying the region of interest in the image, the features of such region are extracted. The feature selection is then performed by applying the GWO algorithm that uses the classification accuracy as fitness function.

Tan et al. describe a method for the diagnosis of skin cancer applied to dermoscopic images, where a modified PSO is used for feature selection [24]. The PSO-based method is applied to the general set of image features to identify the most significant features of benign and malignant skin lesions. The main modifications of the PSO are the use of two subpopulations and a new equation to update the velocity of the particles, which considers the best particle of a sup-population and discards the worst particle. In addition, some updates are applied to selected subdimensions, while others are applied to all subdimensions.

A feature selection method to classify MR images of brain tumors is described in [25]. Said method is based on the Fisher criterion and a variant of BA. The modification introduced in BA tries to improve the exploration capacity of the basic algorithm. Many feature selection methods measure the importance of the feature subset by using the metric of classification accuracy. When the classification accuracy is used as the fitness criteria, the feature subset selected depends on the classifier considered. To avoid this limitation, the method proposed in this article uses the trace obtained via the Fisher criteria as a fitness function, instead of using the classification accuracy to define said function. The system described in the article completes the operation by applying a support vector machine (SVM) to perform the classification.

The proposal of Dandu et al. describes a method for the detection of brain tumors and pancreatic tumors where CSO is used for feature selection [26]. After performing image segmentation, scale-invariant feature transform is applied to extract features. CSO then selects the features that allow to distinguish the objects of different classes. After this, the classification is performed by applying a back propagation neural network. The method was applied to MR images and CT images.

4 Image Segmentation

Image segmentation consists of decomposing an image into regions that do not overlap. This operation makes it possible to identify interesting parts of the image for further analysis. Image segmentation is an important operation in the analysis of medical images, since it allows identifying areas of tissues, bones, or organs affected by different problems (Fig. 2). Segmentation makes it possible to determine the shape or volume of the affected area, and this information helps experts in making medical decisions.

Various approaches can be applied for image segmentation, such as clustering, thresholding, edge detection, or region identification.

Clustering algorithms are commonly used as segmentation techniques. These methods divide the pixels of the image into clusters or groups of similar pixels.

The research presented in [27] proposes a model for blood vessels segmentation that combines the matched filter method with the ant-based method called ant colony system [28]. Matched filter is a method commonly used for blood vessel detection, but the combination with the ant-based clustering method increases the accuracy of the results. In this case, the matched filter algorithm and the ant-based algorithm are applied in parallel, and the results of both methods are combined.

Hancer et al. describe an image segmentation method that applies ABC to extract brain tumors from MR images [29]. Segmentation is carried out by ABC, which is applied as a clustering method. In this case, each food source used by the

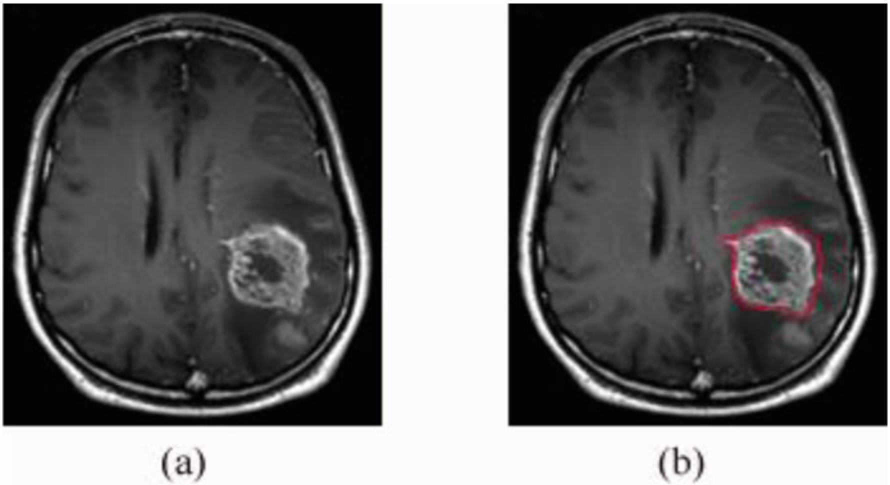

Fig. 2 Original brain image (**a**) and segmented suspicious area (**b**)

algorithm represents the centroid of each cluster. After this, the segmented image is converted into a binary image by applying thresholding, and finally, the brain tumor is extracted by applying connected component labeling.

Mostafa et al. describe a liver segmentation method that applies ABC [30]. This proposal uses ABC as a clustering method that identifies regions with different intensity in abdominal CT images. The initial liver area segmentation obtained by this method is then refined by a region-growing approach.

Fuzzy c-means (FCM) [31] is a clustering method that has been widely applied to image segmentation. This method is the fuzzy version of K-means [32]. Certainly, K-means and FCM are two very popular clustering methods. K-means separates a set of items into a predefined number of groups or clusters. Each item is assigned to the most similar group. Similarity is calculated by comparing the item and the cluster centroid, which is the mean value of the elements associated with that cluster. The process is applied iteratively to refine the centroids. In the case of FCM, each item can be associated with several groups. There is a membership value that determines the degree of association of each item with each cluster. It should be noted that the results of both methods are influenced by the initial centroids used.

The method described by Taherdangkoo et al. in [33] combines ABC with FCM to segment MR images. This proposal considers the method described by Shen et al. in [34] as a starting point. To improve the results obtained for noisy images, Shen et al. introduced two new parameters in FCM (the feature difference between neighboring pixels in the image and the relative location of the neighboring pixels) and computed them by a neural network. Since this operation is time-consuming, Taherdangkoo et al. proposed using ABC to compute these parameters. The proposal of Forghani et al. is also based on the method of Shen *et al*. but uses PSO to calculate the two new parameters [35].

PSO was used in [36] to select the optimal cluster centers for the FCM method that performs segmentation. Then, FCM was applied for MR brain images segmentation. The authors use a variant of FCM described in [37] and improve it by including three main modifications. First, PSO is used to initialize the FCM cluster centers. Second, the membership function of FCM considers outlier rejection. Third, the method considers spatial neighborhood information by using a square window around the pixel being processed.

The proposal of Alagarsamy et al. combines CUS with a variant of FCM (called type-2 FCM) to define a method for MR brain image segmentation [38]. In this case, an iterative process is defined where CUS and the FCM variants are applied sequentially until the solution converges. The same authors proposed another similar method where BA is used instead of CUS [39].

Kavitha and Prabakaran describe a method for the early detection of lung tumor on CT images [40]. In this case, PSO is used to select the initial cluster centers for the FCM clustering method that performs the segmentation. Before applying PSO, the filtered image is divided into five horizontal equidistant strips, and the second strip is taken to apply segmentation.

Thresholding methods are frequently used techniques for image segmentation. They separate the pixels in the image into two or more classes, based on their intensity, and determine the boundaries between classes. The methods used to calculate the thresholds can be divided into nonparametric and parametric, the former being more precise. Nonparametric methods determine the thresholds by optimizing a specific criterion. For example, the Otsu criterion selects optimal thresholds by maximizing the between-class variance [41]. On the other hand, entropy-based criteria maximize the sum of entropy for each class. The Kapur entropy [42], the Tsallis entropy [43], the minimum cross entropy [44], and the fuzzy entropy are very popular entropy-based approaches. Several articles use swarm-based algorithms to find optimal threshold values for the cited criteria. In this case, the fitness function of the swarm is defined based on one of the thresholding criteria described above.

The proposal described in [45] adapts the food-searching behavior of ants to define a thresholding method for medical image segmentation. This method was applied to MR brain images. The ants move on the image looking for food (similar pixels) and can memorize the food they found during this process. When an ant finds a new target, a fuzzy measure is used to evaluate the similarity between the target and the previous position. When the operation of the ants is completed, the pheromone deposited by the ants during their movement generates the segmentation results. The segmentation method described in [46] is the same as that described by [45], and it is also applied to the same type of images.

Menon and Ramakrishnan apply ABC to segment MR brain images and then use FCM to process the segmentation result [47]. The segmentation method is based on the use of gray levels and considers the entropy method for the threshold estimation. ABC is applied to determine the global threshold. In this case, the authors use an ABC-based method previously applied to satellite image segmentation [48]. Then, FCM is applied to cluster the segmented image, which allows identifying the brain tumor.

The proposal of Li et al. uses a variant of PSO to optimize the parameters for the Otsu criterion that is applied to perform image segmentation [49]. The PSO variant was previously proposed by the same authors in [50], using quantum uncertainty and cooperation mechanisms to prevent PSO from being trapped in local optima. The new article of the authors improves on this method by making better use of contextual information, which is evaluated after each particle is processed. The article shows the results of the method applied to CT images of a human stomach cavity. On the other hand, the research described in [51] proposes an improvement of the method presented in [49]. In this case, a set of auxiliary swarms is used to initialize the particles in the main swarm. To reduce the effect of local minima, the search space is partitioned into several regions, and each auxiliary swarm is associated with a region.

Rajinikanth et al. describe a method to extract a tumor from a two-dimensional gray scale brain MR image [52]. The method includes two stages. First, a multilevel thresholding operation is performed by applying the FA method with a fitness function that uses the Tsallis entropy. This operation enhances the tumor region by grouping the similar pixels. To conclude the first stage, the skull region is eliminated. The resulting image is then segmented into different partitions using the Markov random field model combined with an expectation maximization algorithm, which is a common method for gray scale image segmentation [53]. As a result, three image segments are obtained: white matter, gray matter, and tumor mass.

The proposal discussed in [54] uses CUS to define a segmentation method applied to microscopic images. The CUS method was applied considering three different objective functions: Otsu criterion, Kapur entropy, and Tsallis entropy. The article includes results that determine the efficiency of each of the variants in terms of the execution time and the quality of the final solution.

The proposal of Want et al. applies multi-threshold image segmentation by using FPA [55]. They use the Otsu criterion to define the objective function of the swarm-based method. In addition, they modify the basic method to increase population diversity. On the one hand, the article proposes a new mutation mechanism for FPA in which the solution vectors are selected in such a way that each vector represents a different region of the search space. On the other hand, a crossover operator is used to increase the population diversity in the local search process. The method was applied to medical images of several types, most of them corresponding to CT and MR images.

Edge-based methods used for segmentation attempt to detect edges in the image. This requires finding local intensity changes in the image. On the other hand, region-based methods try to identify groups of neighboring pixels with similar intensity.

The method described by Pereira et al. applies ACO to segment the optic disc in retinal images [56]. The pixels in the image are considered as the nodes of the graph that the ants can visit and the ACO algorithm is used as an edge detector. The ants move over the image driven by the local variation of the intensity values of the image. They then update a pheromone matrix with the same size of the image, which represents the edge information at each pixel of the image. At the end of the process, the pheromone matrix is analyzed, and a binary decision is made for each pixel, determining whether it is edge or not. The same authors used a similar approach to define a method for automatic identification of diabetic retinopathy lesions in fundus images [57]. In this case, the ACO algorithm was applied to segment exudates.

Another approach commonly used in image segmentation is that defined by active contour models. These models typically use energy-based segmentation techniques, thus attempting to minimize the energy associated with the active contour as it evolves to fit around the desired object. Therefore, it is necessary to solve an optimization problem whose objective is to minimize the total energy, to guarantee that the active contour is located at the limits of the object. An active contour problem is usually solved by the gradient descent method, but some swarm-based methods have also been applied.

PSO was applied in [58] for image segmentation based on active contours. This solution uses an active contour model method described in [59], which is a popular region-based model. The authors improve the results of said method by using PSO to solve the fitting energy minimization problem. The article shows the results obtained for various types of medical images.

The proposal of Ilunga-Mbuyamba et al. describes an active contour model approach for image segmentation that uses a CUS variant [60]. The method is applied to MR brain images to detect tumors. CUS is used to help control points converge toward the global minimum of the energy function. With this purpose, the method defines a local search space (window) for each control point from the current contour. Then, the control points are placed randomly inside each window, in order to obtain new ones by applying CUS.

The proposal presented in [61] describes an intensity-based statistical method that extracts the three-dimensional cerebrovascular structure from time-of-flight magnetic resonance angiography data. This segmentation method combines a new finite mixture model with an improved PSO variant. The information is modeled by a Rayleigh distribution function and two Gaussian distribution functions. In addition, the finite mixture model is used to fit the intensity histogram of the images. In this case, PSO is used to estimate the parameters of the finite mixture model that fits the intensity histogram of the image. The PSO variant uses a modified method to update the velocity of the particles and also considers that each particle can only share information with the neighbors that are within a ring around its position.

5 Image Classification

Medical imaging classification is generally used to identify suspicious areas. This operation allows identifying the images that correspond to healthy people and those that correspond to people with some disease (Fig. 3).

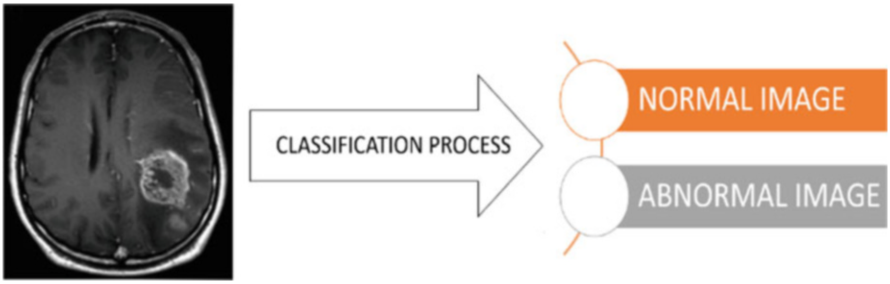

Fig. 3 A classification method can be used to differentiate between normal and abnormal images (images showing a health problem)

In general, a part of the image is selected, and the classification process is applied only to that part. Therefore, the classification operation is usually preceded by a segmentation operation, which identifies the region of interest.

There are several methods frequently referenced in the literature related with the classification of medical images, such as clustering methods, artificial neural networks, SVM, or FCM. The quality of the result obtained by any classification technique depends on the proper selection of its parameters. To aid in this task, swarm methods have been combined with these techniques to set the corresponding parameters.

Neural networks are trainable systems that learn to solve a problem from examples of that problem. The training process adjusts the weights associated with the network connections. Several research articles apply an artificial neural network to classify medical images and use a swarm-based method to train the network. In this case, each individual in the population represents the set of weights of the neural network.

A method that applies a forward neural network to classify MR brain images as normal or abnormal is proposed in [62]. The system applies principal component analysis for feature selection and uses the selected set as input for the neural network. The weights of this network are optimized by a PSO variant. The main difference of this variant with respect to the original algorithm is in the definition of the weights of the equation used to update the velocity of the particles. The fitness function used in this case is the mean squared error.

A method that combines PSO and ABC to classify MR brain images is described in [63]. The method classifies the images as normal and abnormal. It applies principal component analysis for feature selection before applying the swarm-based methods. The selected set is used as input of a feed-forward neural network that is optimized with a combination of two swarm methods. The article investigates the application of three different combinations of ABC and PSO previously proposed by other authors. The results show that the best combination is the one described in [64], which applies PSO and ABC in parallel and, at each iteration, recombines the best solution obtained by both methods.

Dheeba et al. defined a system to detect breast abnormalities on digital mammograms [65]. The method classifies mammograms into normal and abnormal. The feature extraction stage applied to the images allows obtaining texture information that is used in the classification stage. The classification is carried out by means of a neural network that uses the wavelet activation function, combined with the PSO method that is used to tune the initial network parameters. The method described in [66] considers the same problem and uses FA instead of PSO to optimize the parameters of a neural network that also uses the wavelet function.

A method that analyzes skin images to detect melanoma was proposed in [67]. This method combines GWO with a neural network to process cancer images. In this case, GWO is used to define the initial weights of a multilayer perceptron neural network. The method identifies two areas for classification (cancer and healthy) and classifies each pixel in the image into one of the two categories.

A classification method to identify brain tumors based on MR brain images is described in [68]. The images are classified as normal or abnormal by a supervised neural network that is combined with the GWO method to optimize the network parameters.

The proposal described in [69] combines swarm-based methods and deep learning to define a model for the detection and classification of lung cancer nodules from CT images. The model uses a convolutional neural network trained using a swarm-based method. The article analyzes the results obtained for seven swarm methods, including PSO, ABC, BFO, and FA. Computational experiments show that the best results are obtained when PSO is considered.

The method described in [70] for lung cancer diagnosis combines deep learning and a variant of the CRS algorithm. The objective is to find lung nodules in CT images and classify them as benign or malignant. The modified CRS is used to update the weights of the neural network during the training phase. The CRS-variant combines the original algorithm with the sine cosine algorithm proposed in [71]. This is a population-based method that creates a set of random initial solutions and requires them to fluctuate outward or toward the best solution by applying a mathematical model based on sine and cosine functions. Each individual in the resulting CRS-variant can select to update its location according to the CRS method or according to the sine cosine method.

SVM is a useful classification technique that has also been applied to classify medical images. The objective of the SVM algorithm is to find a hyperplane in a multidimensional space that clearly classifies a set of data points. When considering a nonlinearly separable problem, SVM can use a kernel, which is a function that takes a low-dimensional input space and transforms it into a higher-dimensional space, so as it turns a nonseparable problem into a separable problem. For the results obtained by SVM to be good, it is necessary to give adequate values to the parameters. Several researchers have applied swarm-based methods to set these parameters.

Zhang et al. proposed a method to classify MR brain images as normal or abnormal (abnormal images correspond to 17 different types of diseases) [72]. They apply a kernel SVM that replaces the dot product of the original SVM method with the radial basis function kernel. In addition, the method applies PSO to optimize the parameters of the SVM classifier.

ABC was used in [73] to analyze CT images in order to detect cervical cancer. The method classifies the input images as normal or abnormal. The system first segments the images to obtain the region of interest and then extracts textural features from that region. After this, three methods are proposed to perform the classification, which combine ABC with the k-nearest neighbor, SVM with linear kernel, and SVM with Gaussian kernel, respectively. The computational experiments reported in the article show that the best results are obtained with the third method.

Zhang et al. describe a system that classifies three-dimensional MR brain images and can distinguish images corresponding to Alzheimer's disease, mild cognitive impairment, and normal cases [74]. Although other methods initially determine the region of interest and then focus on it, this method considers the entire brain, so it is not necessary to apply a segmentation operation. The article analyzes the use of several SVM variants whose parameters are defined by the PSO algorithm with time varying acceleration coefficient. This PSO method modifies over time the weights of the components used to update the velocity of the particles (it gives more weight to the cognitive component at the former stage and gives more weight to the social component in the latter stage).

In the solution proposed by Ahmed et al., the classification is carried out using a method that combines GWO and SVM [75]. In this case, GWO is used to select the SVM parameters, and the kernel function used by SVM is the Gaussian radial basis function.

6 Image Registration and Fusion

As indicated in the introduction section, medical images can be of different modalities since they can be obtained using different techniques (x-ray, PET, SPECT, etc.). It is common to use different types of images when evaluating a patient, to obtain more information related to pathologies and decide the appropriate treatment. In other cases, several images of the same type taken at different times are used. For images to provide reliable and useful information, they must be properly combined or fused (Fig. 4). Before images can be fused, they must be geometrically and temporally aligned. This alignment operation is called registration. Therefore, image fusion is a general operation that includes image registration as an initial step.

Different approaches have been applied to tackle the image registration problem. One of these approaches is defined by the intensity-based techniques. These techniques use image intensity values (color or gray level) to calculate similarity measures between the images. This information is used to calculate the transformation that maximizes the value of a similarity metric by searching a certain transformations space and comparing intensity patterns. An advantage of these methods is that they do not require the prior application of a feature extraction

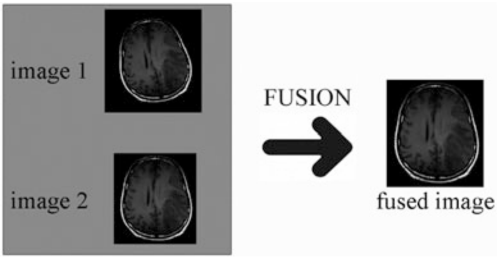

Fig. 4 Fused image obtained from two brain images

or image segmentation operation. These methods use a similarity metric that determines the match between the features or intensity values of two images. There are several similarity metrics that have been used successfully in multimodal image registration, such as mutual information [76], normalized mutual information [77], or Renyi entropy [78]. On the other hand, the methods apply a search strategy to optimize the similarity metric. Powell's method and the conjugate gradient [79] are two local methods commonly used in image registration to optimize the similarity metric. Several global methods have also been applied with this purpose, including genetic algorithms, simulated annealing, and swarm-based methods.

In summary, intensity-based image registration methods include three important elements: finding a transformation that aligns an image with another taken as a reference, choosing a similarity metric that measures the similarity between these two images, and using an optimization technique to find the optimal transformation parameters that maximize the similarity measure.

The following describes several articles that apply swarm-based methods for medical image registration.

PSO was applied for registration of medical images in [80]. Said method was used as a search strategy in a solution that is applied to images obtained from different modalities. Specifically, PSO was used to maximize the similarity metric for registering single slice medical images to three-dimensional volumes. The article analyzes three PSO variants. The first one includes crossover operators to update the position and velocity of the particles. The second variant is based on the first proposal but considers five subpopulations that are initialized using the well-known K-means algorithm. The third variant includes three main modifications. Powell's method is applied to the initial position of the particles, and then particles are generated around the position defined by said method. In addition, this PSO variant includes a constriction coefficient in the expression that updates the velocity of the particles and a relaxed convergence criterion. Once the PSO operations have been completed, the three PSO variants apply Powell's local optimization method to the best particle in the swarm. In the case of the second variant, which considers five subpopulations, this method is applied to the best particle of each subpopulation.

Talbi and Batouche adapted PSO for multimodal medical image registration, [81]. With this objective, they defined a differential evolution operator to improve the best solution of each particle. Differential evolution is an optimization technique that solves a problem by iteratively improving a candidate solution using an evolutionary process [82]. The solution proposed in this article alternately applies the basic PSO operations and the differential evolution operation; that is, one iteration applies the equations to update the position and velocity of each particle, and the next iteration applies the differential evolution operator.

Abdel-Basset et al. applied PSO as search strategy and used modified mutual information as similarity metric [83]. The modified mutual information includes spatial image information by using a linear combination of image intensity and image gradient vector flow intensity.

Dida et al. compare the use of GWO and PSO for multimodal registration of human brain using CT and MR images [84]. In this case, the normalized mutual information is used as similarity metric. The results included in the article indicate that GWO is the best method.

Xiaogang et al. define a multi-resolution medical image registration method based on a wavelet transformation that combines FA with Powell's method [85]. This proposal uses normalized mutual information as similarity measure. The image registration process based on the multi-resolution strategy using the wavelet transform includes two parts: the rough registration with low sampling resolution and the fine registration with high sampling resolution. In the proposed method, both images are decomposed using wavelet transformation, thereby obtaining the associated low-level resolution images. Then, the registration operation is applied. To do this, FA is first used to obtain the approximate registration result from the low-resolution images. The results of this method are used as the initial solution to apply Powell's method, which is applied to the high-resolution images to obtain a better registration result.

Yang et al. described a method for nonrigid multimodal image registration [86]. Image registration methods can be classified as rigid and nonrigid. The main difference is that the transformations applied in rigid methods do not change the shape of the objects, while those applied in nonrigid methods do. The solution proposed by Yang et al. uses CSO as optimization technique and the normalized mutual information as similarity criterion. CSO imitates two behaviors of the cats, called seeking mode and tracing mode**.** The modified CSO used in this article includes the limited memory Broyden–Fletcher–Goldfarb–Shanno into the seeking mode, which is a commonly used method for optimizing the parameters of the deformation model in the nonrigid image registration. In addition, it includes the roulette wheel method in the tracing mode.

The registration method described in [87] uses a similarity metric called enhanced mutual information, defined in [88], and applies an optimization strategy that combines CUS and Powell's method. This solution combines local and global optimization to improve the results. CUS is applied first to perform a global search. Then, Powell's method is applied to perform a local search around the best solution obtained by CUS.

Several methods have been proposed that combine the pulse-coupled neural network (PCNN) [89], with swarm-based algorithms to perform medical image fusion. This neural network is efficient to perform this operation but uses a set of parameters that are difficult to configure.

The research described in [90] presents a method that applies artificial ants for fusing multimodal medical images. The method first applies artificial ants for edge detection and optimization and then uses this information as input for a simplified PCNN that generates the fused image. The method was applied to brain images.

Xu et al. defined a method to fuse multimodal medical images based on the use of an adaptive PCNN that is optimized by a modified PSO, called quantum-behaved (QPSO) [91]. A basic difference between PSO and QPSO is that in the second method, the state of a particle is not defined by its position and velocity, but by a wave function [92]. Xu et al. used QPSO to set the PCNN parameters and defined a fitness function for QPSO that combines three evaluation criteria: average gradient, image entropy, and spatial frequency.

The proposal described in [93] combines PCNN with SFLA for the fusion of CT and SPECT brain images. SFLA was used to optimize the PCNN parameters. First, the intensity-hue-saturation (IHS) of each original image is decomposed using a nonsubsampled contourlet transform (NSCT). This operation generates low-frequency and high-frequency images for each original image. The method that combines PCNN and SFLA is used to fuse both high-frequency images, resulting in a high-frequency fused image. The same method is applied to fuse the low-frequency images to generate the low-frequency fused image. The final fused image is obtained by applying the reversed NSCT and reversed IHS transforms.

Scaling-based techniques are commonly used in multimodal image fusion. Daniel et al. describe a mask-based technique for multimodal image fusion that uses GWO to select the optimal scale values [94]. Mask-based techniques are controlled by the gain factor called scale value. In general, mask-based methods use static scale values, regardless of the input images considered. Rather, the purpose of this article is to dynamically adjust the scale value by GWO. The mutual information metric is used to define the GWO fitness function. The method first transforms the two original images into Fourier space. Then, the Fourier spectrum of the input images is optimally scaled using scale values obtained by the GWO algorithm. The resulting spectrum mask corresponding to each image is fused using pixel-based averaging rule. The resulting fused image is obtained in the Fourier domain, so the inverse Fourier transform is used to obtain the spatial domain fused image.

The method described by Daniel et al. in [95] proposes another mask-based method that shares some characteristics with the one described above. In this case, GWO is also used to select the optimum scale values, but in addition, CUS is used to select the random control parameters of the GWO algorithm. On the other hand, GWO uses the same fitness function as in the previous case. Unlike the previous solution, in this case, each original image is filtered by two masking filters (wavelet filter and Laplacian filter). The filtered input images are scaled using optimal scale values selected using GWO. Then, the Laplacian and wavelet mask corresponding to each original image are fused, generating a mask for each original image. The last operation fuses these two masks to generate the final image.

The method proposed in [96] uses the binary CRS optimization algorithm and discrete wavelet transform. The method was applied to MR and CT image fusion. Both images are decomposed using discrete wavelet transform, producing four subband images that contain approximation and detailed coefficients. An initial fusion is performed that combines the detailed coefficients of an image with the approximation coefficients of the other image. Then, the final fusion is performed by applying an optimal fusion rule whose parameters are optimally selected by the swarm-based method.

7 Conclusions

The popularity of swarm-based algorithms has increased in recent years, and they have been successfully applied to solve complex problems in different fields.

These methods use a set of very simple individuals and each of them looks for a solution in the search space of the problem. The final solution to the problem will be the best solution found by the swarm during the search process. Individuals in the swarm share information to guide their search to promising areas of the search space. Another important feature of these methods is that all the individuals perform similar operations and there is no central control. The characteristics of these models make them easy to implement.

This chapter shows a review of several interesting applications of swarm-based solutions for processing medical images. Processing these images is not an easy task, due to the large amount of information that must be handled, the different image formats, and the variety of operations that can be applied to an image.

As indicated in the previous sections, when applying a processing to an image, successive operations must be carried out on said image. For this reason, image processing usually combines several techniques that are applied to each of these operations. The description in this chapter shows how swarm-based methods can be combined with other methods to define a system that applies certain processing to a medical image. For example, different systems that combine artificial neural networks and swarm algorithms have been described. In this way, the system defined to process the image benefits from the advantages offered by each of the methods integrated in the system.

Medical image processing is a very interesting field that offers the possibility of further work on the application of swarm algorithms to improve systems that analyze images and allow diagnoses.

A.1 Appendix A. Flowcharts of Swarm-Based Algorithms

This appendix shows the flowchart (Figs. 5, 6, 7, 8, and 9) of the swarm-based methods whose algorithm is outlined in Sect. 2. Several tables (Table 1, 2, 3, 4, and 5) are included that describe the variables used in the flowcharts.

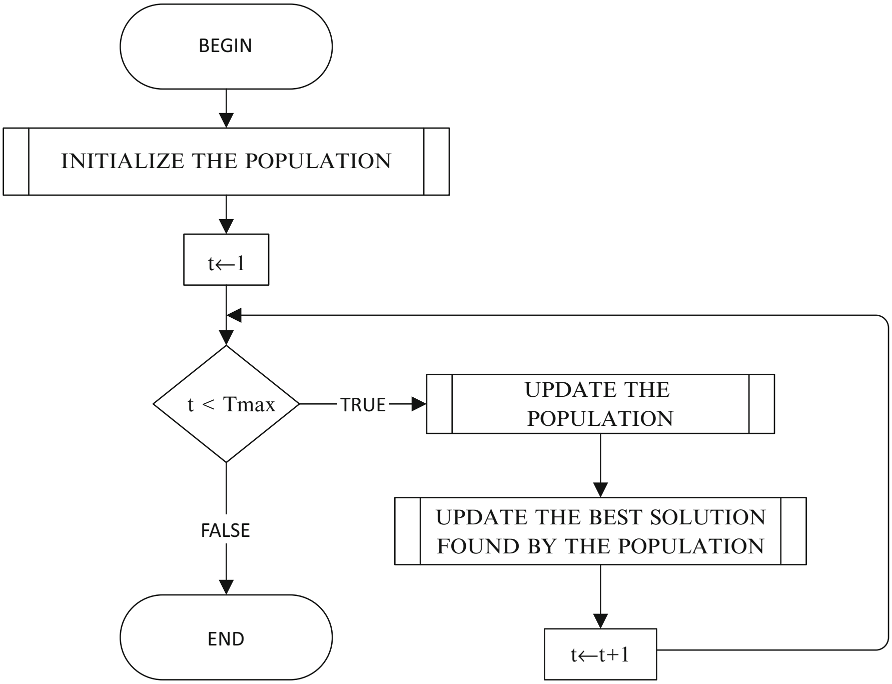

Fig. 5 Main operations of a swarm-based algorithm

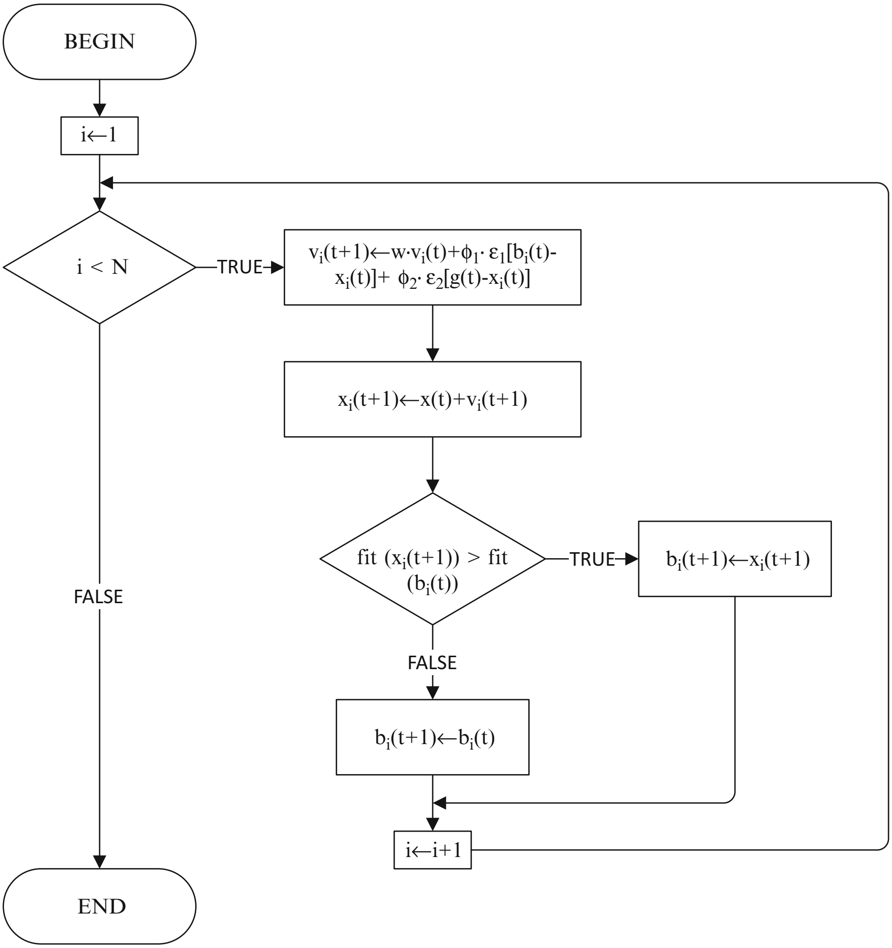

Fig. 6 Flowchart of the operation that updates the population in the PSO algorithm

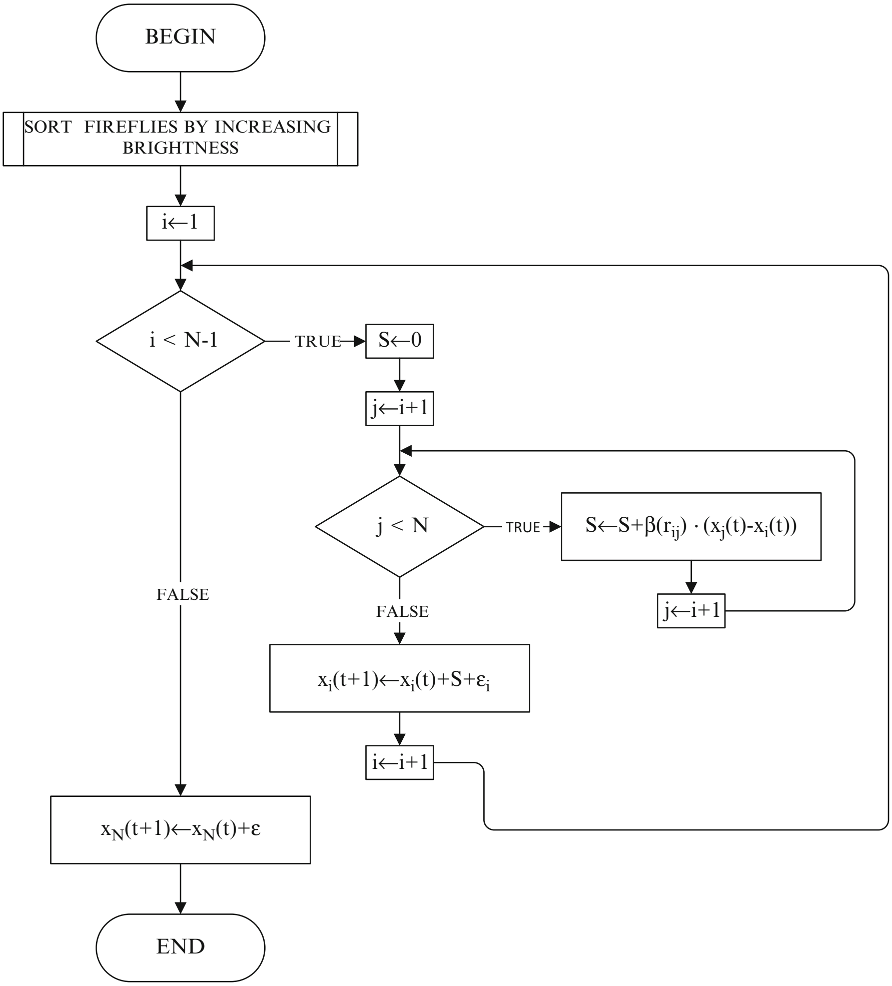

Fig. 7 Flowchart of the operation that updates the population in the FA algorithm

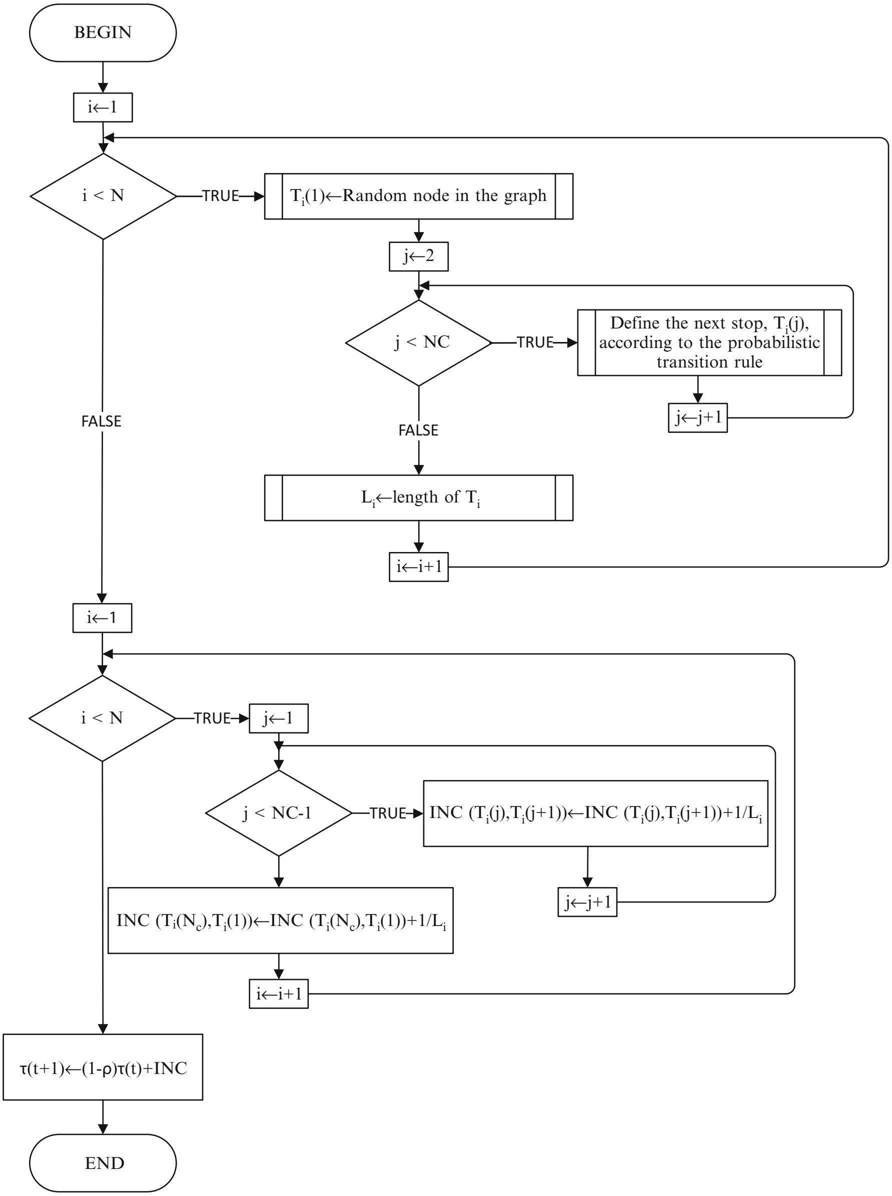

Fig. 8 Flowchart of the operation that updates the population in the ant-based algorithm

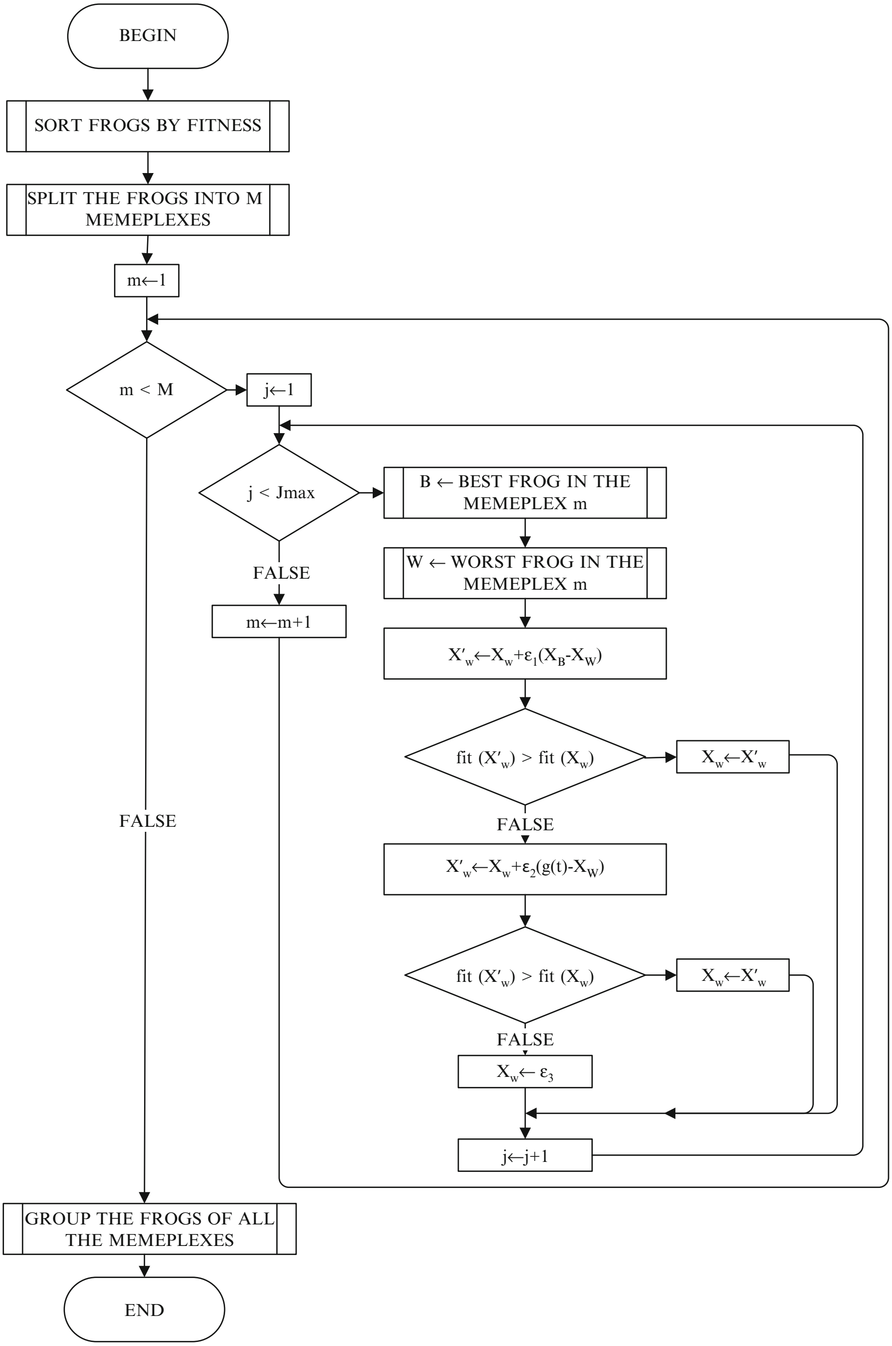

Fig. 9 Flowchart of the operation that updates the population in the SFLA algorithm

Table 1 Variables used in the flowcharts

Variable	Description
T_{max}	Number of iterations performed by the algorithm
t	Current iteration of the swarm-based algorthm
N	Population size
fit(x)	The fitness or quality of the solution x
$x_i(t)$	Position of the individual i (a solution to the problem) at iteration t
g(t)	Best solution found by the population at iteration t

Table 2 Variables used in PSO algorithm flowchart

Variable	Description
v_i	Velocity of particle i
b_i	Personal best position of particle i
w, ϕ_1, ϕ_2	Weights to determine the relative influence of the addends
$\varepsilon_1, \varepsilon_2$	Random vectors

Table 3 Variables used in FA algorithm flowchart

Variable	Description
$\beta(r_{ij})$	Attractiveness between fireflies i and j. It can be computed by the equation: $\beta\left(r_{ij}\right) = \beta_0 e^{-\gamma r_{ij}^2}$
β_0	Attractiveness at distance 0
γ	Light absorption coefficient
r_{ij}	Distance between x_i and x_j
$\varepsilon_1, \varepsilon_2$	Random vectors

Table 4 Variables used in ant-based algorithm flowchart

Variable	Description
NC	Number of nodes in the graph
τ_{ij}	Pheromone of the connection (i, j)
T_i	Tour defined by ant i that includes NC nodes
L_i	Length of T_i (cost of all the connections included in the tour)
ρ	Evaporation rate of the pheromone

Table 5 Variables used in SFLA algorithm flowchart

Variable	Description
M	Number of memeplexes
J_{max}	Number of iterations applied to improve each memeplex
$\varepsilon_1, \varepsilon_2, \varepsilon_3$	Random vectors

The description of the algorithms considers that a maximization problem will be solved.

References

1. Panigrahi, B. K., Shi, Y., & Lim, M. H. (Eds.). Handbook of swarm intelligence: Concepts, principles and applications (Vol. 8). Springer. 2011.
2. Abraham, A., Guo, H., & Liu, H. (2006). Swarm intelligence: Foundations, perspectives and applications. In *Swarm intelligent systems* (pp. 3–25). Springer.
3. Abdulrahman, S. M. (2017). Using Swarm Intelligence for solving NP-Hard Problems. *Academic Journal of Nawroz University., 6*(3), 46–50.
4. Hassanien, A. E., & Emary, E. (2018). *Swarm intelligence: Principles, advances, and applications*. CRC Press.
5. Dorigo, M., & Stützle, T. (2019). Ant colony optimization: Overview and recent advances. In *Handbook of metaheuristics* (International series in operations research & management science) (Vol. 272, pp. 311–351). Springer.
6. Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95-International conference on neural networks* (Vol. 4, pp. 1942–1948). IEEE. https://doi.org/10.1109/ICNN.1995.488968.
7. Yang, X. S., & He, X. (2013). Firefly algorithm: recent advances and applications. *International Journal of Swarm Intelligence., 1*(1), 36–50.
8. Eusuff, M. M., & Lansey, K. E. (2003). Optimization of water distribution network design using the shuffled frog leaping algorithm. *Journal of Water Resources Planning and Management, 129*(3), 210–225.
9. Karaboga, D., & Basturk, B. (2007). A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *Journal of Global Optimization, 39*(3), 459–471.
10. Passino, K. M. (2002). Biomimicry of bacterial foraging for distributed optimization and control. *IEEE Control Systems Magazine, 22*(3), 52–67.
11. Yang, X. S. (2010). A new metaheuristic bat-inspired algorithm. In *Nature inspired cooperative strategies for optimization (NICSO 2010)* (Studies in computational intelligence) (Vol. 284, pp. 65–74). Springer. https://doi.org/10.1007/978-3-642-12538-6_6.
12. Chu, S. C., & Tsai, P. W. (2007). Computational intelligence based on the behavior of cats. *International Journal of Innovative Computing, Information and Control., 3*(1), 163–173.
13. Askarzadeh, A. (2016). A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm. *Computers and Structures, 169*, 1–12.
14. Yang, X. S., & Deb, S. (2009). Cuckoo search via Lévy flights. In *2009 World congress on nature & biologically inspired computing (NaBIC)* (pp. 210–214). IEEE.
15. Yang, X. S., Karamanoglu, M., & He, X. (2014). Flower pollination algorithm: A novel approach for multiobjective optimization. *Engineering Optimization, 46*(9), 1222–1237.
16. Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in Engineering Software, 69*, 46–61.
17. Jona, J. B., & Nagaveni, N. (2014). Ant-cuckoo colony optimization for feature selection in digital mammogram. *Pakistan Journal of Biological Sciences: PJBS., 17*(2), 266–271.
18. Sudha, M. N., & Selvarajan, S. (2016). Feature selection based on enhanced cuckoo search for breast cancer classification in mammogram image. *Circuits and Systems., 7*(04), 327–338. https://doi.org/10.4236/cs.2016.74028
19. Jothi, G. (2016). Hybrid tolerance rough set–firefly based supervised feature selection for MRI brain tumor image classification. *Applied Soft Computing, 46*, 639–651.
20. Mac Parthalain, N., & Shen, Q. (2009). Exploring the boundary region of tolerance rough sets for feature selection. *Pattern Recognition, 42*(5), 655–667.
21. Subashini, M. M., Sahoo, S. K., Sunil, V., & Easwaran, S. (2016). A non-invasive methodology for the grade identification of astrocytoma using image processing and artificial intelligence techniques. *Expert Systems with Applications., 43*, 186–196.
22. Sahoo, A., & Chandra, S. (2017). Multi-objective grey wolf optimizer for improved cervix lesion classification. *Applied Soft Computing, 52*, 64–80.

23. Shankar, K., Lakshmanaprabu, S. K., Khanna, A., Tanwar, S., Rodrigues, J. J., & Roy, N. R. (2019). Alzheimer detection using group grey wolf optimization based features with convolutional classifier. *Computers and Electrical Engineering, 77*, 230–243.
24. Tan, T. Y., Zhang, L., Neoh, S. C., & Lim, C. P. (2018). Intelligent skin cancer detection using enhanced particle swarm optimization. *Knowledge-Based Systems, 158*, 118–135.
25. Kaur, T., Saini, B. S., & Gupta, S. (2018). A novel feature selection method for brain tumor MR image classification based on the Fisher criterion and parameter-free bat optimization. *Neural Computing and Applications, 29*(8), 193–206.
26. Dandu, J. R., Thiyagarajan, A. P., Murugan, P. R., & Govindaraj, V. (2020). Brain and pancreatic tumor segmentation using SRM and BPNN classification. *Health Technology, 10*(1), 187–195.
27. Cinsdikici, M. G., & Aydin, D. (2009). Detection of blood vessels in ophthalmoscope images using MF/ant (matched filter/ant colony) algorithm. *Computer Methods and Programs in Biomedicine, 96*(2), 85–95.
28. Dorigo, M., & Gambardella, L. M. (1997). Ant colony system: A cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation, 1*(1), 53–66.
29. Hancer, E., Ozturk, C., & Karaboga, D. (2013). Extraction of brain tumors from MRI images with artificial bee colony based segmentation methodology. In *2013 8th International conference on electrical and electronics engineering (ELECO)* (pp. 516–520). IEEE. https://doi.org/10.1109/ELECO.2013.6713896.
30. Mostafa, A., Fouad, A., Abd Elfattah, M., Hassanien, A. E., Hefny, H., Zhu, S. Y., & Schaefer, G. (2015). CT liver segmentation using artificial bee colony optimisation. *Procedia Computer Science., 60*, 1622–1630.
31. Bezdek, J. C. (2013). *Pattern recognition with fuzzy objective function algorithms*. Springer.
32. MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability* (Vol. 1, No. 14) (pp. 281–297). University of California Press.
33. Taherdangkoo, M., Yazdi, M., & Rezvani, M. H. (2010). Segmentation of MR brain images using FCM improved by artificial bee colony (ABC) algorithm. In *Proceedings of the 10th IEEE international conference on information technology and applications in biomedicine* (pp. 1–5). IEEE. https://doi.org/10.1109/ITAB.2010.5687803.
34. Shen, S., Sandham, W., Granat, M., & Sterr, A. (2005). MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization. *IEEE Transactions on Information Technology in Biomedicine, 9*(3), 459–467.
35. Forghani, N., Forouzanfar, M., & Forouzanfar, E. (2007). MRI fuzzy segmentation of brain tissue using IFCM algorithm with particle swarm optimization. In *2007 22nd International symposium on computer and information sciences* (pp. 1–4). IEEE.
36. Mekhmoukh, A., & Mokrani, K. (2015). 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, 122*(2), 266–281.
37. Mizutani, K., & Miyamoto, S. (2005). Possibilistic approach to kernel-based fuzzy c-means clustering with entropy regularization. In *International conference on modeling decisions for artificial intelligence* (pp. 144–155). Springer.
38. Alagarsamy, S., Kamatchi, K., Govindaraj, V., & Thiyagarajan, A. (2017). A fully automated hybrid methodology using cuckoo-based fuzzy clustering technique for magnetic resonance brain image segmentation. *International Journal of Imaging Systems and Technology, 27*(4), 317–332.
39. Alagarsamy, S., Kamatchi, K., Govindaraj, V., Zhang, Y. D., & Thiyagarajan, A. (2019). Multi-channeled MR brain image segmentation: A new automated approach combining bat and clustering technique for better identification of heterogeneous tumors. *Biocybernetics and Biomedical Engineering., 39*(4), 1005–1035.

40. Kavitha, P., & Prabakaran, S. (2019). A novel hybrid segmentation method with particle swarm optimization and fuzzy c-mean based on partitioning the image for detecting lung cancer. *International Journal of Engineering and Advanced Technology., 8*(5), 1223–1227.
41. Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics, 9*(1), 62–66.
42. Kapur, J. N., Sahoo, P. K., & Wong, A. K. (1985). A new method for gray-level picture thresholding using the entropy of the histogram. *Computer Vision, Graphics, and Image Processing., 29*(3), 273–285.
43. Tsallis, C. (1988). Possible generalization of Boltzmann-Gibbs statistics. *Journal of Statistical Physics, 52*(1), 479–487.
44. Li, C. H., & Lee, C. K. (1993). Minimum cross entropy thresholding. *Pattern Recognition, 26*(4), 617–625.
45. Huang, P., Cao, H., & Luo, S. (2008). An artificial ant colonies approach to medical image segmentation. *Computer Methods and Programs in Biomedicine, 92*(3), 267–273.
46. Lee, M. E., Kim, S. H., Cho, W. H., Park, S. Y., & Lim, J. S. (2009). Segmentation of brain MR images using an ant colony optimization algorithm. In *2009 Ninth IEEE international conference on bioinformatics and bioengineering* (pp. 366–369). IEEE. https://doi.org/10.1109/BIBE.2009.58.
47. Menon, N., & Ramakrishnan, R. (2015). Brain tumor segmentation in MRI images using unsupervised artificial bee colony algorithm and FCM clustering. In *2015 International conference on communications and signal processing (ICCSP)* (pp. 0006–0009). IEEE. https://doi.org/10.1109/ICCSP.2015.7322635
48. Ma, M., Liang, J., Guo, M., Fan, Y., & Yin, Y. (2011). SAR image segmentation based on artificial bee colony algorithm. *Applied Soft Computing, 11*(8), 5205–5214.
49. Li, Y., Jiao, L., Shang, R., & Stolkin, R. (2015). Dynamic-context cooperative quantum-behaved particle swarm optimization based on multilevel thresholding applied to medical image segmentation. *Information Sciences, 294*, 408–422.
50. Li, Y., Xiang, R., Jiao, L., & Liu, R. (2012). An improved cooperative quantum-behaved particle swarm optimization. *Soft Computing, 16*(6), 1061–1069.
51. Li, Y., Bai, X., Jiao, L., & Xue, Y. (2017). Partitioned-cooperative quantum-behaved particle swarm optimization based on multilevel thresholding applied to medical image segmentation. *Applied Soft Computing, 56*, 345–356.
52. Rajinikanth, V., Raja, N. S. M., & Kamalanand, K. (2017). Firefly algorithm assisted segmentation of tumor from brain MRI using Tsallis function and Markov random field. *Journal of Control Engineering and Applied Informatics., 19*(3), 97–106.
53. Zhang, Y., Brady, M., & Smith, S. (2001). Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm. *IEEE Transactions on Medical Imaging, 20*(1), 45–57.
54. Chakraborty, S., Chatterjee, S., Dey, N., Ashour, A. S., Ashour, A. S., Shi, F., & Mali, K. (2017). Modified cuckoo search algorithm in microscopic image segmentation of hippocampus. *Microscopy Research and Technique, 80*(10), 1051–1072.
55. Wang, R., Zhou, Y., Zhao, C., & Wu, H. (2015). A hybrid flower pollination algorithm based modified randomized location for multi-threshold medical image segmentation. *Bio-Medical Materials and Engineering, 26*(s1), S1345–S1351. https://doi.org/10.3233/BME-151432
56. Pereira, C., Gonçalves, L., & Ferreira, M. (2013). Optic disc detection in color fundus images using ant colony optimization. *Medical & Biological Engineering & Computing, 51*(3), 295–303.
57. Pereira, C., Gonçalves, L., & Ferreira, M. (2015). Exudate segmentation in fundus images using an ant colony optimization approach. *Information Sciences, 296*, 14–24.
58. Mandal, D., Chatterjee, A., & Maitra, M. (2014). Robust medical image segmentation using particle swarm optimization aided level set based global fitting energy active contour approach. *Engineering Applications of Artificial Intelligence, 35*, 199–214.
59. Chan, T. F., & Vese, L. A. (2001). Active contours without edges. *IEEE Transactions on Image Processing, 10*(2), 266–277.

60. Ilunga-Mbuyamba, E., Cruz-Duarte, J. M., Avina-Cervantes, J. G., Correa-Cely, C. R., Lindner, D., & Chalopin, C. (2016). Active contours driven by cuckoo search strategy for brain tumour images segmentation. *Expert Systems with Applications., 56*, 59–68.
61. Wen, L., Wang, X., Wu, Z., Zhou, M., & Jin, J. S. (2015). A novel statistical cerebrovascular segmentation algorithm with particle swarm optimization. *Neurocomputing, 148*, 569–577.
62. Zhang, Y. D., Wang, S., & Wu, L. (2010). A novel method for magnetic resonance brain image classification based on adaptive chaotic PSO. *Progress in Electromagnetics Research, 109*, 325–343.
63. Wang, S., Zhang, Y., Dong, Z., Du, S., Ji, G., Yan, J., Yang, J., Wang, Q., Feng, C., & Phillips, P. (2015a). Feed-forward neural network optimized by hybridization of PSO and ABC for abnormal brain detection. *International Journal of Imaging Systems and Technology, 25*(2), 153–164.
64. Kıran, M. S., & Gündüz, M. (2013). A recombination-based hybridization of particle swarm optimization and artificial bee colony algorithm for continuous optimization problems. *Applied Soft Computing, 13*(4), 2188–2203.
65. Dheeba, J., Singh, N. A., & Selvi, S. T. (2014). Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach. *Journal of Biomedical Informatics, 49*, 45–52.
66. Senapati, M. R., & Dash, P. K. (2013). Local linear wavelet neural network based breast tumor classification using firefly algorithm. *Neural Computing and Applications, 22*(7), 1591–1598.
67. Parsian, A., Ramezani, M., & Ghadimi, N. (2017). A hybrid neural network-gray wolf optimization algorithm for melanoma detection. *Biomedical Research, 28*(8), 3408–3411.
68. Ahmed, H. M., Youssef, B. A., Elkorany, A. S., Saleeb, A. A., & Abd El-Samie, F. (2018). Hybrid gray wolf optimizer–artificial neural network classification approach for magnetic resonance brain images. *Applied Optics, 57*(7), B25–B31.
69. de Pinho Pinheiro, C. A., Nedjah, N., & de Macedo Mourelle, L. (2020). Detection and classification of pulmonary nodules using deep learning and swarm intelligence. *Multimedia Tools and Applications, 79*(21), 15437–15465.
70. Surendar, P. (2021). Diagnosis of lung cancer using hybrid deep neural network with adaptive sine cosine crow search algorithm. *Journal of Computational Science., 53*, 101374. https://doi.org/10.1016/j.jocs.2021.101374
71. Mirjalili, S. (2016). SCA: A sine cosine algorithm for solving optimization problems. *Knowledge-Based Systems, 96*, 120–133.
72. Zhang, Y., Wang, S., Ji, G., & Dong, Z. (2013). An MR brain images classifier system via particle swarm optimization and kernel support vector machine. *The Scientific World Journal.*https://doi.org/10.1155/2013/130134
73. Agrawal, V., & Chandra, S. (2015). Feature selection using Artificial Bee Colony algorithm for medical image classification. In *2015 Eighth international conference on contemporary computing* (IC3) (pp. 171–176). IEEE. https://doi.org/10.1109/IC3.2015.7346674
74. Zhang, Y., Wang, S., Phillips, P., Dong, Z., Ji, G., & Yang, J. (2015). Detection of Alzheimer's disease and mild cognitive impairment based on structural volumetric MR images using 3D-DWT and WTA-KSVM trained by PSOTVAC. *Biomedical Signal Processing and Control, 21*, 58–73.
75. Ahmed, H. M., Youssef, B. A., Elkorany, A. S., Elsharkawy, Z. F., Saleeb, A. A., & Abd El-Samie, F. (2019). Hybridized classification approach for magnetic resonance brain images using gray wolf optimizer and support vector machine. *Multimedia Tools and Applications, 78*(19), 27983–28002.
76. Viola, P., & Wells, W. M. (1997). Alignment by maximization of mutual information. *International Journal of Computer Vision, 24*(2), 137–154.
77. Studholme, C., Hill, D. L., & Hawkes, D. J. (1999). An overlap invariant entropy measure of 3D medical image alignment. *Pattern Recognition, 32*(1), 71–86.
78. He, Y., Hamza, A. B., & Krim, H. (2003). A generalized divergence measure for robust image registration. *IEEE Transactions on Signal Processing, 51*(5), 1211–1220.

79. Maes, F., Vandermeulen, D., & Suetens, P. (1999). Comparative evaluation of multiresolution optimization strategies for multimodality image registration by maximization of mutual information. *Medical Image Analysis, 3*(4), 373–386.
80. Wachowiak, M. P., Smolkov, R., Zheng, Y., Zurada, J. M., & Elmaghraby, A. S. (2004). An approach to multimodal biomedical image registration utilizing particle swarm optimization. *IEEE Transactions on Evolutionary Computation, 8*(3), 289–301.
81. Talbi, H., & Batouche, M. (2004). Hybrid particle swarm with differential evolution for multimodal image registration. In *2004 IEEE international conference on industrial technology* (IEEE ICIT '04) (Vol. 3, pp. 1567–1572). IEEE. https://doi.org/10.1109/ICIT.2004.1490800.
82. Storn, R., & Price, K. (1997). Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization, 11*(4), 341–359.
83. Abdel-Basset, M., Fakhry, A. E., El-Henawy, I., Qiu, T., & Sangaiah, A. K. (2017). Feature and intensity based medical image registration using particle swarm optimization. *Journal of Medical Systems, 41*(12), 1–15.
84. Dida, H., Charif, F., & Benchabane, A. (2020). Grey wolf optimizer for multimodal medical image registration. In *2020 Fourth international conference on intelligent computing in data sciences (ICDS)* (pp. 1–5). IEEE.
85. Xiaogang, D., Jianwu, D., Yangping, W., Xinguo, L., & Sha, L. (2013). An algorithm multi-resolution medical image registration based on firefly algorithm and Powell. In *2013 Third international conference on intelligent system design and engineering applications* (pp. 274–277). IEEE.
86. Yang, F., Ding, M., Zhang, X., Hou, W., & Zhong, C. (2015). Non-rigid multi-modal medical image registration by combining L-BFGS-B with cat swarm optimization. *Information Sciences, 316*, 440–456.
87. Shen, L., Huang, X., Fan, C., & Li, Y. (2018). Enhanced mutual information-based medical image registration using a hybrid optimisation technique. *Electronics Letters, 54*(15), 926–928.
88. Pradhan, S., & Patra, D. (2016). Enhanced mutual information based medical image registration. *IET Image Processing, 10*(5), 418–427. https://doi.org/10.1049/iet-ipr.2015.0346
89. Wang, Z., Ma, Y., Cheng, F., & Yang, L. (2010). Review of pulse-coupled neural networks. *Image and Vision Computing, 28*(1), 5–13.
90. Kavitha, C. T., & Chellamuthu, C. (2014). Medical image fusion based on hybrid intelligence. *Applied Soft Computing, 20*, 83–94.
91. Xu, X., Shan, D., Wang, G., & Jiang, X. (2016). Multimodal medical image fusion using PCNN optimized by the QPSO algorithm. *Applied Soft Computing, 46*, 588–595.
92. Sun, J., Feng, B., & Xu, W. (2004). Particle swarm optimization with particles having quantum behavior. In *Proceedings of the 2004 congress on evolutionary computation* (IEEE Cat. No. 04TH8753) (Vol. 1, pp. 325–331). IEEE.
93. Huang, C., Tian, G., Lan, Y., Peng, Y., Ng, E. Y. K., Hao, Y., Chen, Y., & Che, W. (2019). A new pulse coupled neural network (PCNN) for brain medical image fusion empowered by shuffled frog leaping algorithm. *Frontiers in Neuroscience, 13*, 210.
94. Daniel, E., Anitha, J., Kamaleshwaran, K. K., & Rani, I. (2017b). Optimum spectrum mask based medical image fusion using gray wolf optimization. *Biomedical Signal Processing and Control, 34*, 36–43.
95. Daniel, E., Anitha, J., & Gnanaraj, J. (2017). Optimum laplacian wavelet mask based medical image using hybrid cuckoo search–grey wolf optimization algorithm. *Knowledge-Based Systems, 131*, 58–69.
96. Parvathy, V. S., & Pothiraj, S. (2019). Multi-modality medical image fusion using hybridization of binary crow search optimization. *Health Care Management Science, 23*, 661–669.