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K-Mean Based Hyper-Metaheuristic Grey Wolf and Cuckoo Search Optimizers for Automatic MRI Medical Image Clustering

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Abstract In this paper a new clustering algorithm is proposed for optimal clustering of MRI medical image. In our proposed algorithm, the clustering process implemented by K-means clustering algorithm, due to its simplicity and speed. The optimization process was done by a well-known metaheuristic algorithms Grey Wolf Optimizer (GWO) and Cuckoo Search Optimizer. GWO is a metaheuristic algorithm inspired by the social hierarchy and hunting behavior of grey wolves. It mimics the leadership hierarchy and hunting strategies of wolves to explore the search space efficiently. GWO has shown promising performance in finding high-quality solutions compared to other well-established optimizers. It explores the solution space to find better cluster assignments that minimize the overall intra-cluster variance. By leveraging the exploration potential of GWO, the proposed algorithm aims to improve the quality of the clustering results. Furthermore, the Cuckoo Search Optimizer (CS) is combined with GWO to enhance the algorithm's ability to find a global solution. Cuckoo Search is a metaheuristic algorithm inspired by the breeding behavior of cuckoo birds. It employs random search and Levy flights to diversify the search process and avoid getting trapped in local optima. By combining CS with GWO, the proposed algorithm aims to increase the likelihood of finding the optimal clustering solution.

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Keywords: *Clustering algorithm, MRI medical image, Grey Wolf Optimizer (GWO), Cuckoo Search Optimizer (CS)*.

1. INTRODUCTION

One of the most important fundamentals in medical images processing is improving clustering accuracy. Due to the presence of different forms of diseases that imaged by magnetic resonance technology, a good clustering will give more accuracy in identifying different forms of diseases and help in diagnosis. Clustering data divides data into subsets with high similarity and low similarity to other subsets. To measure how similar the members of the same group are to each other, distance metrics are used such as: Euclidean distance, Chord distance, and the Jaccard index [1-13].

Recently in several papers suggested that a better GWO-based optimizer be used to handle clustering applications. To improve the effectiveness of GWO, a Tabu-Search (TS) technique was used in GWOTS to conduct more searches in close vicinity to the best answers already found. To compare GWOTS' performance to that of earlier algorithms, they used the rank sum statistical test and 13 different clustering datasets. The exhaustive results and analysis showed that the GWOTS was better in terms of the optimality of the results and convergence behaviors in dealing with clustering datasets; this was shown by the complete nature of the results and analysis [14-22].

Recent researchers showed how to use Shannon's entropy maximization in the K-means algorithm's initialization procedure. Compared to other types of initializations, this strategy produced successful results, the parameters Initialization Time (I-T), Computation Time (CP-T), and the Number of iterations (NIK)s were used to illustrate the results of a study comparing the proposed algorithm to those of alternative initialization methods. The relationship between the algorithm's performance and these three factors has been illustrated over a range of cluster sizes [23-39].

As well as there several publications that were used in the Clustering process the Wavelet, Multiwavelet and mixed transforms [40-47].

2. THE PROPOSED OPTIMAL CLUSTERING SYSTEM DESIGN

This section describes the proposed optimal algorithm for clustering medical images using K-means and GWOCS. It consists of four main stages: image collection, image preprocessing, feature extraction, and the optimal clustering process. Figure (1) provides an overview of the main strategic framework of the proposed optimal clustering model. Each stage incorporates various algorithms and processing techniques to achieve accurate and effective clustering results.

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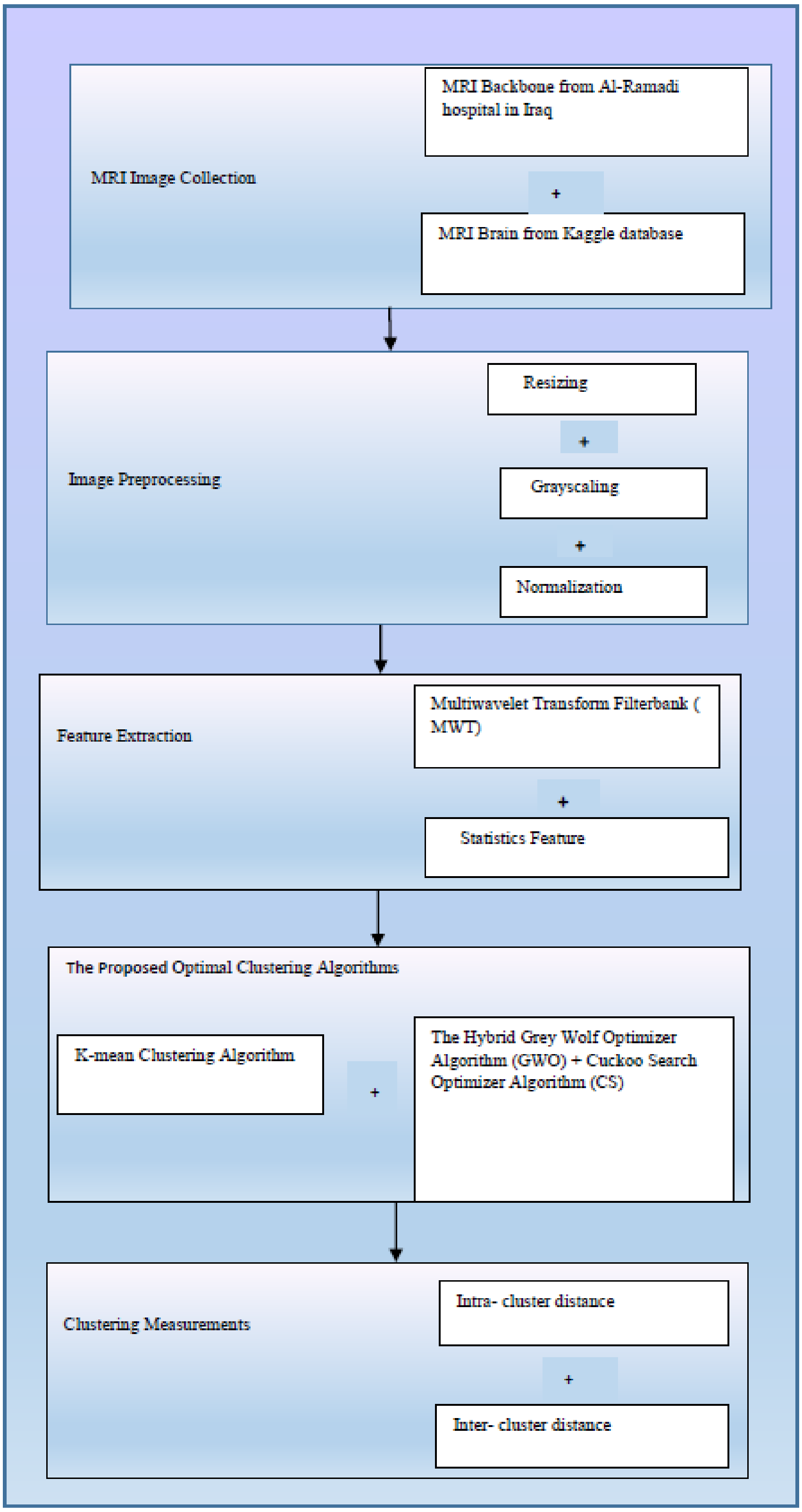

Figure (1) The Proposed Optimal Clustering Model

3. MEDICAL IMAGES COLLECTION

In this stage the Magnitude Resonance Imaging (MRI) was collected in the form of raw imaging data. Two different kinds of MRI scan images were utilized to create the dataset: the first set was taken from the publicly available Kaggle database from the internet. The second set was gathered in-person from Al-Ramadi hospital in Iraq specifically for MRI Backbone in order to algorithm to be tested on the largest possible amount of data.

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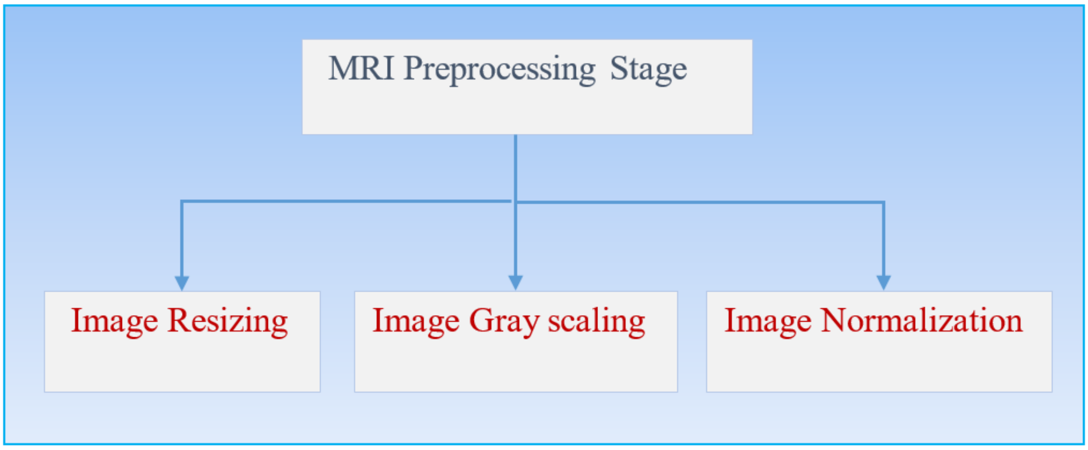
4. MEDICAL IMAGES PRE-PROCESSING

Image preprocessing is an essential step that prepares the images for subsequent stages of the algorithm. It involves several techniques to enhance the quality and remove any noise or artifacts from the images. This stage was implemented through three steps: image resizing, Image gray scaling and image normalization as shown in the figure**.(2)**

By performing these three steps, all the irrelevant data and undesired distortions will be removed from the original image. This stage results in a high-quality image in which even smallest and simplest details are clear and detected. These techniques aim to improve the accuracy of feature extraction and subsequently optimize the clustering process.



4.1. Image Resizing:

In this stage the function of RESIZE in MATLAB was used in order to increases or decreases the number of image dimension. The medical images used in this thesis were from different sources and in different dimensions such as (720×1280×3), (420×380×3) …etc. In order to reduce and unify these dimensions and make them one dimension (512×512×3), this function was used. This process reduces execution time because high-resolution could be slow down the computation process.

4.2. Image Gray scaling

In this stage the function of the (rgb2gray) in MATLAB was used to convert the RGB input image to grayscale image in order to reduce computational complexity and make feature extraction process easier. This process is done by calculating the mean value of Red, Green and Blue (RGB) and multiplying R, G and B with some certain weights, these weights are (0.2989,0.5870, 0.1140) respectively. This process is very important for the next stages such as feature extraction and clustering.

4.3. Image Normalization

In this stage the normalization process was performed to unite the different characteristics of MRI features vector. It utilized through min-max process, all feature values occurred between 0 and 1.

5. FEATURE EXTRACTION

In this stage, meaningful and representative features are extracted from the preprocessed images. The goal is to transform the images into a lower-dimensional feature space that captures relevant information for clustering. Several features were extracted and analyzed in this stage, a contrast feature and the correlation feature are clarified. The Energy feature is extracted due to the statistical features that have been extracted include the Homogeneity, the mean (μ), standard deviation (SD), Entropy, Root Mean Square (RMS), Variance, Smoothness, Kurtosis, Skewness, Inverse Difference Moment (IDM) and Multiwavelet transform (MWT). Table (1) showed each feature extracted from this stage in detailed.

Table (1): *The List of Extracted Features*

Features	Description of features
Contrast	Calculates the average intensity difference between a given pixel and its neighbor across the entire image and returns the result. Range=[0(size(GLCM,1)-1)^2] , The contrast is 0 for a constant image. The property Contrast is also known as *variance* and *inertia*.
Correlation	Returns a value that shows how much a pixel is related to its neighbor across the whole image. Range = [-1 1] Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is N×N for a constant image.

Energy	Gives back the sum of the squared values in the GLCM. Range = [0 1] Energy is 1 for a constant image. The property is also known as uniformity.
Homogeneity	Returns a value that shows how close the GLCM's element distribution is to the GLCM diagonal. Range = [0 1] Homogeneity is 1 for a diagonal GLCM.
Mean	It is the average or median value of matrix elements.
Standard Deviation	The standard deviation is also referred to as the square root of the variance.
Entropy	It is a measure of the degree of randomness in the image
Root Mean Square (RMS)	It is the square root of the mean square, which is the arithmetic mean of the squares of a group of values.
Variance	It is the averaging of the squared distance of its possible value from the mean
Smoothness	Smoothness is included to measure the level of smoothness/roughness of the image intensity.
Kurtosis	Kurtosis is a measure of whether an image's intensity distribution is peak or flat relative to a normal distribution
Skewness	Skewness is a measure of the asymmetry of the pixel values around the image
IDM	It is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high.
MWT	Multiwavelet Transform Filter bank

6. K-Means Algorithm

the form of MRI images to be as input to the algorithm and the number of cluster k=4 was determined. Then calculating the distance between the points and the centers. The recalculating of the cluster center will be achieved until the data distribution will be completed in the cluster.

7. Grey Wolf Optimizer (GWO)

A Grey Wolf Optimizer is a recent swarm intelligence technique, it has been successfully applied to many optimization problems for medical images. It has a sufficient exploration potential and can find high-solutions compared to several well-established optimizers.

The main inspiration of this algorithm came from the social behavior of the grey wolves and their dominant hierarchy. In nature, wolves can often be seen in the packs with 5 to 12 individuals on average.

Usually, two wolves (a dominant wolf and his mate) lead the folk, which is called alpha (α), and other pack's adult wolves follow them in the second level, which is called beta (β), while delta (δ) wolves come at the third level. Other wolves come in the lowest level and are called omega (ω).

Alpha wolves are often responsible for guiding the hunting attacks, decision making for the main activities of the pack such as hunting, maintaining discipline, sleeping places, and waking time.

Beta classes play the role of the advisors for alpha wolves and send the feedback from the other wolves to them.

Delta members are responsible for guarding and protecting the pack from any danger, and delta group contains the scouts, sentinels, elders, hunters, and caretakers.

Group hunting is another interesting behavior of the grey wolves. Wolves first track, chase, and approach a prey, and then, they pursue encircle and harass it until it stops moving. Finally, the wolves attack the stationary prey. The social intelligence of grey wolves and their hunting mechanisms (tracking, encircling, and attacking the prey) are mathematically modeled to design the GWO algorithm. The social behavior is mathematically modeled to solve various problems by assigning the fittest solution of the population as

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α and the next two best solutions as β and δ, respectively. The remaining solutions in the population are called ω.

8. Cuckoo Search Optimizer (CS)

The Cuckoo Search (CS) optimizer algorithm was incorporated into the Grey Wolf Optimizer (GWO) algorithm to improve the optimal clustering results. The CS algorithm draws inspiration from the aggressive reproduction strategy of cuckoo birds and utilizes Levy flights as a search mechanism. It is known for its strong global-search ability and has several desirable characteristics, including fewer parameters and an excellent search path .

The CS algorithm is inspired from the unique nesting way of cuckoo birds and levy-flight-style. The reproduction strategies of some cuckoos are very special, by which they do not hatch their own offspring but to lay down their eggs in the host's nest while the host goes out, sometimes they also remove host bird's eggs away .

Some host birds can find out the eggs belongs to outsider, and it may then move the outsider's eggs away or abandon the nest and find somewhere else to make a new one. Levy-flight-style is a typical characteristic of flight behaviors for many animals. It refers to the individual generally in a smaller range of activities, but it may have a small probability of long-range jump. And it may also have a small probability of significant deviation from the mean value of the activities, as the power to CS algorithm jumping out of the local optimum.

9. The Proposed Hybrid GWO and CS (GWO-CS) Algorithm

In this stage of the proposed algorithm, a hybrid combination is achieved between the two optimization algorithms: Grey Wolf Optimizer (GWO) and Cuckoo Search Optimizer (CS). GWO is a well-known metaheuristic algorithm that draws inspiration from the social cooperation and team-hunting behaviors of grey wolves in nature. In GWO, the movement of the entire population, except the leaders (α, β, and δ), is influenced by the positions of these leaders. The leaders, selected as the best three solutions obtained so far during the iterations, guide the other wolves in their movement. To enhance the algorithm's exploration capability, the Cuckoo Search Optimizer (CS) is integrated into GWO. CS is known for its strong global-search ability and diversification mechanism. The proposed algorithm benefits from the complementary strengths of both algorithms (GWO and CS) and proven to be a powerful approach for optimization problems. In this combined algorithm, the key group parameters in GWO are updated using the position updating formula from CS, as outlined in the flow chart presented in Figure (4). Hybridization of two or more algorithms is recently trended to detect the superior solutions of the optimization troubles and in order to become more efficient to deal with the clustering problem. GWO inspects an individual with a high fitness value, and for global search and the use of high-dimension data sets the integration of CS with GWO become necessary. CS updates the nest's positions with a certain probability independent of the search path, and with random directions. So, in CS, it is much easier to jump from the current region to another. Based on this, CS is a very helpful tool for GWO improvement. This means CS is used to update the positions of current search agents and obtain a new set. This new hybrid algorithm, referred to as GWOCS, exhibits enhanced capabilities in finding efficient solutions to optimization problems. In this concern, the position updated equation of CS is applied to amend the positions, convergence accuracies, and speeds of the grey wolf agent (α) for purpose of balancing among exploring, exploiting, and expanding convergence behaviors of the GWO algorithm. The CS algorithm is responsible for updating the positions of nests by employing random walks and Levy flights. Random walks and Levy flights are utilized with nearly equal probabilities, resulting in both long and short search paths. Moreover, the direction of movement is highly random, facilitating the exploration of different areas. This characteristic of CS enables the algorithm to easily jump from the current area to other regions in the search space. The GWOCS algorithm's flow chart, illustrated in Figure (5), provides a visual representation of the sequential steps involved in this hybrid approach. It outlines the integration of CS within GWO and demonstrates how the positions of the agents are updated using the CS position updating formula.

Overall, the CS-GWO algorithm capitalizes on the exploration capabilities of CS and the cooperative hunting behavior of grey wolves in GWO. This integration leads to an algorithm that exhibits improved search efficiency, convergence behavior, and optimization performance, making it a powerful approach for solving various optimization problems .

In general, the clustering algorithm objective is to maximize the similarity between cluster´s members and minimize the similarity between the members from different clusters. It leverages the cooperative hunting behavior of grey wolves and the exploration abilities of CS to enhance the clustering results. The specific details of the GWOCS algorithm, including the initialization of the wolf population, the exploration and exploitation processes, and the centroid update mechanism, will be further elaborated in the subsequent sections. These steps collectively aim to achieving a clustering solution that maximizes intra-cluster similarity and minimizes inter-cluster similarity. In summary, the proposed GWOCS algorithm offers a hybrid approach that integrates GWO and CS techniques to address the clustering problem. It formulates the problem as the determination of optimal centroids and employs the cooperative hunting behavior of grey wolves and the

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exploration capabilities of CS to achieve improved clustering results. GWO provides the leadership hierarchy and cooperation behavior of grey wolves, while CS introduces diversification and global-search abilities. This integration helps to overcome the limitations of GWO and improve the algorithm's convergence towards an optimal clustering solution for the given medical data. The Algorithm (3.1) and the flowchart in Figure (3.3), (3.4), and (3.5) provide a detailed outline of the GWOCS Hybrid Optimization technique.

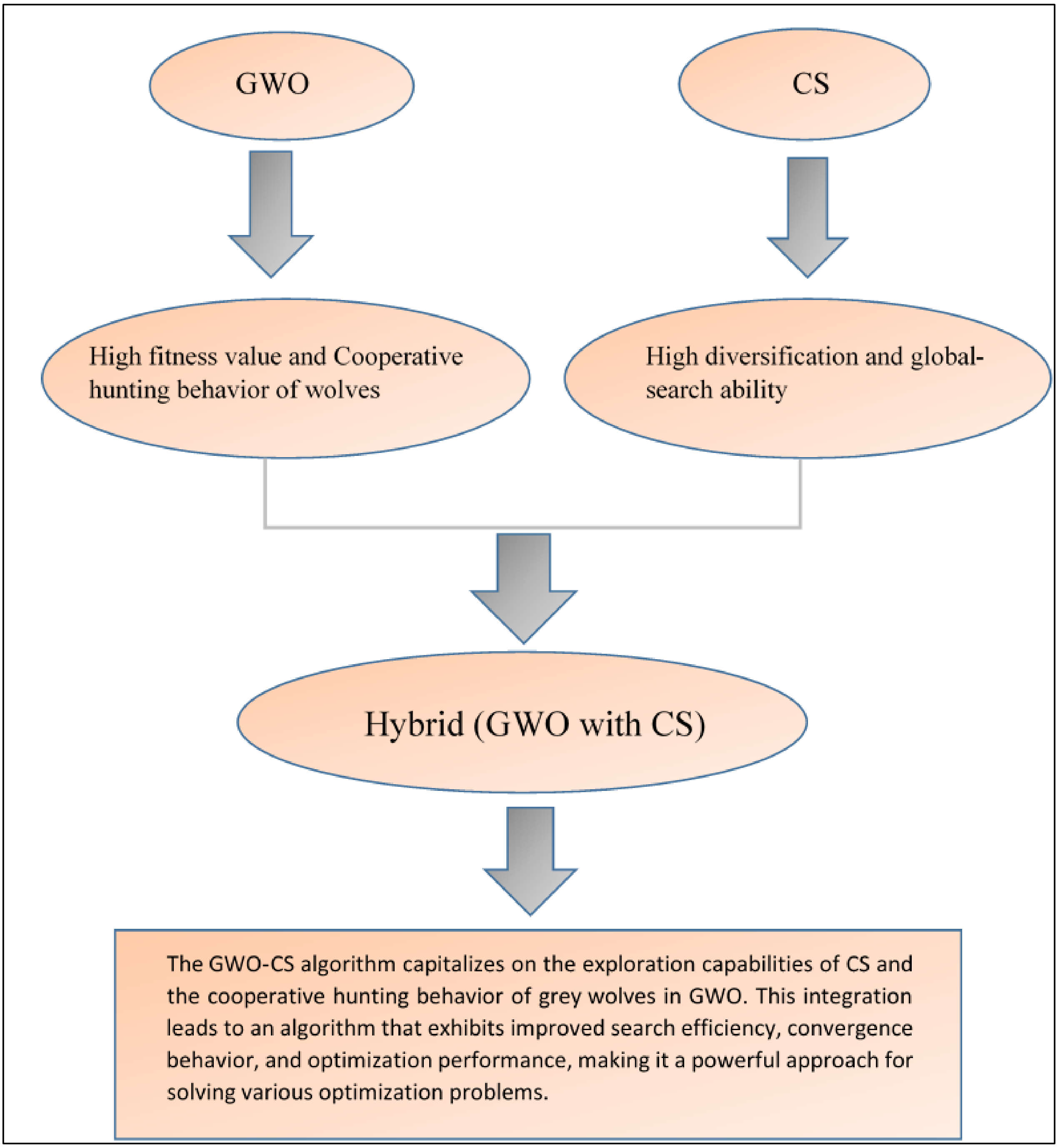

Figure (3) *Hybrid optimization Grey Wolf Optimizer and Cuckoo Search Optimizer*

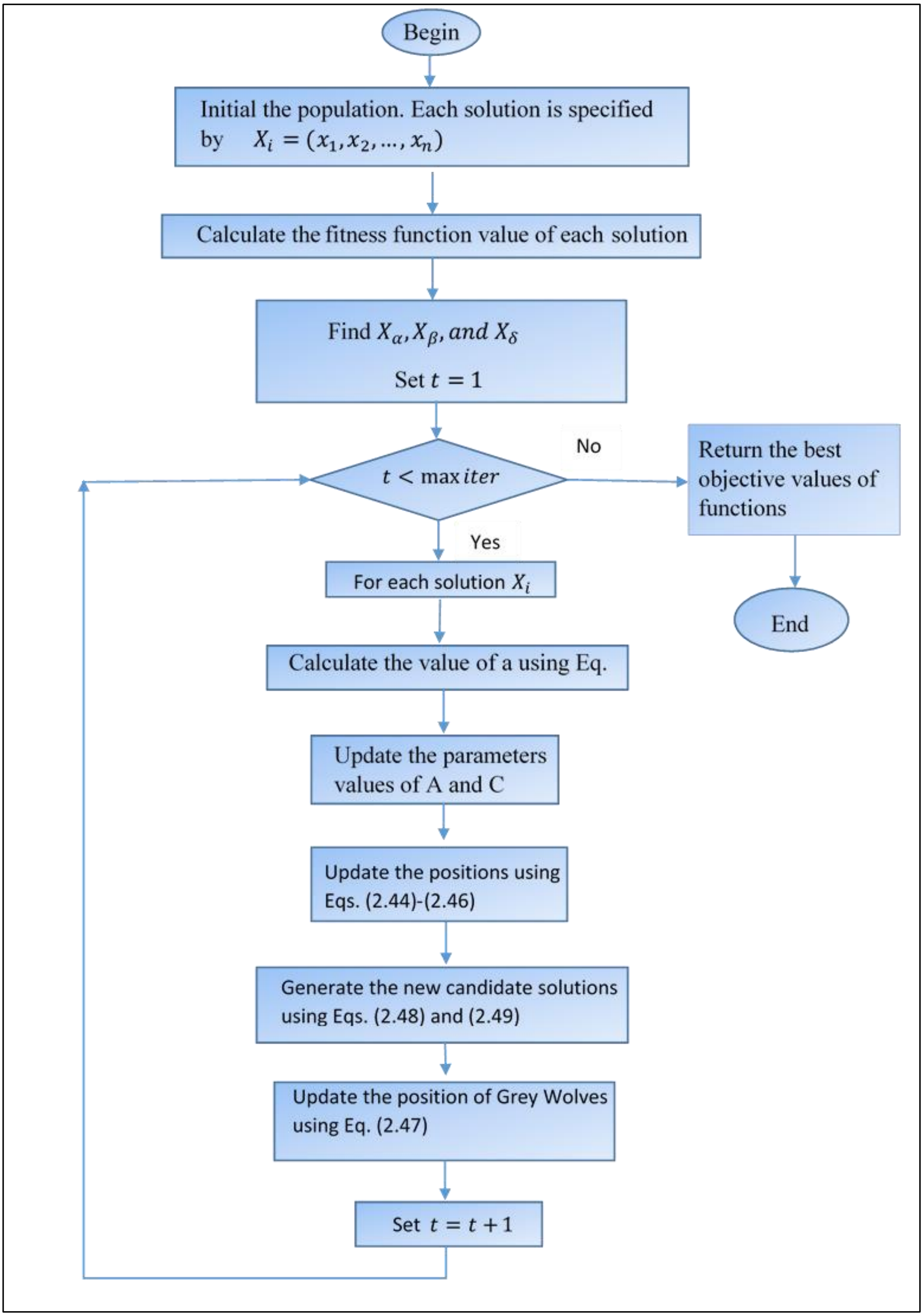

Figure (4) *The Hybrid Optimizer Algorithm (GWO) and (CS)*

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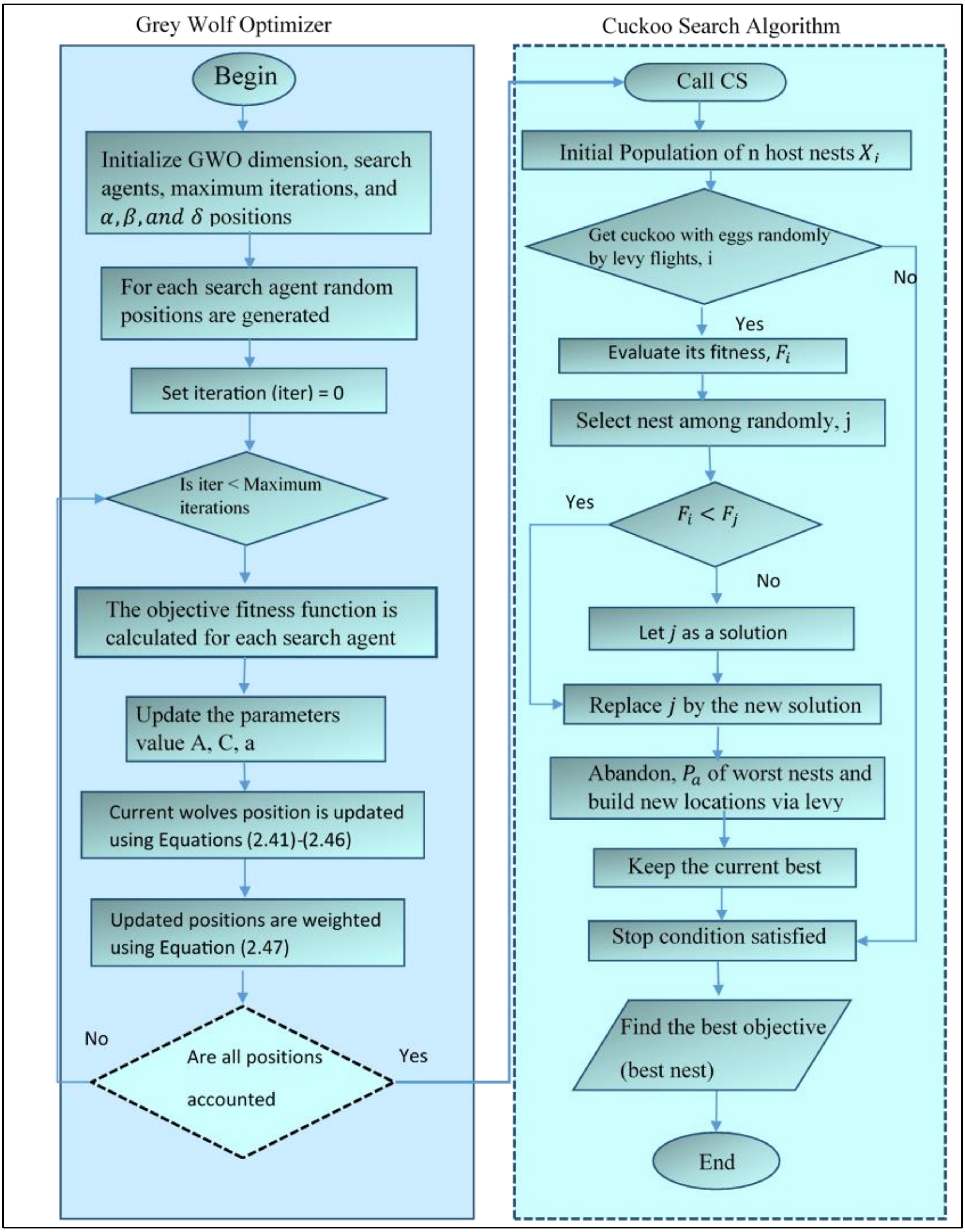

Figure (5) *The Proposed Algorithm (Grey Wolf and Cuckoo Search Optimizer) flowchart*

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10. CONCLUSIONS

The goals of this paper have been successfully accomplished as a result of the test results and assessments presented in the previous chapters. Upon implementation of the proposed system, the following conclusions have been grouped, listed, and summarized :

1. A new optimal clustering algorithm was implemented (GWOCS) for medical images. It consists mainly of the combination of two optimizers, the Grey Wolf Optimizer (GWO) and Cuckoo Search (CS) Optimizer and k-mean clustering algorithm. This new algorithm was achieved through four efficient steps for optimal MRI images clustering. These steps are: medical images collection, preprocessing, feature extraction, and optimal clustering. It is found that, this optimal clustering system effectively tackled medical data clustering problems.

2. The optimal clustering is done with the use of the k-means clustering algorithm and two optimization algorithms (Grey Wolf Optimizer algorithm and Cuckoo Search optimizer algorithm), it was able to cluster MRI medical images efficiency and accurately .

3. The preprocessing step is the significant step for the effective clustering process; it's done through three major phases: image resize, image grayscale and image normalization. These steps help standardize the medical images and enhance their compatibility with subsequent clustering algorithms or analysis. By ensuring consistent size, converting to grayscale, and normalizing the pixel values, the algorithm can effectively analyze and cluster the images based on their intrinsic features.

4.The advantage of using MWT technique in the feature extraction stage enabled data compression. This stage reduced the computational complexity and memory requirements, making the subsequent stage more efficient. By compressing the data, the algorithm could work with a smaller representation of the image while still retaining important features necessary for clustering. The results were evaluated by considering two evaluation parameters which are Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) Higher PSNR values with lower MSE values indicating better denoising results.

5.The use of statistical features led to enhanced the image clustering results since the retrieved feature become more stable and represented. Its enhances the clustering results by providing a stable and representative representation of the image data. These features capture important statistical characteristics, enabling more effective discrimination and clustering of medical images based on their shared statistical properties. This discriminatory capability enhances the clustering process by enabling the algorithm to identify meaningful patterns and accurately group similar images together.

As well as the results demonstrate the effectiveness of the GHM algorithm in reducing noise and boosting image quality. It provides also good filtration results against mixed noise .

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The results suggest that the proposed GWOCS algorithm is efficient in clustering two datasets of medical images and has the capability to accurately distinguish between four types of diseases in MRI images: Pituitary-Tumor, No-tumor, Meningioma-Tumor, and Glioma-Tumor. It's achieved a minimum intra-cluster distance of 3.8452 and a maximum inter-cluster distance of 2.5795. These values indicate that the algorithm successfully formed tight and well-separated clusters, leading to effective disease differentiation in the MRI images. Comparing the proposed approach with related works proves the proposed system's effectiveness

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