Water Cycle Approach with Relevance Vector ML for Brain Tumor Detection and Enhancement from MRI images

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Abstract

In contemporary Ethiopia, a notable surge in cancer-related fatalities, particularly attributed to brain tumor tissues, has become a concerning trend. The insidious nature of these tumors, often remaining undetected at their nascent stages, has led to a substantial loss of life. The early identification of such tumors presents a formidable challenge for medical professionals. This research endeavors to address this critical issue by introducing enhancement and detection techniques for brain tumors from medical MRI images. To augment image quality, we propose the adoption of a pioneering, nature-inspired algorithm known as the Water Cycle Algorithm (WCA) to mitigate complications encountered in grayscale medical MRI images. The WCA algorithm emulates the natural water cycle process, drawing inspiration from the flow of rivers and streams into the ocean. The method's foundation is rooted in the observation of the water cycle in nature. In this paper, we conduct a comparative analysis to underscore the efficacy of WCA in terms of image entropy and fitness, relative to established optimization methods. Furthermore, for tumor tissue detection and noise reduction in MRI images, we introduce a segmentation technique based on the Relevance Vector Machine (RVM). Image enhancement primarily centers on maximizing the information content through intensity transformation functions. We employ a parameterized transformation function that harnesses both local and global image data. To attain optimal image enhancement, we fine-tune the transformation function's parameters using the WCA. The parameters of the proposed Relevance Vector Machine are also harnessed for image segmentation. The results achieved through these methodologies align consistently and are assessed through performance graphs and image-based enhancement results. Simulation outcomes substantiate the superiority of the WCA-based image enhancement and the Relevance Vector Machine-based segmentation algorithm over conventional methods. Comparisons with other optimization techniques, such as Particle Swarm Optimization and Accelerated Particle Swarm Optimization, highlight the advantages of the WCA, while the segmentation comparison demonstrates the merits of the proposed Relevance Vector Machine over Support Vector Machine (SVM) approaches.

Keywords: Accelerated PSO, MRI, PSO, salt &pepper noise, SVM.

1. Introduction

The enhancement and manual detection of tumor tissues from MRI becomes a difficult and tedious task for doctors in present days. An automated system for brain tumor detection and segmentation will help the patients for proper treatment planning. Due to complex structure of human brain, a diagnosis of tumor area in brain becomes a challenging task. So detection of such brain tumor location, identification and classification in earlier stage is a serious issue in medical science. So, segmentation of brain tumor from MR images is the most important task as the tumor varies in terms of size, shape, location, and texture. By enhancing the new imaging techniques, it helps the doctors to observe and track the occurrence and growth of tumor-affected regions at different stages. Bahadure et al. [1] proposed BWT and SVM techniques image analysis for MRI-based brain tumor detection and classification. Joseph et al. [2] proposed segmentation of MRI brain images using K-means clustering algorithm along with morphological filtering for the detection of tumor images. The automated brain tumor classification of MRI images using support vector machine (SVM) was proposed by Alfonse and Salem [3]. For the brain tumor segmentation, Zanaty [4] proposed an approach based on hybrid type, with the combination of seed growing, FCM, and Jaccard similarity coefficient algorithm with the measure of gray and white segmented tissue matter from tumor images. Yao et al. [5] proposed an methodology which included extraction of textures features with wavelet transform and SVM with an accuracy of 83%.

For the classification and brain tumor segmentation, Kumar and Vijaya kumar [6] proposed methodology using principal component analysis (PCA) and radial basis function kernel with SVM and obtained an accuracy of 94% with this method. For the medical image segmentation, a localized fuzzy clustering with the extraction of spatial information was proposed by Cui et al. [7]. The literature survey above gives a clear view of the techniques that were invented only to obtain the segmentation region of interest, some techniques for extracting features and some to train and test using the classifiers. In this research work the RVM is proposed to classify the tumor from the MR images. Many real- world engineering optimization problems, however, are very complex in nature and quite difficult to solve. Meta heuristic algorithms commonly operate with the biological evolutionary process such as genetic algorithms (GAs) proposed by Holland [8] and Goldberg [9], PSO is a recently developed meta heuristic technique inspired by choreography of a bird flock developed by Kennedy and Eberhart [10].

The primary objective of this study is to introduce a novel metaheuristic method, the Water Cycle Algorithm (WCA), for the enhancement of biomedical magnetic resonance (MR) images with a focus on noise reduction in medical MRI. Previous literature reveals that WCA has been successfully employed in various constraint engineering problems, particularly for optimizing the number, location, and size of distributed generation units in distribution systems. Surprisingly, this algorithm has not yet been explored in the realm of image processing, which serves as a driving force behind our decision to apply WCA techniques to improve biomedical MR images. Enhancing the quality of MRI images is of paramount importance, as it can significantly elevate image quality, prompting the development of a nature-inspired WCA method rooted in the principles of the water cycle ecosystem.

The subsequent sections of this paper are structured as follows: Section 2 provides an overview of the methodology, outlining the use of PSO and APSO techniques for image enhancement. Section 3 introduces the proposed WCA algorithm for enhancement. In Section 4, the focus turns to the application of support vector machine and the proposed relevance vector machine for classification. Section 5 encompasses the presentation of results and in-depth discussions. Finally, in Section 6, the paper concludes, followed by the reference section.

2. Methodology

This research introduces a computer-based method for detecting brain tumors in magnetic resonance imaging. The primary objective of this study is to improve, identify, and pinpoint the tumor regions within the brain using the novel techniques of RVM learning and WCA. In pursuit of this goal, we have applied a distinctive enhancement approach grounded in the principles of WCA to MRI images and conducted a comparative assessment against the PSO and APSO algorithms.

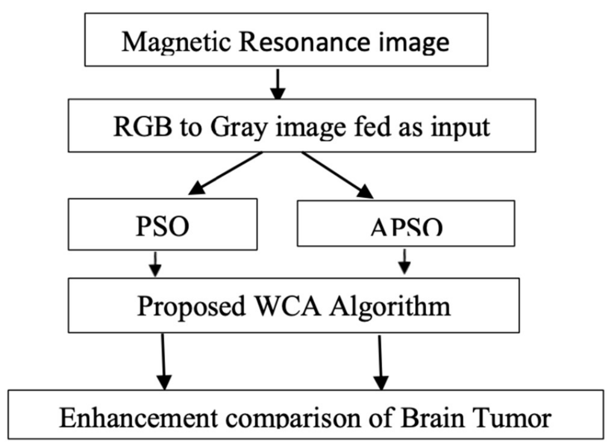


Fig.1 Research flow diagram for image Enhancement

2.1. Particle Swarm Optimization (PSO) and Accelerated Particle Swarm Optimization (APSO)

PSO is a population based stochastic optimization technique inspired by social behavior of bird flocking [11]. PSO uses a population of individuals, to search feasible region of the function space. In this context, each candidate solution is called particle and represents one individual of a population (features). The population is set of vectors and is called swarm (set of feature data points). The particles change their components and move (fly) in a search space.

The standard particle swarm optimization uses both the current global best g^* and the individual best x_i^*. In the accelerated particle swarm optimization (APSO) [12], the velocity vector is generated by a simpler formula

$$v_i^{t+1} = v_i^t + \alpha \in_n + \beta \left[g^* - x_i^t \right] \tag{1}$$

Where $\in_n$ is drawn from N (0, 1) to replace the second term. The update of the position is simply

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

In order to increase the convergence even further, we can also write the update of the location in a single step

$$x_i^{t+1} = (1-\beta)x_i^t + \beta g^* + \alpha \in_n \tag{3}$$

3. Proposed Water Cycle Algorithm for image Enhancement

The water cycle algorithm (WCA) mimics the flow of rivers and streams towards the sea and derived by the observation of water cycle process. The idea of the proposed WCA is inspired from nature and based on the observation of water cycle and how rivers and streams flow downhill towards the sea in the real world. It consists of several phases such as evaporation, precipitation, and surface run-off. The WCA [13, 14] has not been used previously by the researchers for Brain magnetic resonance images. In this paper, we have applied the WCA for enhancement which leads to improvement of image quality of MRI.

3.1. Mathematical model for WCA

Let us assume that there are some rain or precipitation phenomena. Starting the optimization algorithm requires the generation of an initial population representing a matrix of streams of size $N_{Population} \times D$, where D is the dimension. Hence, this matrix, which is generated randomly, is given as

$$Total\ population = \begin{bmatrix} Sea \\ River1 \\ River2 \\ River3 \\ \vdots \\ StreamN_{sr+1} \\ StreamN_{sr+2} \\ StreamN_{sr+3} \\ \vdots \\ StreamN_{pop} \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_D^1 \\ x_2^1 & x_2^2 & \cdots & x_D^2 \\ \vdots & \vdots & \cdots & \vdots \\ x_1^{N_{pop}} & x_2^{N_{pop}} & \cdots & x_D^{N_{pop}} \end{bmatrix} \tag{4}$$

The rows and column of equation 4 represents the population size ($N_{Population}$) and the number of design variables, D, respectively. In the first step, $N_{Population}$ streams are created. Then, a number of best individuals N_{sr} (minimum values) are selected as the sea and rivers. The stream which has the minimum value (objective function) among the others is considered as the sea. In fact, N_{sr} is the summation of the number of rivers (which is defined by the user) and a single sea. The rest of the population (N_{Stream}) are considered as streams flowing into the rivers or may alternatively flow directly into the sea.

At first step, $N_{Population}$ streams are created. Some of N_{sr} (good individuals or minimum values) are selected as a sea and rivers. The rest of the population is calculated using the following equation.

$$N_{sr} = No.of\ rivers + 1(sea) \tag{5}$$

$$N_{Stream} = N_{population} - N_{sr} \tag{6}$$

$$NS_n = round\left\{ \left| \frac{f(River_n)}{\sum_{i=1}^{N_{sr}} f(River_i)} \right| \times N_{Stream} \right\}, \quad n = 1,2,3 \ldots N_{sr} \tag{7}$$

Where, NS_n is the number of streams which flows into the specific rivers and sea, and f is the evaluation function in the algorithm. The designated streams for each river and the sea are calculated using the following Eq. 7.

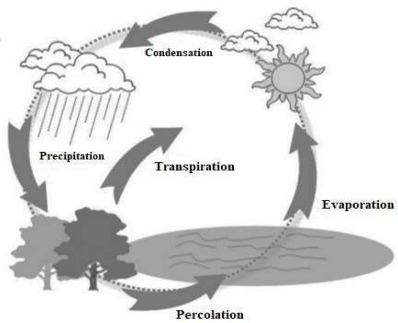


Fig.2 Hydrologic cycle

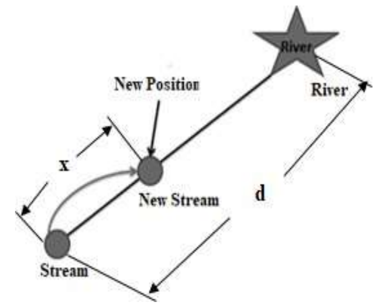


Fig. 3. (a) Schematic illustration of streams flowing into a specific river

Fig. 3 shows a schematic view of a stream flowing towards a specific river along their connecting line. For the exploitation phase of the WCA, new positions for streams and rivers have been suggested as follows.

$$\begin{aligned}
\vec{X}_{Stream}(t+1) &= \vec{X}_{Stream}(t) + rand \times C \times \left(\vec{X}_{Sea}(t) - \vec{X}_{Stream}(t)\right) \\
\vec{X}_{Stream}(t+1) &= \vec{X}_{Stream}(t) + rand \times C \times \left(\vec{X}_{River}(t) - \vec{X}_{Stream}(t)\right) \\
\vec{X}_{River}(t+1) &= \vec{X}_{River}(t) + rand \times C \times \left(\vec{X}_{Sea}(t) - \vec{X}_{River}(t)\right)
\end{aligned} \tag{8}$$

Where t is an iteration index, 1 < C < 2, and the best value for C may be chosen as 2, and 0 < rand <1. Basically, evaporation causes sea water to evaporate as rivers/streams flow into the sea. For that purpose, the following criterion is utilized for the evaporation condition between a river and the sea:

$$\text{If } \left\|\vec{X}^{t}_{Sea} - \vec{X}^{t}_{River\ j}\right\| < d_{\max} \quad or \quad rand < 0.1 \tag{9}$$

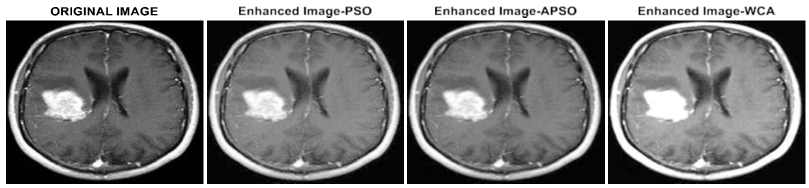
Where, j = 1,2,3, ,$N_{sr}-1$ and perform raining process by uniform random search and the end the process and $d_{\max}$ is a small number close to zero. After evaporation, the raining process is applied and new streams are formed in different locations. Therefore, $d_{\max}$ controls the search intensity near the sea (i.e., best obtained solution). The value of $d_{\max}$ decreases adaptively as follows [15]:

$$d_{\max}(t+1) = d_{\max}(t) - \frac{d_{\max}(t)}{Max.Iteration} \qquad t = 1,2,3,......., Maximum\ \ Iteration \tag{10}$$

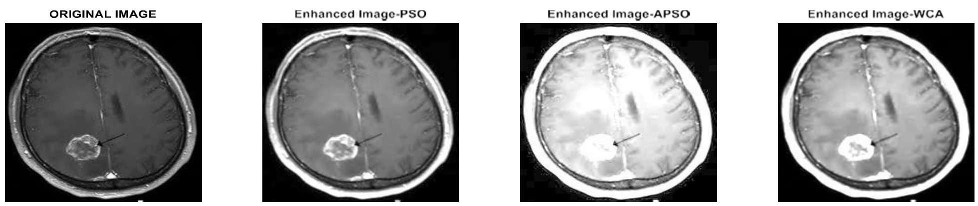
3.2. Enhancement results using PSO, APSO and WCA

It is found that the quality of image is much better in visualization from the Fig.4 and Fig.5 using WCA. The PSO, APSO also somehow increases the image quality, but the proposed

WCA gives better feature in terms of entropy and g_{best} value which is presented in table-1 in result and discussion section.



(a)Image-1



(b)Image -2

Fig. 4 Enhancement result of MRI using PSO, APSO and WCA (a) Image-1 (b) Image-2.

4. Magnetic resonance image Segmentation by SVM and RVM

In this paper, a fully automatic method for brain tissue segmentation has been proposed, in which the RVM classification algorithm has been employed for tumor extraction successfully. Further, with using the obtained tumor areas, the comparison analysis are presented with using RVM and SVM.

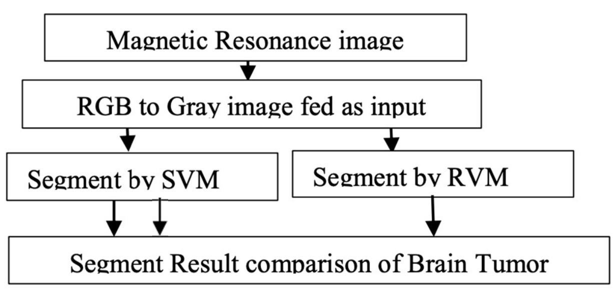


Fig. 5 Research flow diagram for image Segmentation

4.1. Support Vector Machine

For binary classification in SVM [16], the Solution for w can be written in a quadratic equation

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$$W(\alpha)=\left\{\sum_{i=1}^{N}\alpha_i-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\ \alpha_i\alpha_j y_i y_j\left\langle x_i, x_j\right\rangle\right\} \tag{11}$$

Subject $\sum_{i=1}^{N}\alpha_i y_i = 0$ where $\propto_i$ is the hyper parameter or Lagrangian multiplier.

Some advantages of SVM are: (i) it smoothly handles the nonlinear problems, (ii) good prediction accuracy and involved simple mathematical calculations.

4.2. Proposed Relevance Vector Machine (RVM)

The proposed RVM [17, 18] to recast the main ideas behind SVM in a Bayesian context. The RVM decision function can be much sparser than SVM classifier. Considering a two class problem, for given the input **x** , the RVM model follow the **sigmoid** function

$$\sigma(y)= 1\Big/\left(1+e^{-y}\right) \tag{12}$$

A RVM classifier model applying the logistic **sigmoid** function is given by

$$p(t_i=1,w)=\left[\sigma(y(x_i;w))\right]= 1\Big/1+e^{-y(x_i;w)} \tag{13}$$

The RVM classifier function is given by

$$y(x;w)=f_{RVM}(x)=\sum_{i=1}^{N}w_i K(x,x_i)+w_0=\Phi w \tag{14}$$

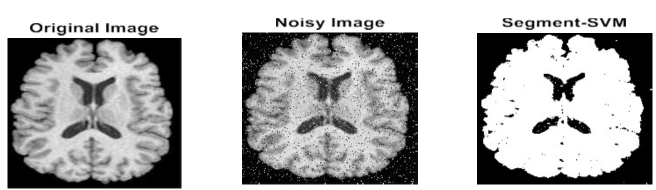
Where N is the length of the data and the weight vector, $w=[w_0,w_1,w_2,......w_N]^T$, and ϕ is $\square\times(N+1)$ design matrix. The matrix ϕ has elements $\phi_{i,j}=K(x_i,x_j)$. The kernel function is given by

$$k(x_i,x_j)=\exp\left(-\frac{\left\|x_i-x_j\right\|^2}{2\sigma_k^{\ 2}}\right) \tag{15}$$

Those training vectors associated with the non-zero weights are called Relevance Vectors and predictions are made based on the posterior distribution over the weights.

4.3. Segmentation results obtained using SVM and RVM

The segmentation results using SVM and RVM has been presented in the Fig.6 and Fig.7. It is found from the Fig.6 and Fig.7 that the noise has been removed and tumor has been detected.



In case of SVM the noise removal accuracy is 87.33% and 98.13% in case of RVM which is reported in table 3 and the computational time is lesser in RVM than SVM is reported here.

Fig.6 (a) Segment result with 30dB salt & Pepper noise using SVM

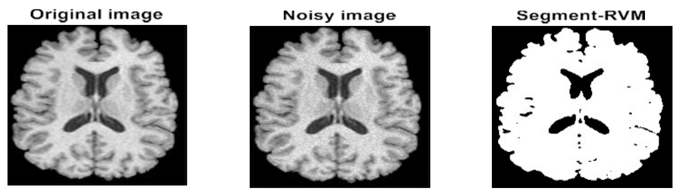


Fig.6 (b) Segment result with 40dB salt &Pepper noise using RVM

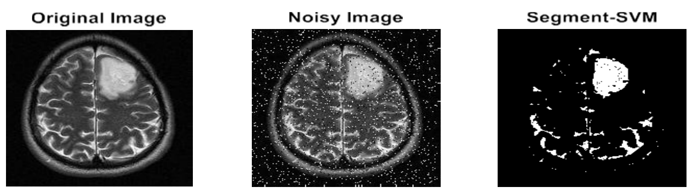


Fig.7 (a) Segment result with 30dB salt &Pepper noise using SVM

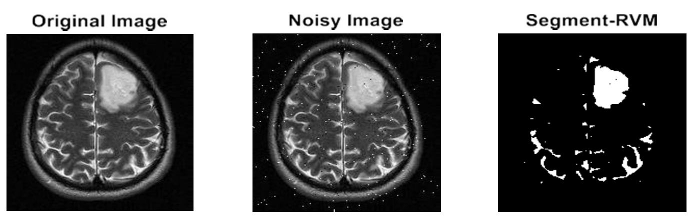


Fig.7 (b) Segment result with 40dB salt &Pepper noise using RVM

5. Results and Discussion

The MRI datasets has been collected from the Harvard medical school architecture and Alzheimer's disease Neuroimaging Initiative (ADNI) public database (http://adni.loni.usc.edu/)[1]. In the experimental part of the study, 75 MRI are used to optimize our system and 25 out-of-sample MRI are also used to test the approach. The comparison of entropy and gbest values using PSO, APSO and WCA method for enhancement has been presented in table-1. It is found that WCA shows good gbest and entropy values in comparison to PSO and APSO.

The bar graph shown in Fig.8, depicts the entropy comparisons for individual figure. It is seen that the entropy value obtained using WCA for enhancement of image is better than the other two PSO and APSO method. The bar graph shown in Fig.9, depicts the gbest value comparisons for individual images. It is seen that the gbest value obtained using PSO is better than APSO and WCA for enhancement of image. But the WCA is preferable as it takes less computational time as compared to PSO and WCA method which is shown in table 2.

Further, Fig.10 to Fig.11 shows the fitness value of all threes PSO, APSO and WCA method for image enhancement. It is found that fitness value for WCA is better in comparison to PSO and APSO method. Magnetic resonance image segmentation has been done by using S VM and RVM with salt & pepper noise. It can be concluded that the proposed RVM shows good accuracy than SVM. Further the computational time is lesser in RVM algorithm which is shown in table 3.

Table:1 Comparison result of Entropy and gbest_value of PSO,APSO and WCA

	PSO		APSO		WCA	
Image	***Entropy***	***g_{best}_value***	***Entropy***	***g_{best}_value***	***Entropy***	***g_{best}_value***
Img-1	0.7008	0.4538	0.7175	0.4511	0.7325	0.4340
Img-2	0.6128	0.4133	0.6266	0.4034	0.6438	0.3825
Img-3	0.6238	0.4250	0.6350	0.4152	0.6578	0.4012
Img-4	0.8815	0.5170	0.8835	0.5142	0.8957	0.5037
Img-5	0.8773	0.5181	0.8853	0.5124	0.8997	0.5041

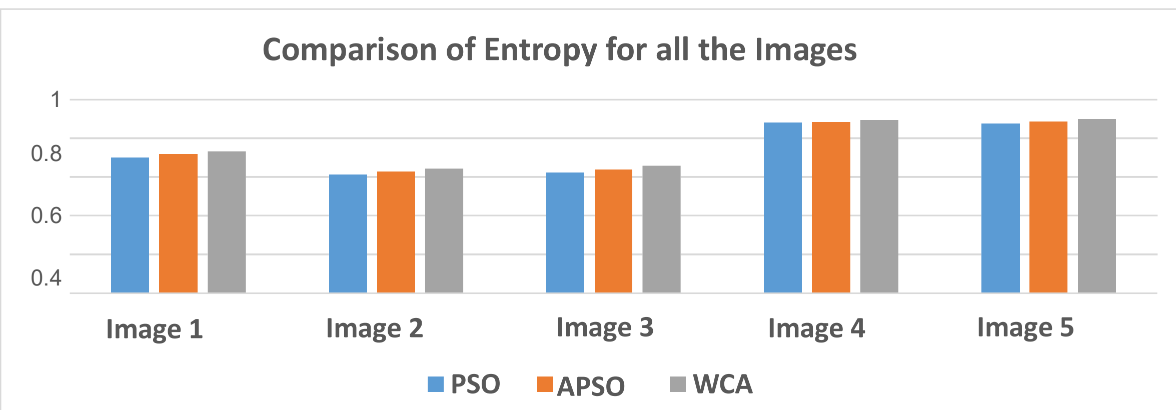


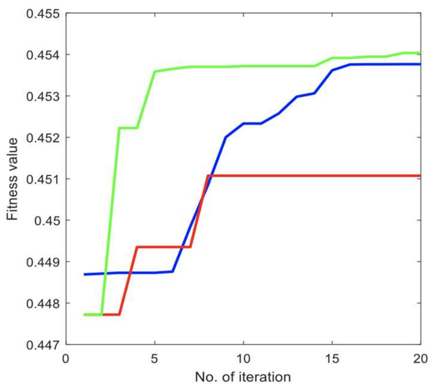
Fig.8 Bar chart for the comparison of Entropy using PSO, APSO and WCA

Computational time in Sec *(PSO,APSP,WCA)*

Image	PSO	APSO	WCA
Image-1	54.8386	51. 0986	31.3861
Image -2	59.2241	52. 3242	29. 4132
Image -3	57.4485	51.4285	27.4428
Image -4	66.9375	62.9955	26. 7595
Image -5	76.3930	72. 0103	23. 3012

Table:2 Computational time Comparison using PSO, APSO and WCA

Fig.9 Bar chart for the comparison of gbest value using PSO, APSO and WCA



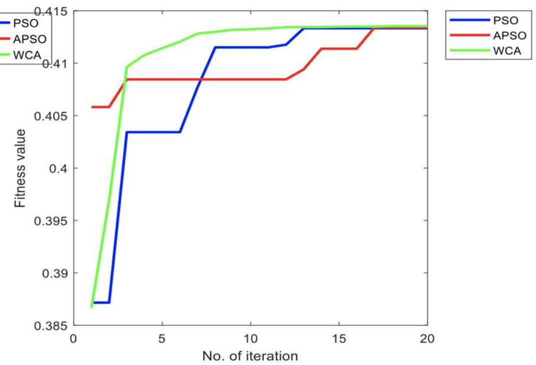


Fig .10 Fitness value curve for image-1 Fig .11 Fitness value curve for image-2

Table 3: Percentage accuracies and computational time comparison using SVM and RVM

Percentage Accuracies (%)			Computational time in Sec	
Image	**SVM**	**RVM**	**SVM**	**RVM**
Image-1	84. 86	97. 06	23.3111	12.3221
Image -2	83.21	98. 32	22. 4245	12. 2315
Image -3	87.45	98.28	22.4836	12.4123
Image -4	86.37	97.99	23. 7554	11. 6754
Image -5	**87.33**	**98. 13**	**23. 3214**	**11. 5414**

6. Conclusion

This paper introduced a novel optimization technique known as the Water Cycle Algorithm, drawing inspiration from the natural processes of the real world, specifically the water cycle. Within this study, we proposed the application of the WCA with an embedded constraint approach to enhance magnetic resonance images, resulting in improved image quality. Our statistical findings, which encompass fitness, entropy, and gbest values, were compared with various other optimization methods, including PSO and APSO. These comparisons highlight the effectiveness of the proposed method in handling diverse types of constraints, as evidenced by bar graphs, fitness curves, and computational time data. Additionally, we introduced segmentation methods based on support vector machines and relevance vector machines for tumor detection and noise reduction in magnetic resonance images. The results, complete with computational time and accuracy percentages in noisy environments, are presented in this paper. Nevertheless, further research is needed to assess the efficacy of the proposed WCA, SVM, and RVM on large-scale medical magnetic resonance imaging challenges, which can give rise to significant data-related research issues.

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