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Comparison of K-Means, Variant of K-Means, Genetic Algorithm, Particle Swarm Optimization, Weighted Particle Swarm Optimization and Firefly Algorithms For Image Classification

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Abstract

This paper addresses the problem of classifying an image into different regions. In this paper, we intend to show the performance (Distortion , Error Minimization and Computational time) of the new optimization algorithms such as Weighted Particle Swarm Optimization(WPSO) and Firefly algorithms over other more standard algorithms like k-Means Clustering, Genetic algorithm, Adaptive k-Means, Particle Swarm Optimization. In this work, we tackle this problem with six algorithms and presented a set of results that could hopefully foster future comparisons by using a Thyroid cancer cell image.

Index Terms: Image Classification, Optimization, Genetic Algorithm, Particle Swarm Optimization, Weighted Particle Swarm Optimization, Firefly Algorithm, Clustering.

Introduction

Images are the most important medium of conveying information. Understanding images and extracting the information from it such that the information can be used for other tasks is an important aspect of Machine learning [1][2]. One of the steps in course of understanding images is to classify them and find out diverse objects in them. In this work, clustering algorithms namely k- Means clustering and Optimization algorithms like Genetic algorithm, Genetic K-means, Particle Swarm Optimization, Weighted Particle Swarm optimization and fire fly algorithms are used for classification of image into different regions and are being compared. The comparison is based on various error metrics and time intricacy.

Optimization Algorithms have been an active area of research for several decades. As many real-world optimization problems become more complex, better optimization algorithms were needed. In all optimization problems the goal is to find the minimum or maximum of the objective function. Thus, unconstrained optimization problems can be formulated as minimization or maximization of D dimensional function:

Minimize (or Maximization) f(x), $x=(x_1, x_2, x_3,\ldots, x_D)$ (1)

where 'D' is the number of parameters to be optimized. Many population based algorithms were proposed for solving unconstrained optimization problems. Genetic algorithms (GA), particle swarm optimization (PSO), and k-Means algorithms are most popular optimization algorithms which employ a population of individuals to solve the problem on hand. The success or failure of a population based algorithm depends on its ability to establish proper trade-off between exploration and exploitation [3]. A poor balance between exploration and exploitation may result in a weak optimization method which may suffer from premature convergence, trapping in a local optima and stagnation. This paper discusses the employability of different optimization algorithms for Image Classification. The Flow of the paper is as follows: Section II gives a brief discussion of the different optimization algorithms used in this work. Section III discusses the performance analysis of these algorithms for the problem under consideration and the experimental results. Section IV presents conclusions and future scope of this work.

Optimization Algorithm

K-means Clustering Algorithm: K-Means algorithm is an unsubstantiated clustering algorithm that classifies the input data points into multiple classes based on their intrinsic distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them [4]. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriori. The main idea is to define 'k' centroids, one for each cluster. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. After these 'k' new centroids are obtained, a new binding has to be done between the same data set points and the nearest new centroid. The termination condition taken for this experiment is fixed number of iterations .The points are clustered around centroids $\mu_i \forall_i = 1\ldots.$ K which are obtained by minimizing the objective

$$V = \sum_{i=1}^{k} \sum_{x_i \in s_i} \left(x_j - \mu_i\right)^2 \quad (2)$$

Where there are k clusters S_i, i = 1, 2,….. k and μ_i is the centroid or mean point of all the points $x_i \in s_i$

The algorithm is composed of the following steps:

(1) Compute the intensity distribution in the image to be classified.
(2) Initialize the centroids with k random intensities.
(3) Repeat the following steps until the cluster labels of the image does not change anymore.
(4) Cluster the points based on distance of their intensities from the centroid intensities.

$$C^{(i)} := arg \min_j \left\| x^{(i)} - \mu_j \right\|^2 \quad (3)$$

(5) Compute the new centroid for each of the clusters.

$$\mu_i := \frac{\sum_{i=1}^{m} 1\{C_{(i)} = j\} x^{(i)}}{\sum_{i=1}^{m} 1\{C_{(i)} = j\}} \quad (4)$$

Where, k is a parameter of the algorithm (the number of clusters to be found), i iterates over all the intensities, j iterates over all the centroids and μ_j are the centroid intensities.

The k-Means algorithm suffers from the following two major drawbacks:

(1) It needs to predetermine the cluster number k. When the predetermined value equals the actual value, the algorithm can correctly find out the clustering centers. Otherwise it will lead to an incorrect clustering where some of the centers are not located at the centers of the corresponding clusters. Instead they are either at some boundary points among different clusters or at points biased from some cluster centers.
(2) If some units are initialized far away from the input data set in comparison with other units, they then become dead without learning chance any more in the whole learning process.

The drawbacks of the k-Means algorithm led the researchers to look into alternative methods that provide an improvement over k-Means.

Modified K-means clustering Algorithm

A technique is suggested that allows the segregation of a given data set without having to depend on the initial identification of elements to represent clusters. The method is based on rearranging the clusters, to better reflect the partitions when new elements are added. In addition, some clusters may be fused and new clusters are formed when needed. The technique is adaptive in nature and has been used to classify the image. The clustering process is carried out based on the concept that the inter cluster distance should be maximum and the intra cluster distance should be minimum. This is being formulated as the fitness function

$$\text{Fitness function} = \sum_{i=1}^{4} \frac{\sum_{j=1}^{G} C_{ij} - G_{ij}}{\sum_{j=1}^{G} [\sum_{k=1}^{4} C_i - G_{kj}]} \qquad (k! = i, 1 < k < n) \quad (5)$$

Where

G – Number of elements in a group i
$C_i -$ *Cluster head of Group i*
$G_{ij} -$ *Group Elements of group i*
$G_{kj} -$ *Group elements of group k*
The process is iterated and the average distortion is calculated using the formula

$$\text{Average distortion}=\sum_{i=1}^{4}\frac{\sum_{j=1}^{G} C_i - G_{ij}}{N_i} \tag{6}$$

$C_i -$ *Cluster head of Group i*
$G_{ij} -$ *Group Elements of group i*
$N_i -$ *Number of elements in group i*

Modified k-Means clustering Algorithm with Crossover Operation

The Modified k-Means algorithm is still enhanced with the Genetic Crossover technique. The initial population for the crossover is obtained from the results of the Modified k-Means algorithm executed for lesser number of iterations compared to the previous case. Randomly a member from each cluster is chosen as a cluster head and initialized as a chromosome. For this experiment, Single point Crossover is done between pairs of the group of cluster centers in every iteration. This process is executed for the remaining number of iterations such that the total number of iterations is the same for Modified k-Means Algorithm and Modified k-Means Algorithm with Cross-over operation.

Modified k-Means Algorithm with Mutation

The mutation is used to avoid local optimum and to make the cluster center to propagate toward the global optimum. Due to the random nature of initialization, cluster center will be improper during the initial stages and it requires at least 10 generations to be settled. It is performed only after 10^{th} generation. A Similar procedure as for k-Means with crossover is done with an exception of including Mutation in each iteration (after 10 iterations) instead of crossover along with the k-Means algorithm.

Genetic Algorithm

A popular evolutionary algorithm is Genetic algorithm, which is well known for its robustness even in large search spaces [9]. Genetic algorithm is being used for the pattern classification. Initially a population is assigned with certain pixel values from the image. Then this population is tested for the quality required using a fitness function given as

$$\text{Fitness function} =\sum_{i=1}^{4}\frac{\sum_{j=1}^{G} C_{ij} - G_{ij}}{\sum_{j=1}^{G}[\sum_{k=1}^{4} C_i - G_{kj}]} \tag{7}$$

G – Number of elements in a group i
$C_i -$ *Cluster head of Group i*
$G_{ij} -$ *Group Elements of group i*
$G_{kj} -$ *Group elements of group k*

Assuming the number of segments to be four initially, crossover is done between selected pairs to produce new chromosomes. Mutation is performed making small probabilistic modifications to the new chromosomes. The new population is made to replace the existing one and again the process is repeated starting from the fitness function for a fixed number of iterations.

Particle Swarm Optimization:

One of the evolutionary algorithm Particle Swarm Optimization (PSO), shares many similarities with another evolutionary computation technique Genetic Algorithm. The system is initialized with population of random solutions and searches for optima by updating generations. However unlike Genetic Algorithm, PSO has no evolution operator such as crossover and mutation. In PSO the potential solutions called particles fly through the problem space by following the current optimum particles.[7]

The particles in the customized PSO are initialized using the modified k-Means algorithm. The k-Means algorithm which is a well-known algebraic algorithm provides very good sources for initialization. The 'k' cluster centers are gained for the image and used for initialization. The Modified k-Means is run for a number of iterations and the values are fed as input for the particle initialization.

The velocity update equation for the swarm optimization technique is given as

$$\mathrm{V} = \mathrm{V}_{\mathrm{initial}} + \mathrm{C}_1 * \mathrm{rand} * (\mathrm{pbest} - \mathrm{particle}) + \mathrm{C}_2 * \mathrm{rand} * (\mathrm{gbest} - \mathrm{particle}) \quad (8)$$

$\mathrm{V} - \mathrm{Velocity}$,
$\mathrm{V}_{\mathrm{initial}} - \mathrm{Initial\ Velocity}$
$\mathrm{rand} - \mathrm{random\ integer}\ (0 < rand < 1)$
$\mathrm{C}_1 = 1, \mathrm{C}_2 = 1$
pbest – particle with best fitness value when compared with itself
gbest – fittest particle out of pbest particles
particles – cluster centers assigned to groups

The particle update equation is given as

$$\mathrm{P}_\mathrm{i} = \mathrm{P}_\mathrm{i} + \mathrm{V} \quad (9)$$

P_i – Particle initially assigned for i^{th} iteration

The algorithm is run for a fixed number of iterations as the before mentioned algorithms and the particle values are updated which leads to a better cluster centers.

Weighted particle Swarm optimization. The Weighted Particle Swarm optimization has a velocity update equation with a Constriction factor and weight which makes it to give more optimized ouput than the normal PSO [8].

The Velocity update equation of weighted PSO algorithm is given as

$$\mathrm{V} = \mathrm{CF}(\mathrm{W} * \mathrm{V} + \mathrm{C}_1 * \mathrm{rand} * (\mathrm{pbest} - \mathrm{particle}) + \mathrm{C}_2 * \mathrm{rand} * (\mathrm{gbest} - \mathrm{particle}) \quad (10)$$

$$\mathrm{CF} = \frac{2}{2 - \varphi\sqrt{\varphi^2 - 4\varphi}} \quad (11)$$

$$\varphi = \mathrm{C}_1 + \mathrm{C}_2 \quad (12)$$

$$\mathrm{Weight} = \mathrm{W}_{\max} - (\mathrm{W}_{\max} - \mathrm{W}_{\min}) * \frac{\mathrm{m}+1}{\mathrm{m}} \quad (13)$$

CF – Constriction Factor
$\mathrm{C}_1 = 1, \mathrm{C}_2 = 1$
V – Velocity
W – Weight
$\mathrm{W}_{\max} = 1, \mathrm{W}_{\min} = 0.4$
m – Current Iteration
rand – random integer ($0 < rand < 1$)
pbest – particles with fitness values
gbest – fittest particle out of pbest particles
particles – pixel values assigned to groups
The particle update equation is given as

$$\mathrm{P_i} = \mathrm{P_i} + \mathrm{V} \tag{14}$$

$\mathrm{P_i}$ – Particles initially assigned for i^{th} iteration

Firefly Algorithm

The firefly algorithm (FA) is a metaheuristic algorithm, inspired by the flashing behaviour of fireflies [5] [6]. The firefly algorithm uses the following three idealized rules:

(1) Fireflies are unisex so that one firefly will be gripped to other flies regardless of their sex.
(2) The attractiveness is proportional to the brightness, and they both decrease as their distance increases. Thus for any two flashing fireflies, the less bright one than a particular fly, it will move randomly.
(3) The brightness of a firefly is determined by the landscape of the objective function.

As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the variation of attractiveness β with the distance r by

$$\beta = \beta_0 e^{-\gamma r^2} \tag{15}$$

Where β_0 is the attractiveness at r = 0

$$X_i^{t+1} = X_i^t + \beta \exp[-\gamma r_{ij}^2]\left(X_j^t - X_i^t\right) + \alpha_t \varepsilon_t \tag{16}$$

$X_i^t - All\ flies$
$X_j^t - Few\ flies$
$\beta = 1$
$\alpha_t = 0.2$
$\gamma = 1$
$\varepsilon_t - Randomness\ Constant$
$\varepsilon_t = (randomn\ integer - 0.5)$

$$r_{ij} = \sqrt{\left(X_{ij} - Y_{ij}\right)^2} \tag{17}$$

Comparison of Performance Measures

The performance measures considered here for comparison of different optimization algorithms for image classification are Fitness Error Minimization over number of iterations and Average Distortion over number of iterations.

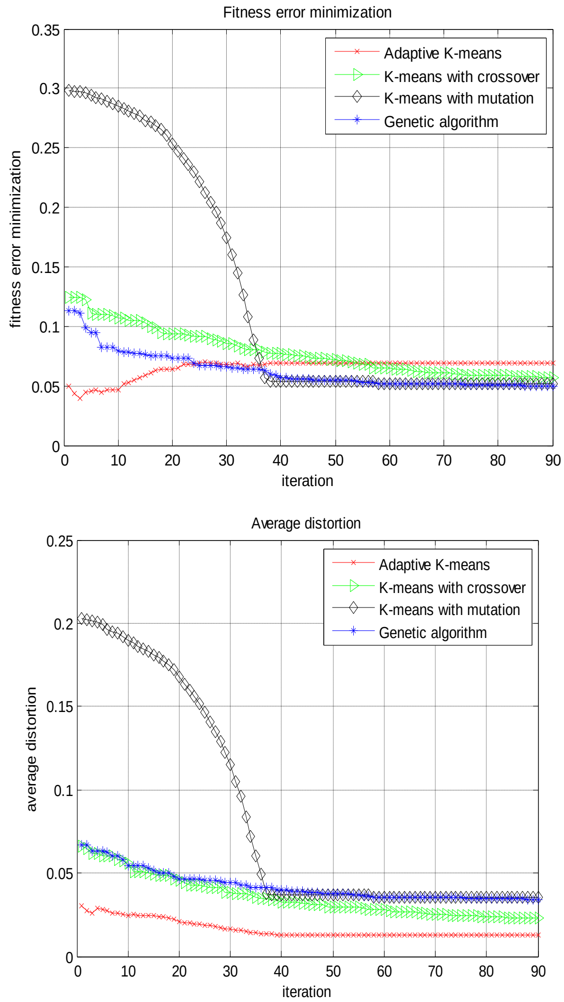


Figure 1: Fitness Error Minimization & Average Iteration comparison between Adaptive k-means, K-means with crossover and Mutation, Genetic Algorithm

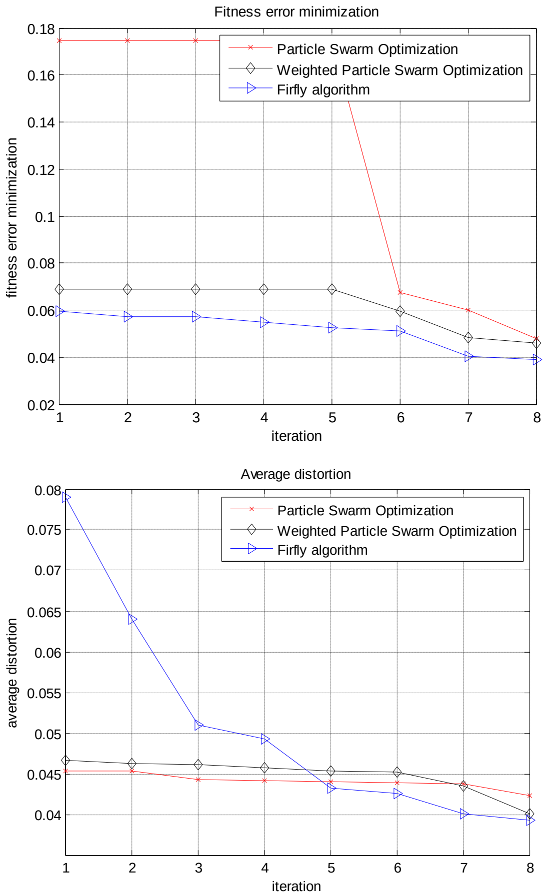
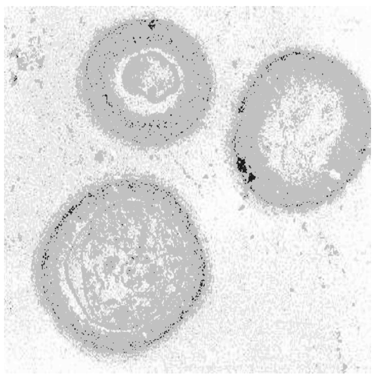
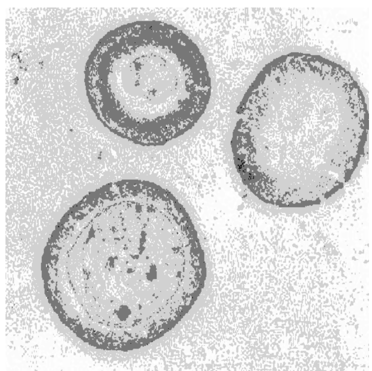


Figure 2: Fitness Error Minimization & Average Iteration comparison between PSO, WPSO and Firefly Algorithm

	
Adaptive K means	K-means with mutation

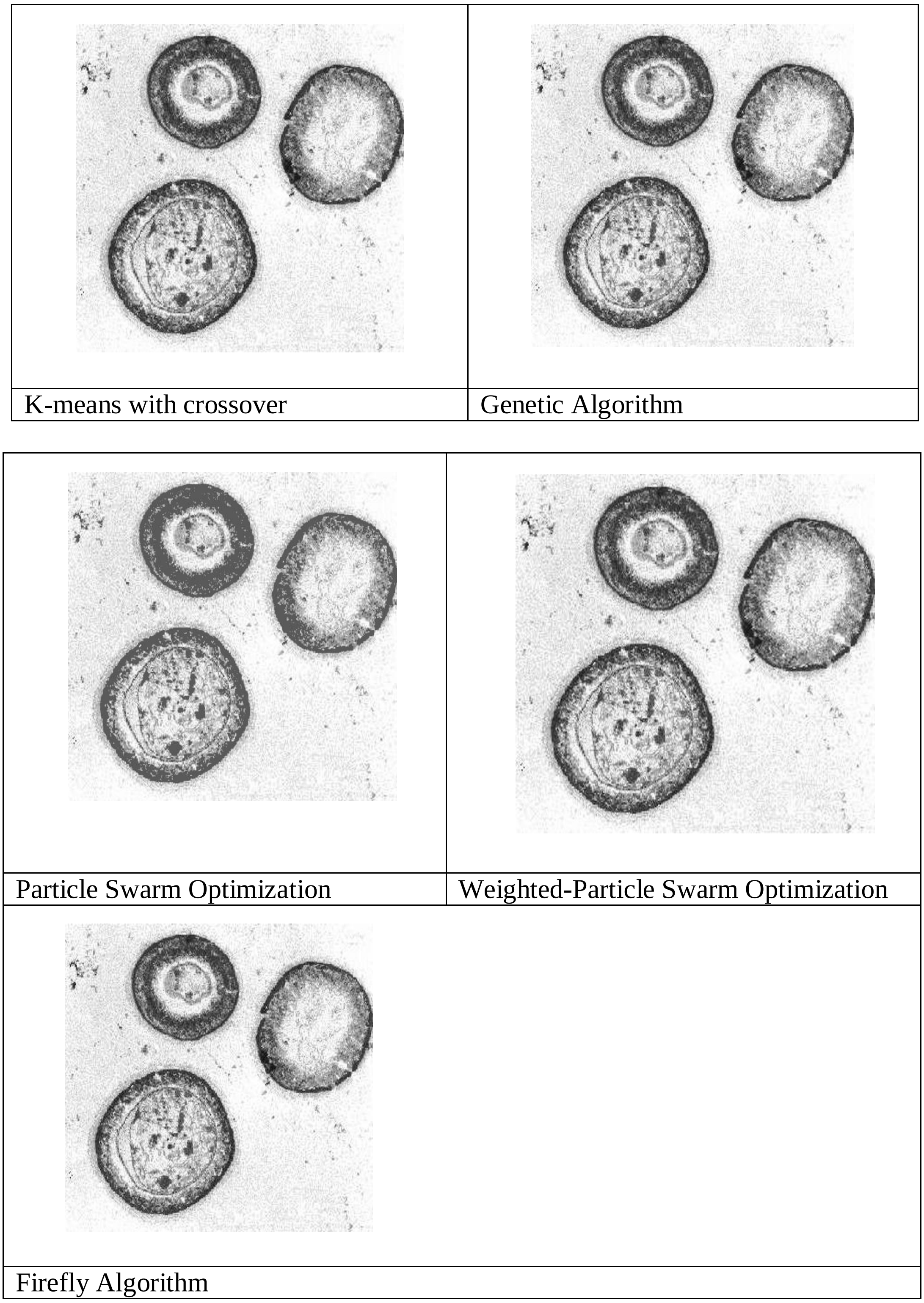
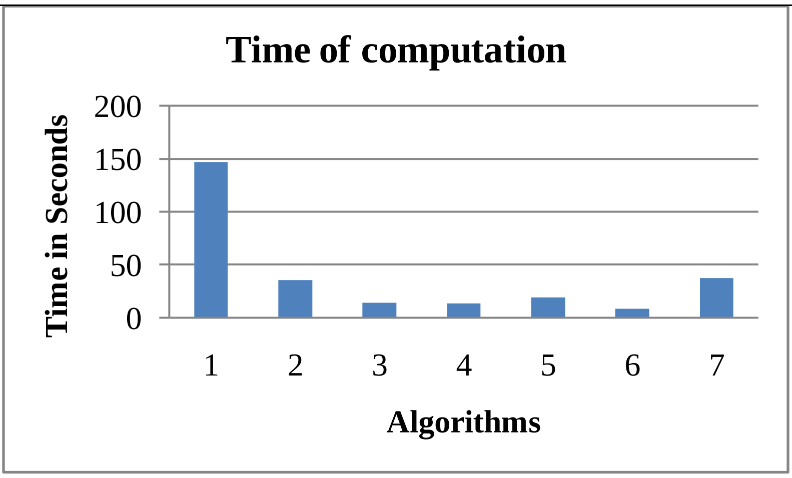


Figure 4: Image Classification by various algorithms



1 – Adaptive k-means
2 – K-means with mutation
3 – K-means with crossover
4 – Genetic Algorithm
5 – Particle Swarm Optimization
6 – Weighted Particle Swarm Optimation
7 – Firefly Algorithm

Figure 5: Computation Time

Consummation

The presented work combines several ideas such as Adaptive k- means clustering, k-means with mutation, k-means with crossover, Genetic Algorithm , Particle Swarm Optimization , weighted Particle Swarm optimization and the Firefly Algorithm for unsupervised content based image classification. The experimental results show that the PSO and WPSO have the highest accuracy and their time of computation is much less than other algorithms. The scope of this dissertation is to try out the image clustering by Bat search and Ant colony optimization algorithms and to compare their performance measures with the so far achieved results.

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