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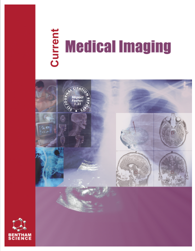

RESEARCH ARTICLE

A Novel Invasive Weed Optimization and its Variant for the Detection of Polycystic Ovary Syndrome

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Abstract:

Introduction:

This study intends to provide a novel Invasive Weed Optimization (IWO) algorithm for the detection of Polycystic Ovary Syndrome (PCOS) from ultrasound ovarian images. PCOS is an intricate anarchy described by hyperandrogenemia and irregular menstruation. Indian women are increasingly finding reproductive disorders, namely PCOS.

Methods:

The women having PCOS grow more small follicles in their ovaries. The radiologists take a look into women's ovaries by use of ultrasound scanning equipment to manually count the number of follicles and their size for fertility treatment. These may lead to error diagnosis.

Results:

This paper proposed an automatic follicle detection system for identifying PCOS in the ovary using IWO. The performance of IWO is improved in Modified Invasive Weed Optimization (MIWO). This algorithm imitates the biological weeds' behavior. The MIWO is employed to obtain the optimal threshold by maximizing the between-class variance of the modified Otsu method. The efficiency of the proposed method has been compared with the well-known optimization technique called Particle Swarm Optimization (PSO) and with IWO.

Conclusion:

Experimental results proved that the MIWO finds an optimal threshold higher than that of IWO and PSO.

Keywords: Follicles, Polycystic ovaries, Invasive weed optimization, Particle swarm optimization, Modified Otsu, Modified Invasive Weed Optimization.

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1. INTRODUCTION

Reproductive system anomalies, hormone imbalance, characterize Polycystic Ovary Syndrome, increased testicular production, and miscarriage. PCOS is already spreading like wildfire among adolescent girls. This abnormality makes it difficult to get pregnant. Apart from reproductive irregularities, PCOS causes serious health issues such as diabetes and heart disease. As a result, early diagnosis of PCOS is critical for effective therapy [1]. Furthermore, if PCOS is not addressed, it can progress to more significant health issues such as diabetes, infertility, and heart disease. As a result, radiologists must pay close attention to PCOS patients, evaluating their ovaries on a regular basis and measuring the size and number of follicles present [2]. Transvaginal ultrasound is a type of imaging technique used to take a glance at the internal organs like the ovaries, cervix, and uterus. Radiologists carry out transvaginal ultrasound examinations to create imaging of ovaries [3]. From the captured image, the number of follicles is manually counted. In reference to that, the ovaries are classified as normal and polycystic. American Society for Reproductive Medicine describes that the normal ovary contains less than 10 follicles with a size of 2.0 to 9.0 mm, and the polycystic ovaries have 12 or numerous follicles with a size below 10. 0 mm [4]. Manual detection and classification of the ovary is time-consuming and may lead to error diagnosis. To solve this problem, this paper introduced a novel IWO algorithm to automatically identify the follicles from the ovarian images. To enhance the performance of the IWO, MIWO is also

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introduced in this paper [2, 5].

To automate the detection of follicles from the ovary, a region growing algorithm is introduced [6]. SAR images are detected using an optimization algorithm [7]. Various types of segmentation algorithms are developed to detect follicles from the ovaries [3]. The results suggested that the active contour method extracts the follicles better than other existing algorithms. To optimize the results, an optimization algorithm was developed. An effective evolutionary method namely Ant Colony Optimization, was introduced, to improve the segmentation process for brain image segmentation [4]. Nowadays, optimization algorithmss play a major role in both engineering and medical applications. Evolutionary algorithms, namely Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Bacterial Foraging (BFO), Genetic Algorithm (GA), and Differential Evolution (DE) have been appraised and effectively applied to optimize the threshold value for image segmentation. These algorithms have exposed better performance for searching the optimal value [5]. A multilevel thresholding method was used to segment the hyperspectral images. By using Fractional Order Darwinian particle swarm optimization, the thresholding technique was reduced to an optimization problem [8]. Ant colony optimization method was used, combined with thresholding methods, to obtain a better threshold value. This technique can efficiently segment the objects from their background [9]. For image classification, k means, and fuzzy c means clustering method with differential evolution method was presented [10]. This optimization algorithm is a powerful technique inclined from the colonization of weeds behavior [11]. Many literatures present invasive weed optimization algorithms used for antenna array and electromagnetic problems [12]. In the existing system, the PSO algorithm was developed to detect the optimal threshold value. However, it did not produce an optimal threshold value. In this paper, a novel IWO algorithm is introduced to optimize the threshold value used for image segmentation. It achieved better accuracy compared to the existing PSO algorithm.

2. METHOD

To automate the detection of follicles from the ultrasound ovarian images, the optimal threshold value is essential. In this proposed system, a new optimization algorithm, IWO, has been introduced. Mehrabian and Lucas proposed [13] the IWO algorithm in 2006. The IWO algorithm emulates the colonization of weed's behavior and its distribution. All individuals in the colony are known as seeds. The fitness of each seed is evaluated; after fitness evaluation, the seed is represented as a plant. The algorithm is preceded as follows.

2.1. Initialization

A population of a finite number of seeds is arbitrarily dispreaded in the search space.

2.2. Reproduction

In the reproduction phase, each member of the population is allowed to produce seeds depending on the colony's smallest and highest fitness and its own fitness. The plant with higher fitness produced the largest number of seeds than the plant with lower fitness. The seed production increases linearly from lower to higher.

2.3. Spatial dispersal

The seeds reproduced by the weeds are randomly distributed over the search space by normally distributed random numbers with a mean value of zero and with changing variance values. However, the *S* (standard deviation) is made to decrease from a formerly defined S_{ini} to an S_{fin} over the iteration. *itr* represents the current iteration, and the maximum number of iterations is denoted as itr_{max}. The standard deviation formula for IWO is given in Eq. (**1**).

$$S_{itr} = \frac{\left(itr_{\max} - itr\right)^{nmi}}{\left(itr_{\max}\right)^{nmi}} \left(S_{ini} - S_{fin}\right) + S_{fin} \tag{1}$$

$$S_{itr} = \frac{\left(itr_{\max} - itr\right)^{nmi}}{\left(itr_{\max}\right)^{nmi}} \,|\cos(itr)|\, (S_{ini} - S_{fin}) + S_{fin} \tag{2}$$

where Eq. (**2**) represents the standard deviation for MIWO. *nmi* is denotes the nonlinear modulation index. This spatial dispersion step ensures that the plants with poor fitness are eliminated from the colony and that those with good fitness are grouped together.

To improve the performance of the conventional IWO, a few alterations are included. The Modified Invasive Weed Optimization (MIWO) has performed better than the IWO. The $|\cos(it)|$ is included in the standard deviation equation. This term helps to obtain the optimal solution faster. If the S_{itr} is larger, the chance of rejecting the optimal solution is higher. The modified IWO solved this problem by introducing this new term. In any problem, the objective is to obtain an optimal solution by using minimum capital. In the conventional IWO method, the seeds are produced with the S_{ini} value, and this value decreases towards the S_{fin} when the number of iterations increases. The S_{fin} value has been obtained at the end of the iteration. However, in the case of MIWO, the S_{fin} values are attained before reaching the maximum number of iterations. Fig. (**1**) depicts the reduction of S_{itr} value over iterations by conventional IWO and the MIWO. The MIWO finds the optimal values quicker than the conventional IWO.

2.4. Competitive Exclusion

To restrict the maximum number of plants in a colony, a rivalry among plants is needed [14]. As a result of quick reproduction, maximum number of colonies is reached in some iteration. The seeds produced are included in the existing colony and placed near the parent plant. The plants with better fitness produce a maximum number of seeds than the plants with lower fitness. Eliminating plants with a lower fitness value is needed when the maximum number of plants reaches P_{max} [15, 16]. Once the maximum number of plants is reached, those plants are allowed to produce seeds based on step 2. Then, the seeds are spread over the search space as specified in step 3. Furthermore, the seeds are ranked in concert with their parents. To reach $P_{max,}$ the plants with lower fitness values are eliminated from the colony. This process is continued until it reaches the maximum number of iterations.

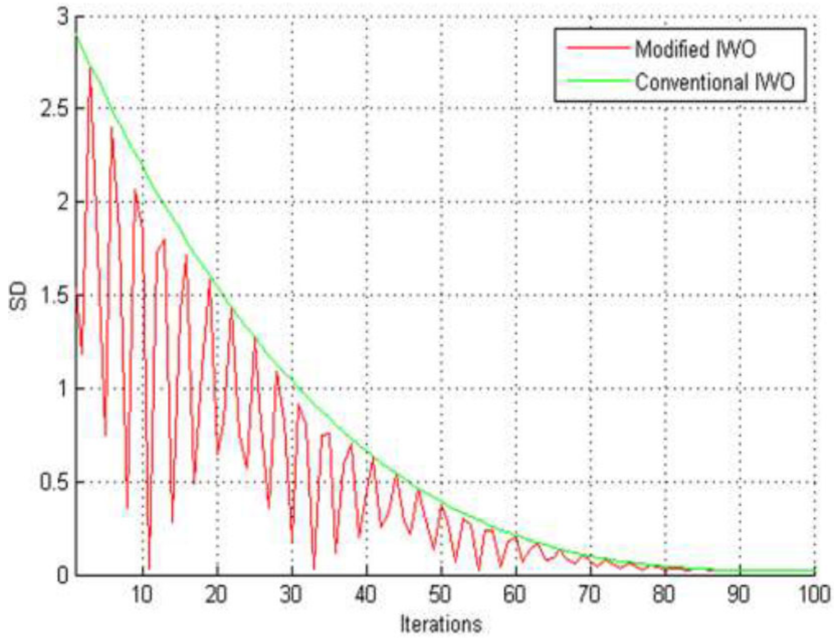

Fig. (1). Comparison of conventional IWO and MIWO by the difference of standard deviation.

2.4.1. Problem Definition

To solve the problem of manual detection of PCOS, an automatic detection system has been introduced. For this system, the ultrasound ovarian image is given as input. The input images contain follicles along with tissues and blood vessels; extracting the follicles from these images is a difficult task [17]. It necessitates an efficient method for segmenting the follicles. Invasive weed optimization is a weeds colonization behavior, where each seed signifies the solution to the problem [18]. The invasive weed optimization and modified invasive weed optimization have been used to maximize the between-class variance of the modified Otsu to obtain the optimal threshold. The obtained threshold is used to automatically detect the follicles from the input image. From the detected follicles, the shape features like Area, Extent, Circularity, and Tortuosity have been extracted to classify the ovary image as normal ovary and polycystic ovary.

2.4.2. Fitness Evaluation

The objective is to maximize the between-class variance of the modified Otsu method to obtain the optimal threshold value for the detection of follicles. The initial threshold value is calculated iteratively using the modified Otsu method. The obtained threshold split the image into two groups. The mean of the two groups is calculated. This process is continued until the threshold value converges.

The iteratively calculated threshold value is given as an initial threshold to the conventional Otsu method [12]. The between-class variance is given in Eq. (**3**).

$$\sigma_{Be}^2(t) = B_1(m_{g_1} - m_t)^2 + B_2(m_{g_2} - m_t)^2 \quad \textbf{(3)}$$

where σ_{Be}^2 is the between class variance . B_1 and B_2 are the estimated group probabilities. m_{g1}, m_{g2} are the mean values of the two groups, and m_t is the total mean. The means of the two groups are computed as follows. Where $t*$ is the iterative threshold calculated by the modified Otsu method Eq. (4, 5).

$$m_{g_1}(t^*) = \sum_{k=1}^{t^*} \frac{k\,P_o(k)}{B_1(t^*)} \quad m_{g_2}(t^*) = \sum_{k=t^*+1}^{S} \frac{k\,P_o(k)}{B_2(t^*)} \quad \textbf{(4)}$$

σ_{wi}^2 is the within-class variance

$$\sigma_{wi}^2(t^*) = B_1(t^*)\sigma_{g_1}^2(t^*) + B_2(t^*)\sigma_{g_2}^2(t^*) \quad \textbf{(5)}$$

Where B_1 *and* B_2 are the estimated group probabilities and $\sigma_{g_1}^2 \sigma_{g_2}^2$ are the group variances. They are calculated as Eq. (5, 6).

$$B_1 = \sum_{k=1}^{t} P_o(k) \qquad B_2 = \sum_{k=t+1}^{S} P_o(k) \quad \textbf{(6)}$$

$$\sigma_{g_1}^2(t^*) = \sum_{k=1}^{t^*} [k - m_{g1}(t^*)]^2 \frac{P_o(k)}{B_1(t^*)}$$
$$\sigma_{g_2}^2(t^*) = \sum_{k=t^*+1}^{S} [k - m_{g2}(t^*)]^2 \frac{P_o(k)}{B_2(t^*)} \quad \textbf{(7)}$$

2.4.3. Implementation of IWO Algorithm for Follicle Detection

The invasive weed optimization algorithm is the proposed method used to detect the follicles from the ovarian images. The performance of the proposed method is improvised in the MIWO algorithm. Each pixel in the population is represented as a seed. The target is to obtain the objective function. An initial population of a finite number of seeds is randomly spread over the search space [19]. In the consequent step, the fitness of the seeds is calculated. The fitness of the plants has been evaluated using Eq. (**3**). In the spatial dispersion stage, the

IWO method calculates the standard deviation S_{itr} using Eq. (**1**), and MIWO calculates the standard deviation using Eq. (**2**). Once the populations of the plants reach the maximum population, the elimination of weak plants isperformed. In other words, the plants with the worst fitness values have been identified and eliminated. This process is stopped until it reaches the allowable number of iterations or there is no improvement in the solution. The flowchart shown in Fig. (**2**) describes the above procedure.

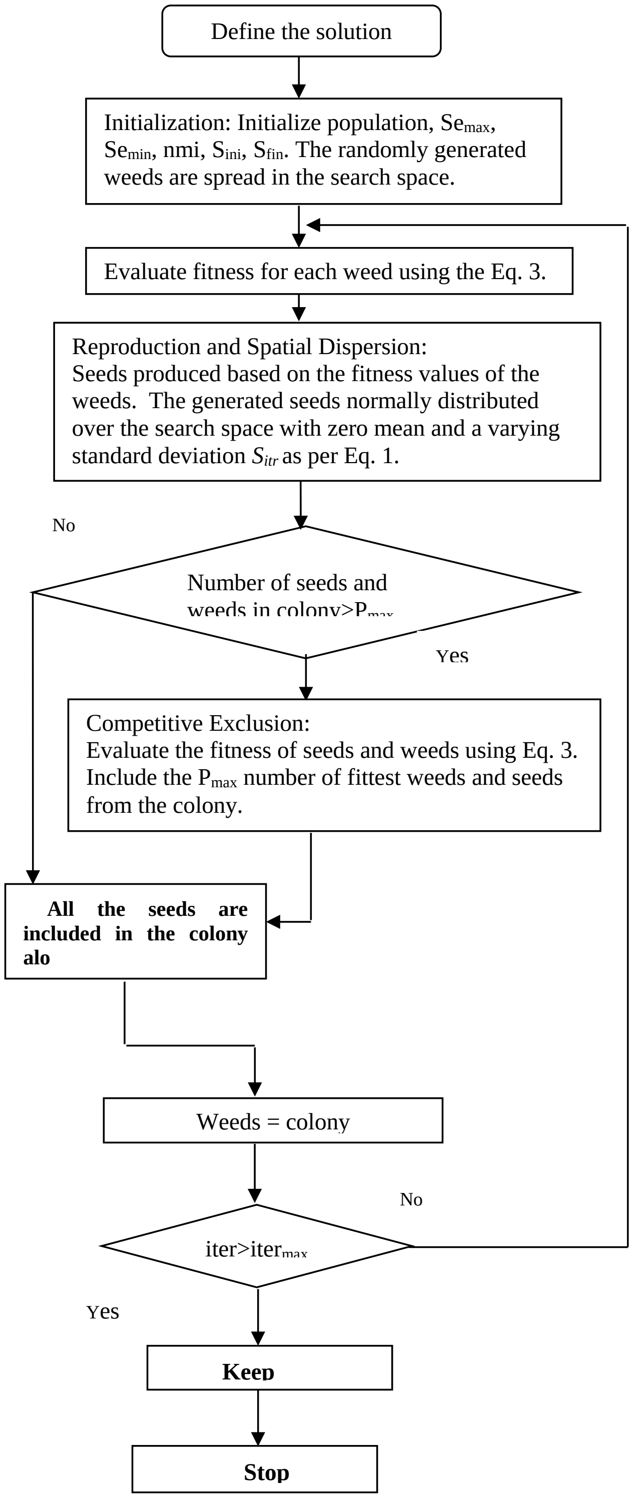

Fig. (2). Flowchart of the proposed Invasive weed optimization algorithm.

This section discusses the classification of ovarian images. The follicles are extracted from the image by the MIWO method. The detected follicle's shape features are extracted to classify ovarian images. The shape-based parameters are calculated from identified follicles. The follicle area is calculated to measure the size of the follicle. The Area of a follicle in an ovary image is computed as the number of pixels inside the segmented follicle. Medical Experts recognize follicles based on their Circularity, Tortuosity, and Extent. Based on the number of follicles and their size, medical experts classify the ovarian image. In this paper, the SVM classifier is used to classify the ovarian image into normal and polycystic ovaries. According to the expert report, the ovary contains 1 to 10 follicles with a size of 2 to 10 mm, is known as a normal ovary, and the polycystic ovary contains 12 or more follicles with a size of up to 10 mm. The parameters, namely the Total Number of Follicles (TNF) and Area of the Follicles (AF), are used in both the training and testing phase of the SVM classifier to classify the ovarian image.

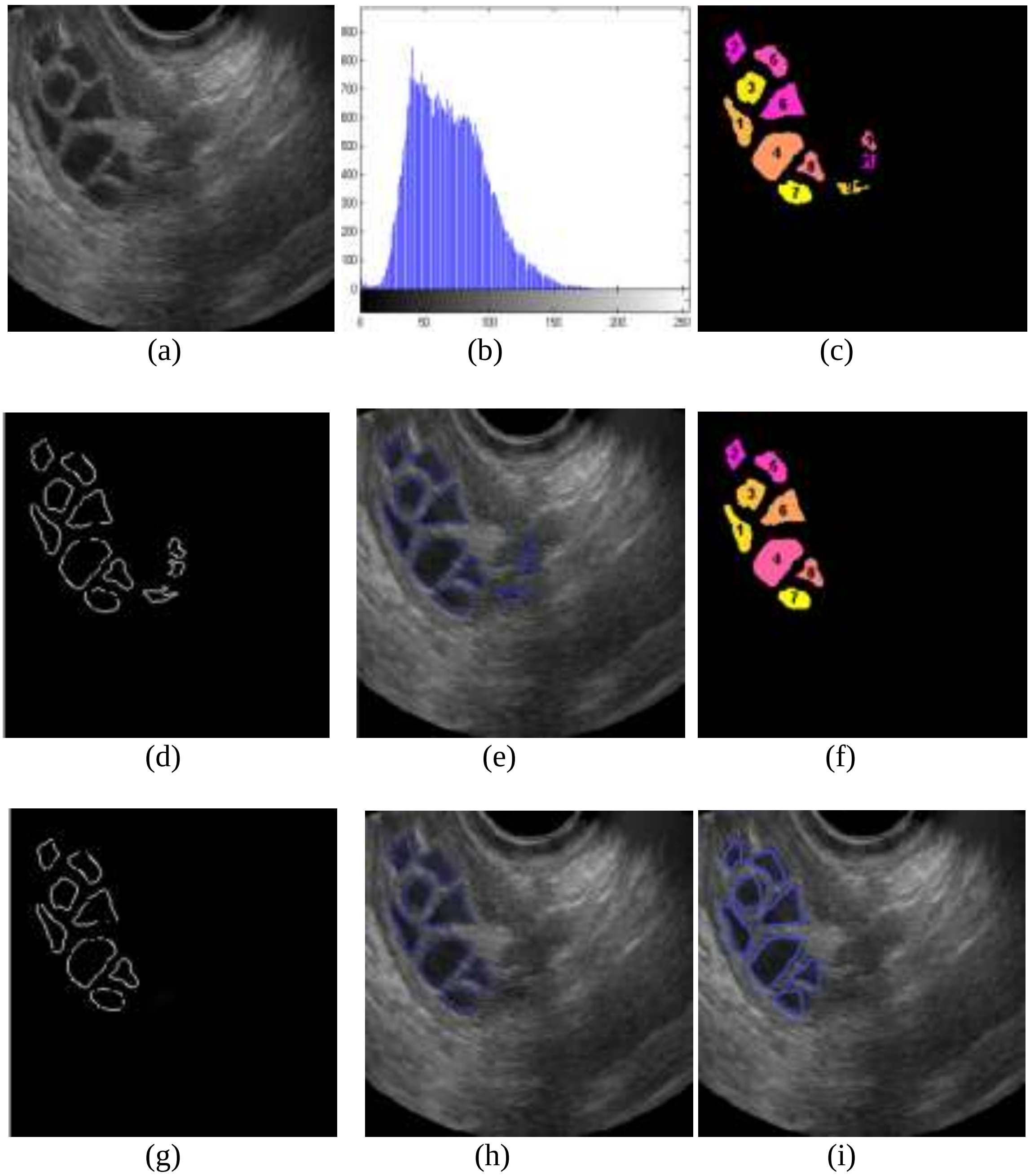

Fig. (3). Segmentat ion result. **a**) Original image **b**) Histogram of an original image **c**) Ident ified follicles by PSO **d**) Edge detected from the PSO result **e**) PSO result overlaid on original image **f**) Ident ified follicles by MIWO **g**) Edge detected from the MIWO result **h**) M IWO result overlaid on original image **i**) Medical expert result.

TNF Total Number of Follicles in normal ovary

AF Area of the Follicles in normal ovary

TNF1 Total Number of Follicles in polycystic ovary

AF1 Area of the Follicles in polycystic ovary

The features called the number of follicles and the follicle size of normal and polycystic ovarian images are used in the training phase. In the testing phase, the SVM classifier is used to classify the ovarian image as normal and polycystic using the calculated feature values.

3. RESULTS AND DISCUSSION

In this section, the performance of the proposed method has been evaluated based on the experimental results. Also, the proposed method is compared with the existing algorithm [6], and the performance is evaluated. The problem was experimented on 95 ultrasound ovarian images collected from various scan centers in Coimbatore. The proposed method is developed using Matlab 2012a. The experiments have been conductedon HP Pavilion dv5 with Intel® Core™ 2 Duo CPU @ 2.00GHz with 3 GB RAM running on Microsoft Windows 7 platform. By using the number of correctly identified follicles, the performance of the proposed method was analyzed. The objective of the proposed method is to maximize the objective function. Using the optimal threshold value obtained from the proposed MIWO method was applied to ovarian images. It efficiently extracts the follicles from the image. The result of the identified follicles is shown in Fig. (**3**). Fig. (**3a**) shows the original image, and the histogram of an original image is given in Fig. (**3b**).

The identified follicles by the PSO are shown in Fig. (**3c**). Totally 11 number of follicles are identified by using the threshold obtained from the PSO method. The edges of the follicles are extracted, as seen in Fig. (**3d**). The edges are overlaid on the original image seen in Fig. (**3e**). Fig. (**3f**) shows the 8 identified follicles by the proposed MIWO method. The result is similar to the medical expert's result shown in Fig. (**3i**). The IWO method also extracts the accurate number of follicles. But MIWO converges quicker and finds the optimal threshold value faster. Similarly, the edges of the follicles identified by the proposed method have been extracted and are superimposed on the original image given in Fig. (**3g**) and (**3h**), respectively. The proposed MIWO method provides a more optimal threshold value than the IWO and PSO method. The parameters of the IWO and MIWO, namely, initial and final standard deviation values, assist in improving the convergence rate. These parameters have been optimally tuned to achieve the better result. In every iteration, to attain appropriate standard deviation, tuning of parameters S_{ini}, S_{fin}, Non-linear Modulation Index (NMI) should be essential. The value of S_{ini}, $S_{fin,\ is}$ chosen carefully; selecting a high S_{ini} permits one to search around the entire area.

To accurately obtain the optimum solution S_{fin} value is tuned cautiously. In the reproduction process, the parameters called minimum number of seeds, maximum number of seeds, and maximum number of plants are initialized. All plants in the colony are allowed to produce the seeds. Based on the fitness value, the seeds can survive. The plant with better fitness yields more seeds when compared to a lower fitness plant. In many problems, a minimum number of seeds is chosen as zero. The maximum number of seeds is always set in the midst of 3 and 5 for better algorithm performance. The allowable number of plants is preferred based on the problem. The standard deviation value has been reduced from S_{ini} to S_{fin}. The invasive weed optimization algorithm can search around the entire solution space by using an initial high standard deviation. Finally, to obtain the optimal solution by increasing the number of iterations, the standard deviation is reduced gradually.

From Fig. (**4**), it is observed that the selection of the nonlinear modulation index into 3 is an optimum choice. In this paper, MIWO is compared with IWO and PSO. The number of populations and the number of iterations are chosen the same for both algorithms. In PSO, to control the convergence, a suitable selection of parameters, maximum and minimum inertia weight, and acceleration coefficients C_1 and C_2 are necessary. Similarly, in the case of IWO and MIWO, tuning the initial and final standard deviation values, non-linear modulation index, and maximum and minimum number of seeds is essential. The parameter and their values of these three algorithms are given in Table **1**. From the identified follicles, the shape features, specifically Extent, Tortuosity, Circularity, and Area are extracted. PSO method wrongly recognizes three follicles. Those follicle's features, Extent, Circularity, and Tortuosity exceed the range given by the medical expert. With the help of a medical expert given report, the true follicles are recognized from the identified follicles. Tables **2** and **3** show the number of detected follicles by proposed methods, PSO method, and by medical expert. From these tables, it is noticed that the proposed methods correctly recognize the follicles, which accurately matches the results of the medical expert. The maximum between-class variance was attained by varying population size and a maximum number of allowable population sizes. In IWO and MIWO, the population size was initially set as 50, and the maximum number of iterations was set as 50. The maximum value for between-class variance is obtained while increasing population size and iteration to 100. Moreover, the proposed method is compared with the existing method, and the results are compared based on the number of follicles detected, as shown in Table **4**.

Table 1. Parameter values for IWO, MIWO, and PSO.

IWO/MIWO		PSO	
Parameter	**Value**	**Parameter**	**Value**
Initial Population	100	Population	150
Population Maximum	150	Iteration	100
Maximum Iteration	100	C_1	2.0

(Table 1) contd.....

IWO/MIWO		PSO	
Parameter	**Value**	**Parameter**	**Value**
Se_{min}	3	C_2	2.0
Se_{max}	5	Inertia Weight Minimum	0.1
S_{ini}	3		
S_{fin}	0.00002	Inertia Weight Maximum	0.9
nmi	3		

Table 2. Comparison of proposed MIWO and IWO method and PSO method based on identified follicles.

Original Image	Number of Identified Follicles									
	Proposed MIWO Method			Proposed IWO Method			PSO Method			Manual Expert
	Total	True	False	Total	True	False	Total	True	False	
Ovary Image1	7	7	-	7	7	-	11	8	3	7
Ovary Image2	13	13	-	13	13	-	17	12	5	13
Ovary Image 3	5	5	-	5	5	-	9	4	5	5

Table 3. Comparison of follicle detection results of the proposed IWO and MIWO method with the PSO and manual follicle detection by the medical expert.

Number of Images Used for Experiment	Identified Follicles by Proposed MIWO Method	Identified Follicles by Proposed IWO Method	Identified Follicles by PSO Method	Follicle detection by Medical Expert
95	197	199	214	192

Table 4. Comparision of follicle detection results of the proposed MIWO method with the existing method and manual follicle detection by the medical expert.

Number of Images Used for Experiment	Identified Follicles by Proposed MIWO Method	Identified Follicles by Existing Method	Follicle Detection by Medical Expert
205	289	347	292

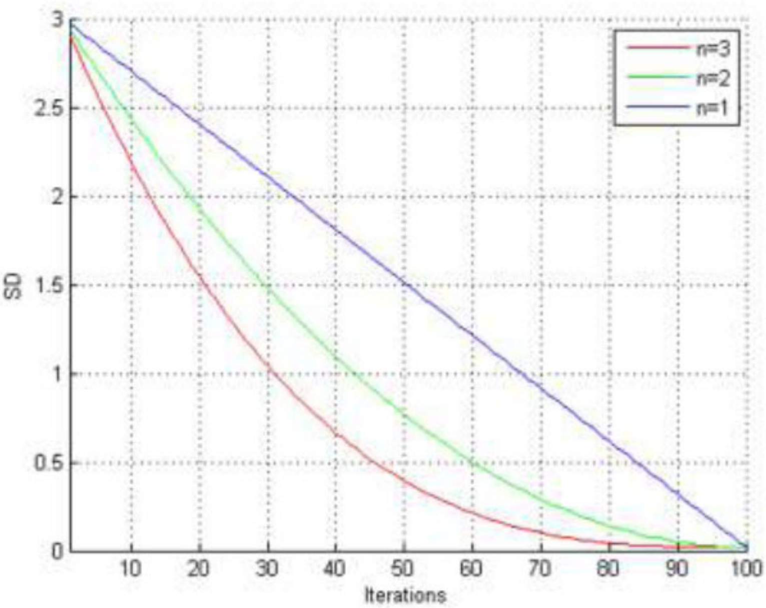

Fig. (4). Standard deviation for different nonlinear modulation index.

The fitness value initially produced by IWO is 12.2683. The IWO method waits for the standard deviation value to be reduced. As shown in Fig. (**5**), the increasing number of iterations also increases the fitness value. The IWO attained a maximum fitness value of 910.7944, and it converges at 80_{th} iteration for the input image. However, the proposed MIWO finds the maximum fitness value at the 10_{th} iteration itself. Varying standard deviation value, which helps to attain the maximum fitness value faster. Compared to IWO, the maximum optimal value is found by MIWO in fewer iterations, that is, convergence occurs quicker. In the case of MIWO, the maximum optimal value is attained even if the standard deviation value is high. Hence, the MIWO reaches the maximum value at 74_{th} iteration, and the value remains the same until the maximum number of iterations is reached. The parameters are tuned carefully until a better parameter value is found that facilitates to obtaining the optimal solution. An increase in the population size leads to an enhancement in the average fitness value. Compared to other techniques, in the proposed methods, parameter settings play a main function in the convergence rate, and also generates better results. The proposed MIWO method produces better results compared to all other existing algorithms for this problem.

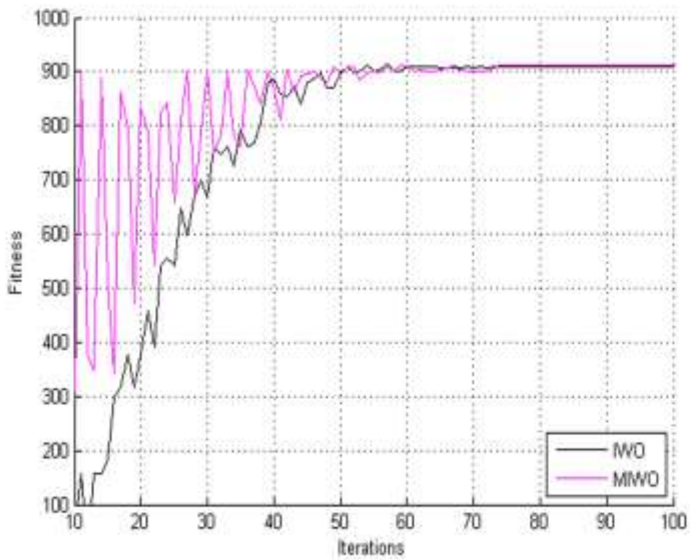

Fig. (5). Comparision graph for MIWO and IWO algorithm for input image by varying number of iterations.

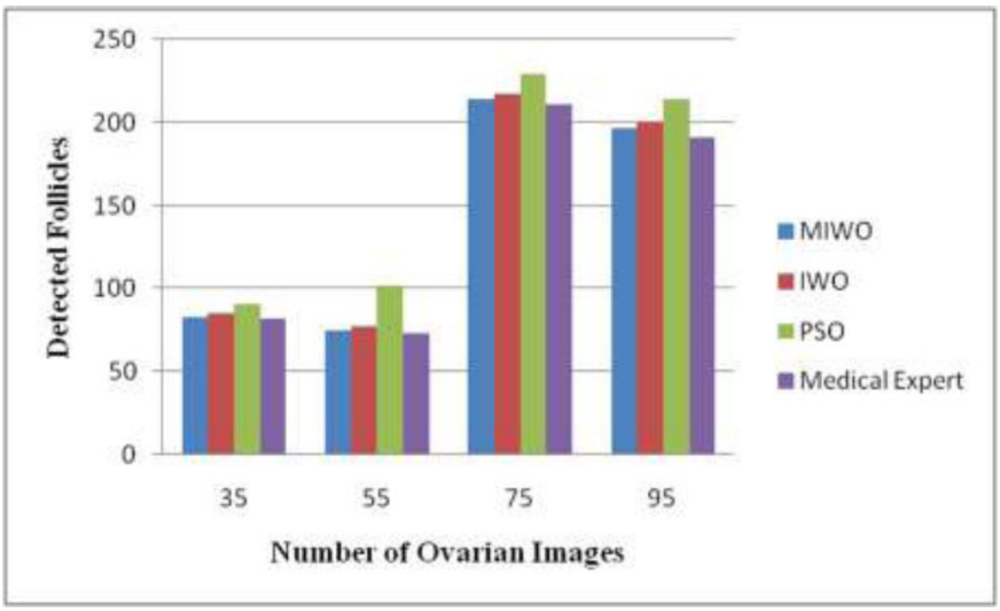

Fig. (6). Comparision graph of MIWO, IWO and PSO for varying number of ovarian images.

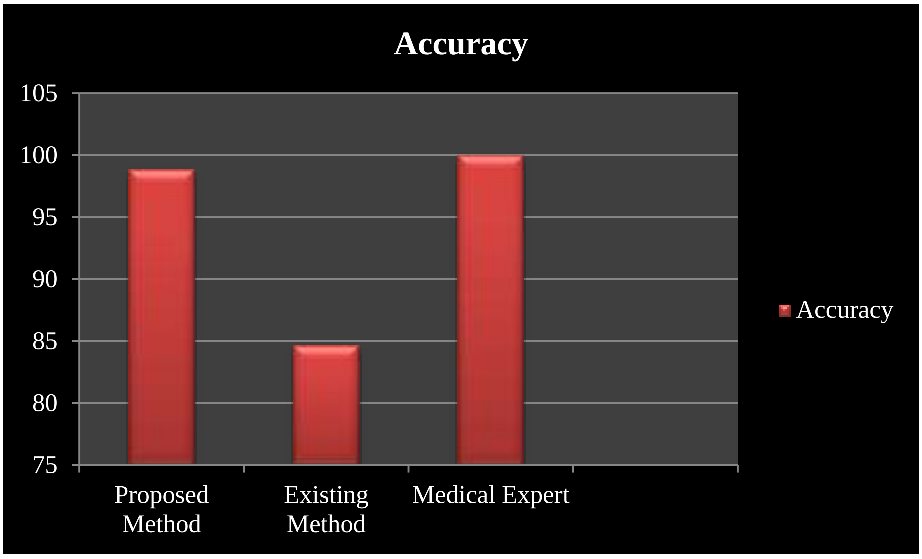

Fig. (7). Comparison between proposed and existing method.

The SVM classifier is used for the classification of ovary images. The parameters, total number of follicles, and the area of the follicles are used in classification. Ovarian image of 95 images has been used for the experiment, 40 images are used in training, and the remaining 55 images are used in the testing phase. The follicle detection rate of the proposed method is 96.69%, and the false acceptance rate is 1.79%. The proposed method and PSO-based method have been compared and are shown in Fig. (**6**). From Fig. (**6**); it is clearly identified that the proposed method provides a better identification rate when compared to PSO. The proposed MIWO method outperforms IWO and PSO in terms of follicle detection rate. The proposed method is compared to the existing method [6]. The existing method recognized follicles using a thresholding mechanism. On the other hand, the existing approach failed to optimize the threshold value, which is a limitation of the current MIWO method. The proposed strategy provides 98.8% accuracy, but the existing method achieved only 85%, as shown in Fig. (**7**) [20, 21].

CONCLUSION

This study presents a novel Invasive Weed Optimization (IWO) for solving the problem of manual detection of polycystic ovary syndrome from ovarian images. The Modified IWO (MIWO) algorithm outperforms the existing IWO and PSO methods in terms of quicker convergence and accuracy. The key disadvantage of the existing method is that it did not optimize the threshold value. The proposed approach overcomes the limitation of the existing method by optimizing the threshold value, resulting in an accuracy of 98.8%. In the medical field, proper diagnosis is critical for effective therapy. The proposed method applied only to a few images. So, future work will concentrate on developing the deep learning algorithm to improve the segmentation results for larger databases.

AUTHOR'S CONTRIBUTION

The author confirms sole responsibility for the study's conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

LIST OF ABBREVIATIONS

PSO	=	Particle Swarm Optimization
ACO	=	Ant Colony Optimization
BFO	=	Bacterial Foraging
GA	=	Genetic Algorithm

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

Not applicable.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

Real-time dataset is collected from various scan centers in Coimbatore.

FUNDING

None.

CONFLICT OF INTEREST

The author declares no conflict of interest, financial or otherwise.

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Declared none.

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