



Detection of Follicles using Improved Salp Swarm Algorithm as a vital Tool in the Resolution of Infertility in Women

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ABSTRACT

Follicle is a sac filled with fluid in the woman's reproductive organ and it usually appears darker compared to other objects in the ovary. The ovarian follicles and their sizes are imaged by ultrasound machine. The detection of these follicles is affected usually by other organs such as tissues, blood vessels contained in the ovary. Thus, the need to process the image using appropriate method in order to detect, and extract the required features for better classification of the follicles and non-follicles present in the ovarian image. Feature extraction is a major task in follicles classification of scanned image, therefore proper analysis of image features provides useful information that aid detection of follicle and non-follicle spot in the ovary. This work considers an Improved Salp Swarm Algorithm known as Elite Opposition Based Learning Salp Swarm Algorithm to select features with best fitness from the extracted features. The selected features were served as input to the Multilayer Perceptron Artificial Neural Network classifier. The objective is to evaluate the performance of the developed system based on the benchmark figures already obtained by other researchers in terms of follicle detection rate such as accuracy, sensitivity and specificity of the system. Upon training and testing the network in terms of the False Acceptance Ratio and False Rejection Ratio, 98.6% accuracy, 100% sensitivity and 98.1% specificity were achieved. These results give a better and more reliable classification output that will facilitate the diagnosis of infertility and other related reproductive diseases in women.

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INTRODUCTION

Early detection and treatment of infertility significantly improves the chances of conception as well as offer better long-term health prognosis, especially as often the disease is manifested early in puberty and worsen with the age and lack of treatment (Mehrotra et al., 2011). For the

infertility in a woman, ovary obviously is the first organ of choice to be examined and scanned through the use of an ultrasound machine. That is the status of ovary and the observation of follicle behavior/formation play significant roles in the evaluation of infertility in women. Ultrasound scan imaging of the follicles in the ovary offers



vital information about the ovarian aging condition such as the number of follicles, size, position, and response to hormonal stimulation. Analysis of several follicles is error-prone and could be quite tasking (Hiremath and Tegnoor, 2010).

Scanning and analyzing ovulation enable the clinicians to know precisely the ovarian condition, which is the period of egg maturity and ovulation. This is usually the first step in the treatment of most infertility issues since the treatment is about ovulation. Therefore, ultrasound imaging are carried out to capture the growth of follicles. Follicles are fluid filled sacs seen inside the ovary in the woman's reproductive organ and they usually appear darker when compared to other objects in the ovary on screen and bubble-like in nature. Hence, the need to monitor the growth of follicles in order to know whether it reaches full maturity (ovulation) or die before maturity (anovulation) cannot be over emphasized in infertility. (Hiremath and Tegnoor, 2010).

Proper and adequate detection of follicles is a major challenge in this field of research and a lot of works has been reported in the literature in order to address some of the problems.

Hiremath and Tegnoor (2010), developed an improved technique for follicle detection by using contour-let transform for denoising the scanned images. The contrast of the images was enhanced by histogram equalization. Then an active contour without edge method was used for segmentation of enhanced images followed by morphological erosion to eliminate any spurious regions caused by noise and finally, fuzzy logic was applied to classify the ultrasound images based on seven geometric features of the ovary. Though, the follicle detection rates for two different datasets were 97.61% and 98.18%, but False Acceptance Ratio and False Rejection Ratio of 9.05% and 4.52% were still high

which could lead to wrong diagnosis and it also failed to distinguish between different ovarian images. However the technique serves as fundamental step for the automatic detection of the follicles.

Another work carried out by Isah *et al* (2016), is a model designed for the detection of follicles. The model adopted was a combination of Bat algorithm and particle swarm optimization that uses ANN for automatic follicle classification. The texture features were extracted using Gray Level Co-occurrence Matrix (GLCM). A remarkable achievement was made in improving the performance metrics such as accuracy, and this resulted on the overall enhancement of the system. However, the error difference between the outputs (desired and target) can be improved.

The focus of this present work is to propose an automatic follicles detection model that uses an improved Salp Swarm algorithm (ISSA) called elite opposition based learning salp swarms algorithm to adequately detect follicle in the ovary after pre-processing and segmentation of the scanned image of an ovary. The results obtained from training and testing of this new technique depicted the efficiency of the proposed method.

PROPOSED METHOD

Salp Swarm Algorithm

Swarm intelligence techniques mimic the intelligence of swarms, herds, schools, or flocks of creatures in nature. The main foundation of these algorithms originates from the collective behaviour of a group of creatures (Mirjalili *et al.*, 2017).

Among the family of Salpidae is Salps, it has a transparent barrel-shaped body. The important parameter which is of interest in this work is the swarming behaviour known as salp chain. The salp chain is modeled mathematically by grouping the population of the salps into leader and followers. The leader guides the



swarm in the group movement. The salps' position is defined in an n -dimensional search space with n as the number of variables for the problem under study. The food source designated as F is assumed as the swarm's target in the search space. Mirjalili *et al.*, (2017) proposed the determination of the leader's position using equation 2.1

$$X_j^1 = \begin{cases} F_j + C_1((ub_j - lb_j)C_2 + lb_j), & C_3 \geq 0 \\ F_j - C_1((ub_j - lb_j)C_2 + lb_j), & C_3 < 0 \end{cases} \quad (2.1)$$

Where:

X_j^1 Depict the leader's position in the j^{th} search space,

F_j is the source of food in the j^{th} search space

ub_j is the upper bound of j^{th} search space

lb_j is the lower bound of j^{th} search space

C_1 , C_2 , and C_3 are the variables randomly selected.

The C_1 parameter balances both exploration and exploitation, and is defined as in equation (2.2).

$$C_1 = 2e^{-\frac{A}{L}^2} \quad (2.2)$$

Where l is the present iteration and L is the maximum number of iterations. The variables C_2 and C_3 are randomly generated in uniform interval of 0 and 1. They determine whether the next higher position in j^{th} search space is towards negative or positive infinity, as well as the step length.

Newton's law of motion (equations 2.3) is used to determine the new position of the followers.

$$X_j^i = \frac{1}{2}at^2 + v_0t \quad (2.3)$$

Where $i \geq 2$, X_j^i gives the position of i^{th} salp (follower) in j^{th} search space, t is the time taken, v_0 is the initial velocity, and its acceleration, $a = \frac{v}{t}$ where $v = \frac{x-x_0}{t}$.

Because the time in optimization is iteration, and the difference between iterations is equal to 1, considering $v_0 = 0$, equation (2.3) can be expressed as shown in equation (2.4)

$$X_j^i = \frac{1}{2}(X_j^i + X_j^{i-1}) \quad (2.4)$$

The simulation of the salp chains can be achieved using equations (2.3) and (2.4).

Elite Opposition-Based Learning Strategy

Elite opposition-based learning (EOBL) is a computational method used in searching for more effective areas in order to improve exploration capability and maintain population diversity of an optimization algorithm. It also guides the algorithm to avoid premature convergence and help it to approach global optimal solution (Qu, *et al.*, 2017). The EOBL model can be illustrated as follows:

Suppose the elite individual in the current population is $X_a = (x_{a,1}, x_{a,2}, \dots, x_{a,D})$, for an individual $X_t = (x_{t,1}, x_{t,2}, \dots, x_{t,D})$, the elite opposition solution $\tilde{X}_t = (\tilde{x}_{t,1}, \tilde{x}_{t,2}, \dots, \tilde{x}_{t,D})$ of X_t is given in (2.5), (Li, *et al.*, 2017):

$$\tilde{x}_{t,j} = k * (du_j + dl_j) - x_{a,j}$$

where,

$$t = 1, 2, \dots, NP$$

NP is size of the population

$$j = 1, 2, \dots, D$$

k is the generalized coefficient

$(du_j + dl_j)$ is the dynamic boundary of the j^{th} dimensional search space given in (2.6).

$$du_j = \min(x_{t,j}),$$

$$dl_j = \max(x_{t,j}),$$

To prevent individual from jumping out of the boundary, equation (2.7) was used (Qu, *et al.*, 2017):

$$\tilde{x}_{t,j} = (du_j, dl_j) \quad (2.7)$$

Elite Opposition Based Learning Salp Swarm Algorithm

The population diversity of the Salp swarm was improved using Elite opposition based learning algorithm. This is because the elite individuals tends to provide adequate search information compared to ordinary individuals. Therefore the algorithm focuses mainly in selecting the best fitted features for classification. The fitness values of the particles is given by equation (2.8).

$$\frac{1}{N} \sum E^2 = MSE \quad (2.8)$$

Where,

MSE = the mean square error

N = the number of tested samples

E = the difference between the actual and the predicted class

Selection of Best Features using an Improved Salp Swarm algorithm (ISSA).

The Improved Salp Swarm Algorithm improve the accuracy of the system by selecting the optimal features. This was achieved by tuning the Artificial Neural Network parameters until low error difference is obtained. The flowchart for the ISSA feature selection is shown in Figure 1.

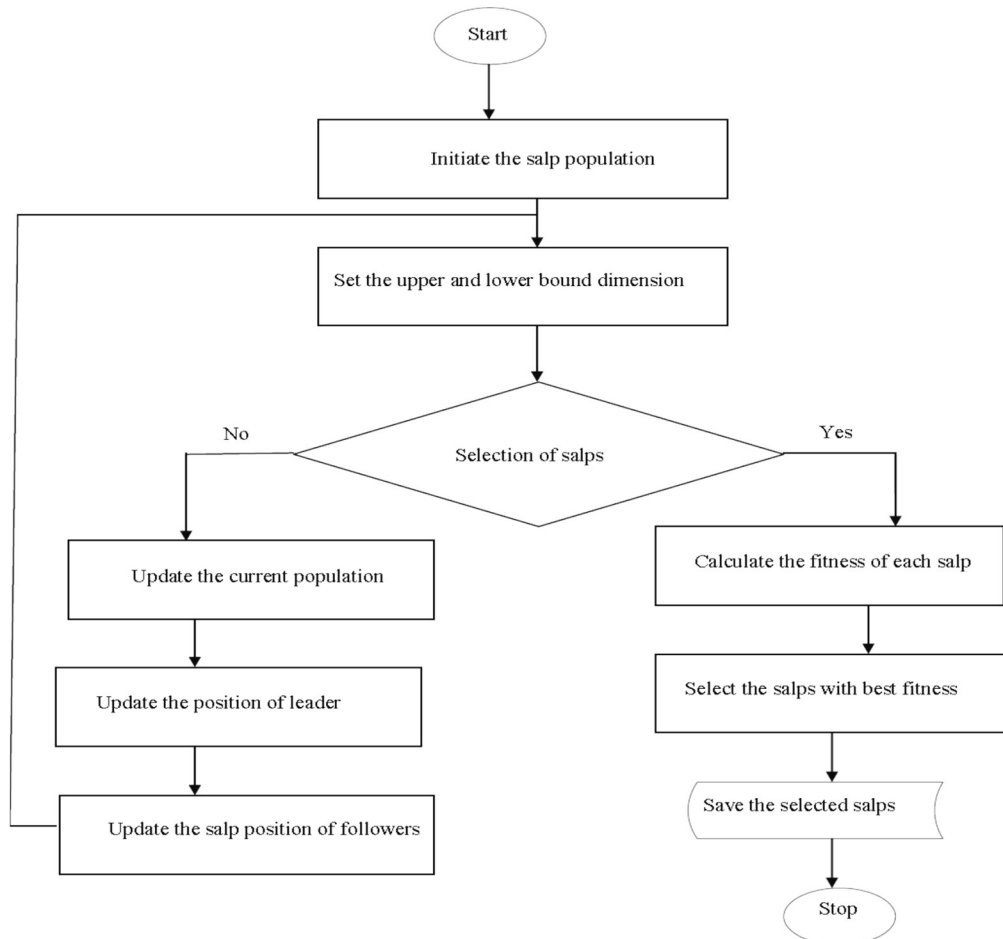


Fig. 1: The flowchart for the Improved Salp Swarms Algorithm feature selection



RESULTS AND DISCUSSION

Features Selection using EOBLSSA-ANN Algorithm

This section shows the results of optimal features selected by the EOBLSSA algorithm for various models of Multilayer Perceptron Artificial Neural Network. The multi-layer perceptron network classifier is

used to identify follicles and non-follicles present in the ovary. Table 3.1 shows the results obtained in terms of accuracy, specificity and sensitivity together with the number of hidden neurons, number of features selected and their corresponding index during training and testing of the network.

Table 1: EOBLSSA-MLP Algorithm Classification Results

| S/N | Numbers of Features | Numbers of Hidden Neurons | EOBLSSA-MLP Algorithm | Selected Features Index |
|-----|---------------------|---------------------------|-------------------------------------|---|
| | | | Specificity, Sensitivity, Accuracy. | |
| 1 | 4 | 2 | 96.6%, 93.5%, 95.0% | 1, 5, 11, 12 |
| 2 | 5 | 3 | 97.9%, 92.3%, 95.0% | 4, 13, 6, 2, 10 |
| 3 | 6 | 3 | 83.1%, 97.6%, 89.0% | 1, 15, 10, 3, 6, 2 |
| 4 | 7 | 5 | 96.7%, 94.7%, 97.1% | 15, 5, 3, 13, 7, 8, 4 |
| 5 | 8 | 5 | 96.6%, 93.5%, 95.0% | 8, 5, 15, 2, 11, 3, 12, 6 |
| 6 | 9 | 6 | 90.9%, 100%, 95.0% | 2, 8, 9, 12, 3, 4, 6, 1, 13 |
| 7 | 10 | 7 | 96.8%, 100.0%, 98.6% | 7, 8, 9, 13, 12, 3, 10, 14, 5, 6 |
| 8 | 11 | 7 | 88.2%, 99.0%, 93.3% | 4, 8, 1, 5, 9, 6, 2, 13, 14, 3, 10 |
| 9 | 12 | 8 | 98.1%, 96.8%, 98.3% | 11, 7, 14, 5, 3, 13, 6, 1, 2, 8, 9, 4 |
| 10 | 13 | 9 | 93.8%, 98.5%, 96.7% | 7, 2, 5, 14, 12, 3, 13, 11, 6, 9, 10, 15, 4 |
| 11 | 14 | 9 | 85.7%, 100%, 91.7% | 8, 15, 5, 12, 6, 10, 1, 13, 2, 14, 7, 3, 11, 4 |
| 12 | 15 | 10 | 97.7%, 96.8%, 94.9% | 2, 13, 6, 14, 8, 4, 9, 15, 3, 12, 11, 1, 10, 7, 5 |

Table 1, showed the results of specificity, sensitivity and accuracy obtained from several network training and testing based on the performance metric (false acceptance rate and false rejection rate). Rows seven (7) with ten features, seven neurons has the highest values of accuracy (98.6%). Out of 180 samples, 120 was used

for the training while 30 was used each for testing and validation.

Validation of the Developed EOBLSSA-MLP Algorithm

This sub-section compares the developed algorithm (ISSA) with the PSO of (Isah, *et al.*, 2016). Based on the results, the

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EOBLSSA shows significant improvement over PSO in terms of accuracy and sensitivity. Figure 2, 3 and 4 respectively presents specificity, sensitivity and accuracy results of the EOBLSSA and PSO algorithm. The features selected using these algorithms were used to tune the

multi-layer perceptron to reduce the error difference between the output and the target. This error difference was found to be minima in EOBLSSA as compared with that obtained with PSO. Thus affirming the improvement of this proposed method.

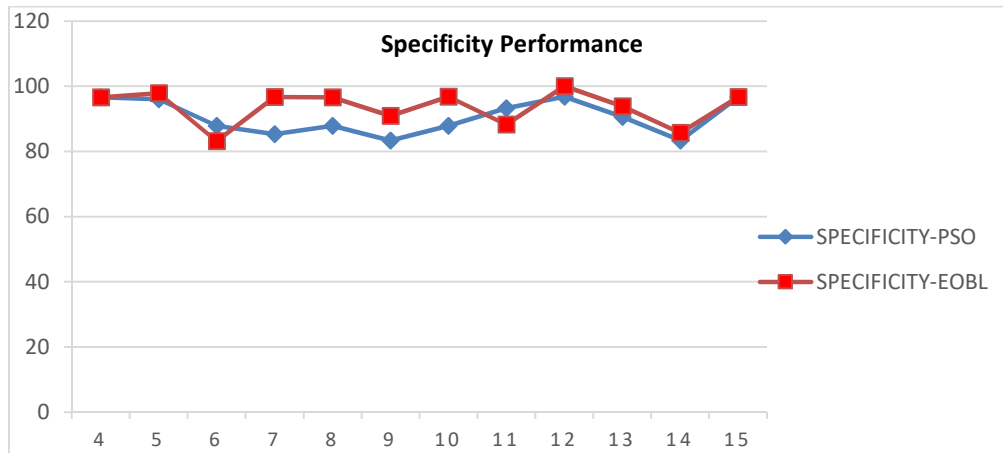


Figure 2: Comparison of Specificity Performance of the Algorithms

Figure 2, presents comparison of specificity performance between the developed algorithm and the PSO-MLP algorithm. The red line depicts specificity values of the EOBLSSA while the blue line depicts the specificity values of the PSO

algorithm. It is observed from the graph that the developed algorithm performed better at 5, 7, 8, 9, 10, 12, 13, 14 number of features, and performed a bit poorly at 6 and 11 features and their performances are at par at 4 and 15 features

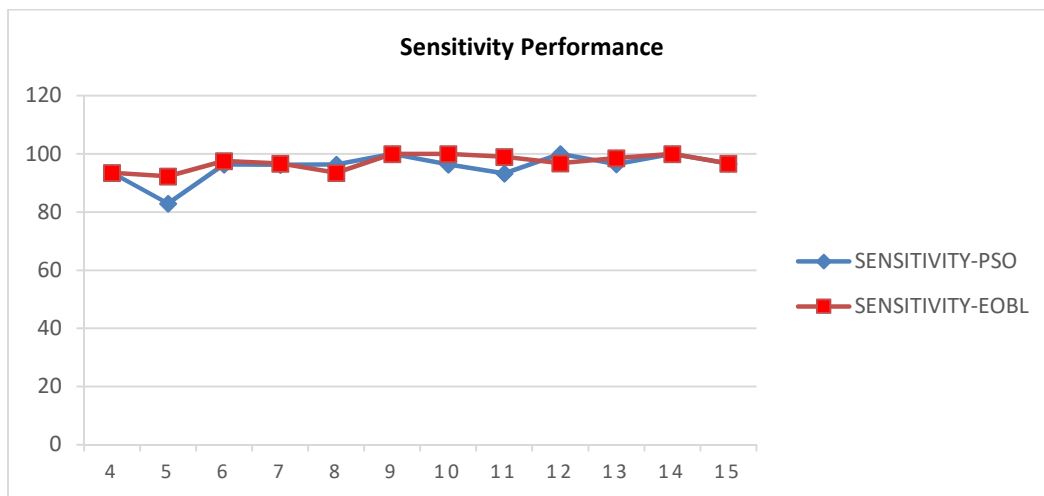


Figure 3: Comparison of Sensitivity Performance of the Algorithms

Furthermore, comparison of sensitivity performances between the EOBLSA-MLP and the PSO-MLP algorithm is presented in Figure 3. The red line depicts sensitivity values of the EOBLSA while the blue line depicts the sensitivity values of the PSO algorithm. It is observed from the

graph that the developed algorithm performed better at 5, 6, 10, 11, 9 and 13, 14 number of features, and performed a bit poorly at 8 and 12 features and their performances are same at 4, 7, 9, 14 and 15 features.

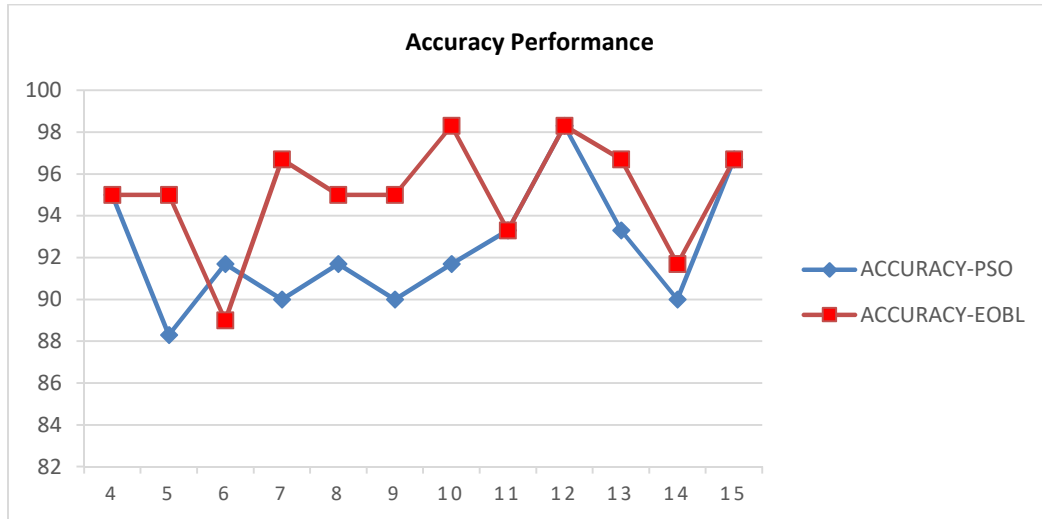


Figure 4: Comparison of Accuracy Performance of the Algorithms

Also, comparison of accuracy performances between the EOBLSA-MLP and the PSO-MLP algorithm are presented in Figure 4. The red line depicts sensitivity values of the EOBLSA while the blue line depicts the sensitivity values of the PSO algorithm. It is observed from the graph that the EOBLSA performed better at 5, 7, 8, 9, 10, 13, 14 number of features, and performed a bit poorly at 6 features and their performances are the same at 4, 11, 12 and 15 features.

Finally, it can be deduced from the above results that, on the average the EOBLSA performs better when compared with the PSO algorithm. The highest Accuracy of 98.6%, 100% Sensitivity and 98.1% Specificity recorded in EOBLSA is a clear indication of significant improvement. That is, EOBLSA was able to reduce the error difference better than PSO. What is

depicted in figures 2, 3 and 4 is to show that EOBLSA outperformed PSO despite the overlapping at some points or otherwise.

CONCLUSION

The main motivation of this study is the swarming nature of salps and the ability to mathematically update the position of both the leading and follower salps in the salp chain. The developed automatic follicle classification system uses an improved Salp swarm algorithm to effectively and accurately identify follicles and non-follicles present in the follicular region. The Elite opposition-based learning Salp swarm algorithm deployed for this work perfectly explore the region of interest (ROI) to enhanced the features selection process so that features with best fitness serves as input to the MLP-ANN classifier. The reason is to eliminate the



possibility of having follicles with jagged and irregular edges that can result to wrong classification of follicles. This follicle detection and classification algorithm (EOBLSSA-MLP) was developed in MATLAB R2015a and results obtained were evaluated using the performance metric (Accuracy, Specificity and Sensitivity). It was further compared with the one obtained with PSO algorithm and a significant improvement is recorded. The improved algorithm (EOBLSSA) was able to minimize the chances of incorrectly classified follicles and also reduce the error difference between the actual output and the desired output (target). This improvement would save considerable time spent on manual detection and it is expected to aid experts in accurate diagnosis of ovarian diseases such as ovarian cystic, polycystic, tumor, and ovarian cancer, thus, reducing infertility, pains, and traumas many women undergo. However the challenges of acquisition of images (that is, mode of acquiring the scanned image of ovary) need to be improve upon and is highly recommended in this work.

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