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An Efficient Follicle Segmentation and Optimized Deep Learning Based PCOS Prediction System

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ABSTRACT

Polycystic Ovary Syndrome (PCOS) is the most complex hormonal disorder that is hardly affects the women's health during the reproduction stage. It is caused due to the excess production of androgens and hormone changes in their body. The result of PCOS may lead to the issues such as miscarriage, pregnancy complications, and infertility issues. The physicians are manually detecting PCOS using the ultrasound Images. But it is very critical to identify the cyst accurately, which is prone to laborious errors. Therefore, this research aims to develop a series of automotive processes for identifying PCOS using deep learning methodologies. Effective detection is enhanced with the preprocessing, segmentation and feature extraction process. The PCOS is classified as usual or follicles using the proposed Optimized CNN with Fruitfly Optimization approaches (CNN-FOA). The hyperparameters of the CNN are optimized with FOA. The model's efficiency is evaluated and compared with the existing systems where the proposed model obtained the accurate prediction of critical PCOS. This investigation helps the medical professionals to detect the PCOS early to avoid the miscarriage rate.

1. INTRODUCTION

Polycystic Ovary Syndrome (PCOS) is a significant medical ailment affecting women's reproduction because of hormonal disorders [1, 2]. The collections of fluids are called as follicles that are created in the ovaries and the situation of failing to release the eggs. The different sizes of follicles are developed in the ovary, called as hormonal disorder. This hormonal disorder is known as PCOS. The entire research shows the results of 70% of women are not able to detect the PCOS to cure. The condition of PCOS is described as the failure of the ovary to release the ovum due to the follicle's formation in the ovaries. The women affected by PCOS have been struggling with hormone balance which creates various health issues such as irregular menstrual cycle, miscarriage, and pregnancy issues. People are suffered from these imbalanced hormones from the age of 16 to 40 years [3]. It will cause the diseases such as cardiovascular disease (CVD), obesity, hypertension, Type 2 Diabetes, gynecological cancer, and risks in pregnancy.

The appropriate method for the detection of PCOS is the Rotterdam criteria. The principle is to identify the ovaries with a capacity larger than or equals to 10 cm cube or the follicle of size 2-9 mm with a count of 10 or more. The ultrasound image (US) of normal and PCOS-affected ovaries is shown in Figure 1.

The early detection of PCOS symptoms helps the affected persons to adapt to the changes in their lifestyle. PCOS women undergo infertility which leads to gynecological cancer [4]. The early identification of PCOS can save their miscarriage and lifespan. The automation systems will overcome these issues. It plays a significant role in healthcare industries [5]. The ML models can deal with enormous dataset processing for diagnosis. ML can be used in medical fields for image processing, documentation, and genetics assessment in the medical field [6].

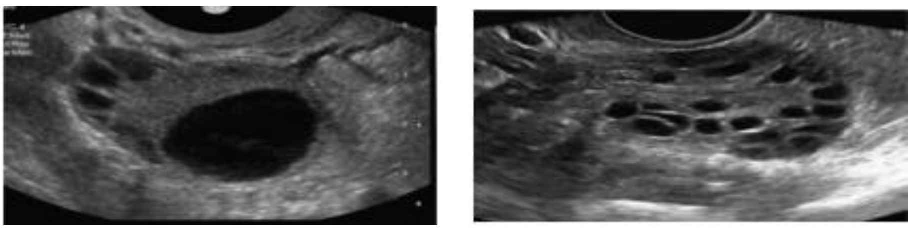

Figure 1. Normal ovary (left) and Polycystic Ovary Syndrome (PCOS) affected ovary (right)

2. LITERATURE REVIEW

In this section, it composes literature on PCOS segmentation and prediction models. Nasim et al. [7] proposed a PCOS detection using follicle segmentation with genetic operation. Nilofer and Ramkumar [8] proposed automatically detecting cyst dimension using U-Net and ResNet DL models with EUS (endoscopic ultrasonography) images.

The paper [9] offers a unique method for segmenting polycystic ovarian cysts by enhancing an adaptive K-means algorithm with a reptile search algorithm. This novel approach shows enhanced segmentation accuracy, indicating the possibility of merging metaheuristic optimization with clustering methods for medical picture analysis.

In a work, Madhumitha et al. [10] investigate the use of improved machine learning classifiers for the prediction of PCOS. The authors present a thorough analysis of numerous classifiers and optimization strategies, providing insightful information about how AI may improve PCOS diagnosis accuracy. In the article [11], address the use of machine learning methods for polycystic syndrome identification in the ovary.

In the study by Isah et al. [12] present an integrated framework for polycystic ovarian syndrome detection that makes use of an adaptive bilateral filter and attention residual U-net. By combining deep learning with sophisticated image processing methods, this framework significantly improves detection robustness and accuracy. A machine learning model for PCOS detection based on explainable AI and improved feature selection is presented in the study by Kottarathil [13]. There are still certain research gaps in the field of PCOS detection and diagnosis, despite the notable progress achieved in recent years in the use of AI and machine learning.

3. PROPOSED WORK

This paper aimed to develop efficient follicle segmentation and deep learning with meta-heuristic (MH) based classification of UI ovary images. Through the segmentation process, this paper finds the more accurate follicle parameters such as location, size, and shape. This incorporates it with the DL model to find the prediction of the US as PCOS or normal ovary.

3.1 Dataset description

The PCOS dataset [14] helps for this study consists of 541 patients with clinical and physical parameters 223, which form the dataset. This dataset has 41 features [15] that are used for this feature extraction process. Unnecessary data is removed from preprocessing stage. Out of these records, 364 patients exhibit typical data patterns, while 177 patients exhibit signs of PCOS. The data about PCOS has been gathered from ten hospitals across Kerala, India.

3.2 Proposed materials and methods

The proposed PCOS detection and classification system overview architecture is illustrated in Figure 2. The input US image from the dataset is given as input to the model with the features such as BMI, cycle, menstrual LH and FSH data etc. Initially, the image data is preprocessed using techniques like image resizing, histogram equalization, and noise removal to enhance the image efficiency and then the relevant features are selected using Chi-Square (CS) model. Second, the cyst region segmentation is performed using the active contour Otsu method (ACOM), which efficiently segments the position of cyst, size, and location for good classification. Using the method of first convolution layer of CNN, the relevant features are extracted from the segmented image.

The classification task considered in this study is a binary classification problem. Based on the extracted follicle features from ultrasound images, the proposed CNN with Fruitfly Optimization approaches (CNN-FOA) model classifies each input ovary image into one of two categories: The classification is performed using both image-based features obtained from segmented follicle regions and selected clinical features.

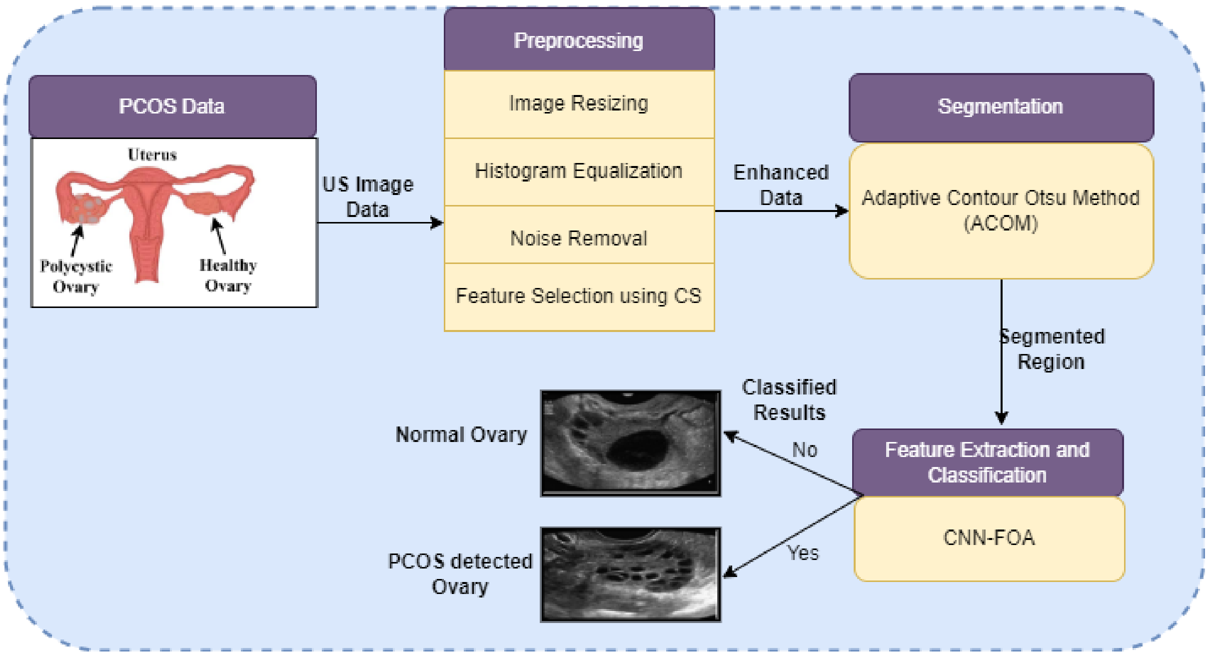

Figure 2. Proposed Polycystic Ovary Syndrome (PCOS) detection and classification system overview architecture

3.2.1 Preprocessing

It is used image preprocessing techniques such as image resizing, histogram equalization, and median filter-based noise removal approaches [16].

Image Resizing: The input US image is resized using the Object Carving algorithm, which will minimize artifacts and salient alteration using the quick multi-operator method [17].

Histogram Equalization: The image's brightness is enhanced using the histogram equalization approach. Using the uniform intensity, the image quality is increased. The image equalization methods are executed using the mathematical expression,

$$HE = histeq(image), H = imhist(Image, 64)$$

The transformed intensity levels are obtained by mapping the original pixel values using the normalized CDF. This operation improves follicle boundary visibility and contrast, which is critical for accurate segmentation.

Noise Removal using Median Filter: This paper utilized the nonlinear statistical filter called median filter to denoising the image [18]. The output of the median filtering is shown in Eq. (1).

$$(X, Y) = med\{f(X - i, Y - h)i, j \in M \tag{1}$$

where, the actual image is represented as f(X,Y), the output filtered image is represented as g(X,Y), and M is the 2D mask with the size n*n [19]. The preprocessing of the input Ultra sound (US) image is given in Figure 3.

Feature Selection: Among the 41 features, the Serial no and patient file numbers are discarded. The remaining 39 features are fed as input to the selected appropriate feature. Using the CS model, the feature importance values are examined [19]. The element with the value zero is nonvital, and it is dropped. In this process, the characteristics include age, BMI, cycle, cycle length, marriage status, FSH, LH, AMH, Vitamin D3, weight gain, PRG, hair growth, hair loss, pimples, skin darkening, left and right follicle no and fast food.

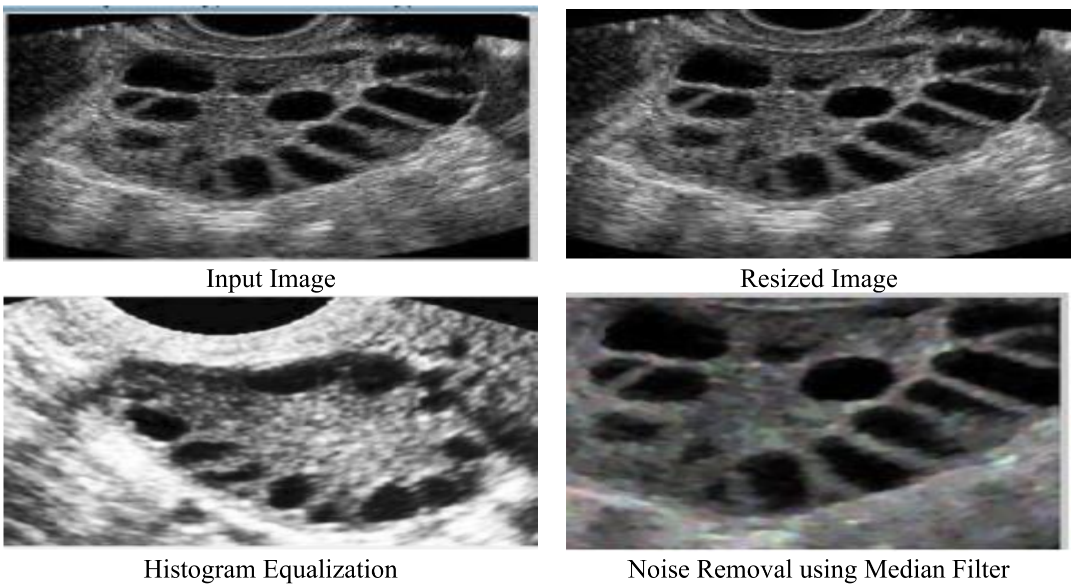

Figure 3. Preprocessing outcomes of input US image

3.2.2 Segmentation using active contour Otsu method

Segmentation is partitioning the image into the region of desired features. Due to the occurrence of soft tissues and blood vessel, segmenting the follicles regions from the ovary picture is a difficult process. To discriminate the object from the background, thresholding is the best model based on the minimization function. Otsu's Method from the study by Alagarsamy et al. [20] has been used to find the optimal threshold which separates the preprocessed into two groups of binarized image. The mean of these groups is computed as in Eq. (2).

$$\mu_1(t) = \sum_{i=1}^{t} \frac{i.f(i)}{g_1(t)} \; and \; \mu_2(t) = \sum_{i=t+1}^{k} \frac{i.f(i)}{g_2(t)} \tag{2}$$

where, k is the number of gray level ranges from 1 to k. The optimal threshold is computed as t'.

$$t' = arg \min_{t} \sigma_m^2(t) \tag{3}$$

where, σ is the class variance and it is denoted in Eq. (4).

$$\sigma_m^2(t) = g_1(t)\sigma_1^2(t) + g_2(t)\sigma_2^2(t) \tag{4}$$

where, $g_1, g_2, \sigma_1^2(t)$ and $\sigma_2^2(t)$ are the group probabilities and variances which is computed as in Eq. (5).

$$g_1 = \sum_{i=1}^{t} f(i) \; and \; g_2 = \sum_{i=t+1}^{k} f(i) \tag{5}$$

$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{f(i)}{g_1(t)} \tag{6}$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{k} [i - \mu_2(t)]^2 \frac{f(i)}{g_2(t)} \tag{7}$$

The conventional Otsu method is not producing proper results in follicle segmentation and it is modified with the active contour to provide accurate segmentation. The Otsu method is modified with the computation of new threshold value with the iterative manner. Initial threshold t1 is computed by averaging the image value of ovary. Next, the above the mean value and below the threshold value is computed and it is denoted as m1 and m2. The new value of threshold is computed as in Eq. (8).

$$t1 = \frac{m_1^t + m_2^t}{n} \quad (8)$$

where, t is the number of iterations, the $t1$ is forwarded to the next iteration to compute t2 and so on. In the 2nd iteration, the image value is greater or equal to t1. In this, the mean value below and above the threshold t1 is computed. The iteration process is continuing till the converge [t(k)-t(k-1)] and the last iteration is computed as,

$$t^* = \frac{m_1^k + m_2^k}{n} \quad (9)$$

Now, this iteratively computed threshold t^* is computed in the traditional Otsu method Eq. (2) as in Eqs. (10) and (11).

$$\mu_1(t) = \sum_{i=1}^{t^*} \frac{if(i)}{g_1(t)} \quad (10)$$

$$\mu_2(t) = \sum_{i=t^*+1}^{k} \frac{if(i)}{g_2(t)} \quad (11)$$

The total mean of the entire image is computed as in Eq. (12):

$$\mu_t = \sum_{i=1}^{k} if(i) \quad (12)$$

The position of the initial contour closest to the preferred boundaries is found using the level set method proposed by Osher and Sethian [20]. The segmentation process using the ACOM is illustrated in Figure 4.

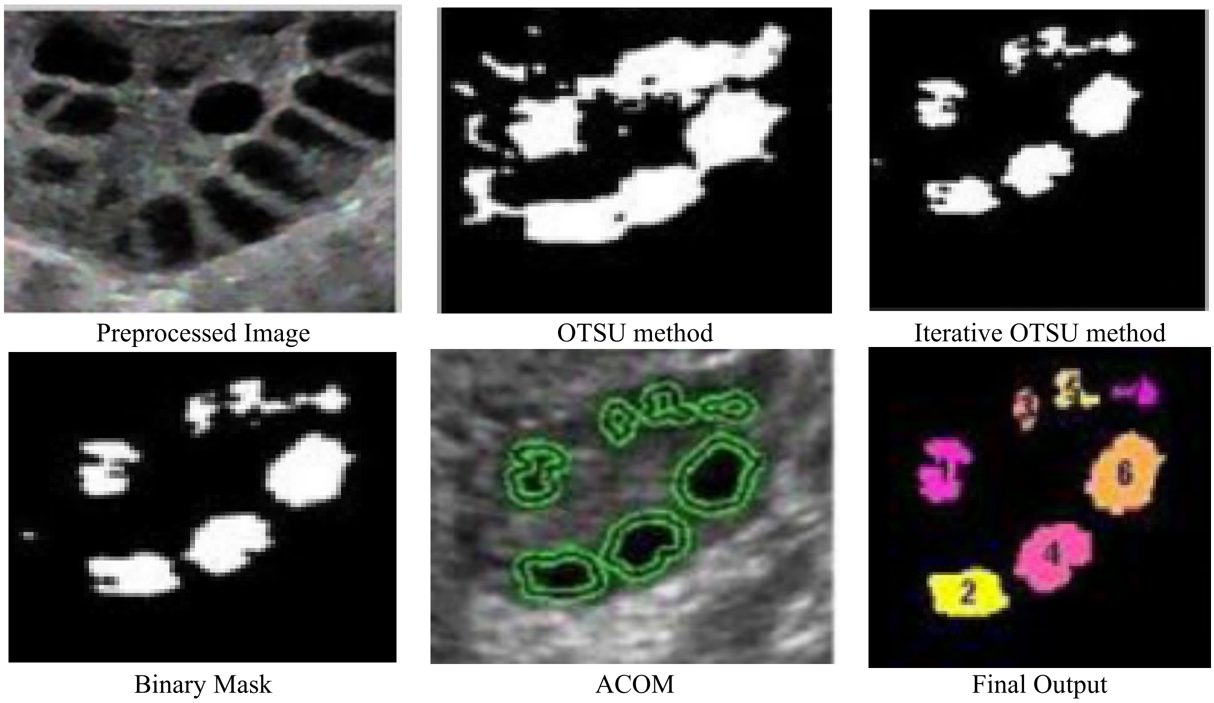

Figure 4. Segmentation follicles using active contour Otsu method (ACOM)

3.2.3 Fruitfly Optimization algorithm

The Fruitfly Optimization Algorithm (FOA) to use the foraging behavior of fruit flies to determine a globally optimal solution (Pan 2012). The fruit fly can fully utilize its instincts to find features with disorder since it has superior vision and smell compared to other species. In the proposed CNN-FOA framework, the Fruitfly Optimization Algorithm is employed to optimize CNN hyperparameters including weights, biases, batch size, and number of epochs. The population size is set to 30 fruit flies, and the maximum number of iterations is fixed at 100. At each iteration, candidate CNN parameters are evaluated using classification accuracy on the validation set as the fitness value [21]. First, fruit flies use their smell parts to detect the presence of follicles and then fly in that direction. Second, fruit flies can identify follicles and other fruit flies thanks to their keen vision when they get close to the diet source.

3.2.4 Feature extraction and classification using CNN-FOA

From these segmented results, the details about the follicles features are extracted using the first convolution layer of CNN and the follicles are classified using the CNN-FOA model. The features are like as such as perimeter, area, aspect ratio (AR), major axis, minor axis and the eccentricity. In the proposed CNN-FOA model, the first convolution layer has been used for feature extraction process. The CNN architecture is stated in Figure 5. It consists of two convolution, two pooling and four fully connected layers. The first convolution layer has 64 filters and each filer size is 1*3 with astride of size 1, followed by a ReLU activation function [22]. The second convolutional layer uses 128 filters of size 1 × 3. Max-pooling layers with a pool size of 2 × 2 are applied after each convolutional layer to reduce spatial dimensionality. The data fed as input is 2D array representation of the input image. Using the data construction, the CNN model studies the complex features and the convolution procedure have been used to extract the features.

$$ReLu(X) = \max(0, X) \quad (13)$$

The over fitting issues are prevented and the complexity is reduced using Dropout layers. The regularization rate is fixed as 0.5. The input data convolution operation for the previous X^{l-1} layer is declared in Eq. (14).

$$X^l = \omega^l . X^{l-1} + b^l \quad (14)$$

where, weight is represented as w and b of l^{th} layer bias respectively and output is X^l. The last pooling layer extracted features listed in Table 1 are fed as input to fully connected layer (FC). To obtain the output with SoftMax activation function, FC4 is employed. CNN, as a regularization technique, utilizes batch normalization (BN) to normalize the input data for FC4. The extracted feature vector is given as input to the classification process from the convolution layer of size (1*64), which. The output layer data computation is stated as:

$$Y = T + \delta^l \tag{15}$$

where, T is the target value and δ is the error of the neuron.

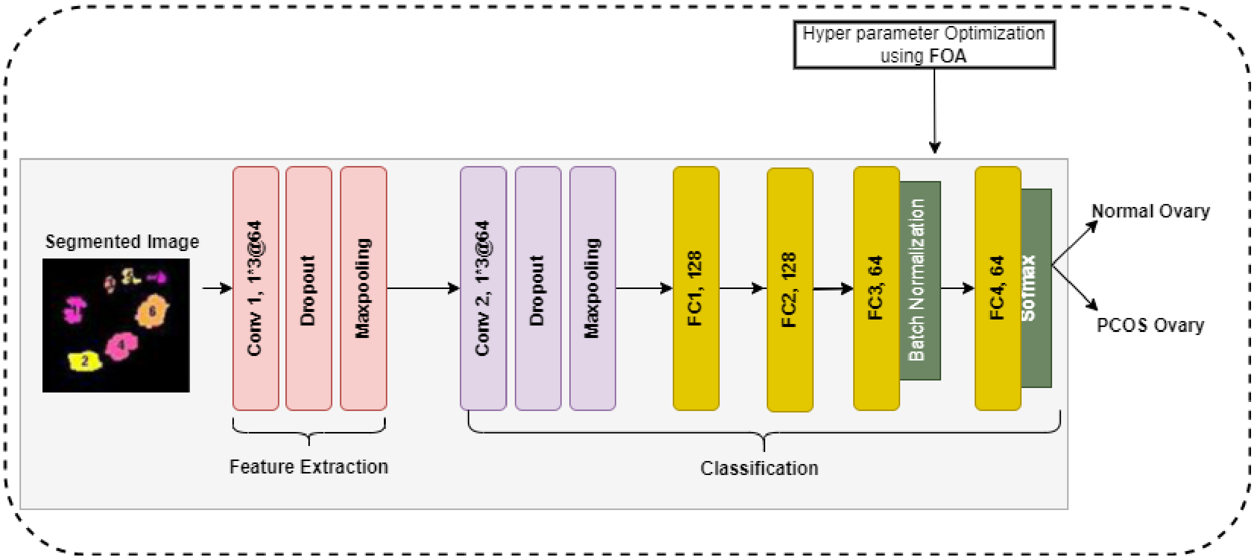

Figure 5. CNN with Fruitfly Optimization approaches architecture based feature extraction and classification

Table 1. Extracted features of follicles

Image	Follicles	Kernel Size	Area	Perimeter	AR	Major and Minor Axis	Eccentricity
	1		1401	145.78	1.54	[47.7,8.8]	0.575
	2		830	122.12	0.871	[39.4,29.4]	0.633
	3		395	76.54	1.238	[25.6,19.5]	0.672
	4	(7,7)	486	100.34	1.452	[41.4,15.3]	0.926
	5		854	112.42	0.977	[35.8,31.9]	0.452
	6		73	34.65	1.567	[14.6,6.8]	0.881
	7		669	98.37	1.693	[33.1,26.5]	0.597
Identified follicles					7		

3.2.5 Hyper parameter optimization using FOA

The proposed CNN-FOA based classification process comprised of two process such as parameter optimization and classification process. During the parameter optimization process, the CNN parameters are adjusted using FOA. The fitness function is considered as classification accuracy which isstated in Eq. (16).

$$fitness = \frac{\sum_{i=1}^{k} A_i}{k} \tag{16}$$

where, A is the obtained accuracy from CNN classifier. The process involved in steps is stated as follows:

Initialize value of size of population, maximum iterations number, variables upper and lower bounds, problem dimension like bias and weight. Consider the best FF position as the FF position called global optimum. Each FF position is updated as in Eq. (17) with the levy flight method and the fitness is evaluated.

$$X_i^{levy} = X_i + X_i \oplus levy\ (s) \tag{17}$$

where, X_i^{levy} is i^{th} search agent new position of X_i. The levy distribution is described as,

$$levy\ (s) \sim |s|^{-1-\beta},\ \ 0 \le \beta \le 2 \tag{18}$$

where, β is the levy index and s is the step length.

Check with the best individual population, if it better than the global optimum means update the values in global solution. To initiate the values of weight w and bias b in the CNN model structure. For each of training sample X in D and for each input layer unit i. Check with input unit with the output value $X_i = Y_i$. For each and every hidden layer (or output layer) unit *i*

$$X_i = \sum_{j=1-m} w_{ij} X_i + b_j \tag{19}$$

$$Y_i = T + \delta^l \tag{20}$$

For each weight w_{ij} in the network, the weight increment is computed as $\Delta w_{ij} = (l) E_i Y_j$. The weight is then updated as $w_{ij} = w_{ij} + \Delta w_{ij}$. For each bias b in the network. To increase the bias $\Delta b_i = (l) E_i$ and update the bias as $b_j = b_j + \Delta b_j$. Return the follicle detection as normal or PCOS.

4. EXPERIMENTAL SETUP WITH RESULTS AND DISCUSSIONS

In this section, proposed model evaluation and comparison is to be discussed with conventional PCOS detection methods. The proposed model is implemented using Python language. The packages are used for the implementation such as Scikitlearn, matplotlib with Jupiter notebook. The CNN model is trained using a batch size of 32, with the number of epochs varied between 50 and 650 to analyze convergence behavior. The learning rate is initialized at 0.001. The categorical cross-entropy loss function is used, and classification accuracy is selected as the fitness function for optimization.

4.1 Evaluation metrics

In the PCOS Problem, the proposed method of segmentation, classification and confusion matrix is implemented. The evaluation metrics are computed like accuracy, precision, recall and F1-Score and also ROC-AUC score, cross validation accuracy computed using the confusion matrix. For experimental evaluation, the dataset is divided into training and testing sets in the ratio of 70:30. To ensure the reliability and stability of the proposed method, each experiment is repeated five times with different random initializations.

ROC-AUC: The computation involves the utilization of true positive rate (TPR) and false positive rate (FPR) with the different thresholds. A value closer to 1 in which indicates a value more effective classifier.

Cross validation accuracy: Randomly the set of instances are divided into k groups. For our analysis, five no of fold cross validation has been chosen to reduce overfitting and to validate the consistency of the proposed model.

4.2 Performance evaluation of proposed ACOM-CNN-FOA based PCOS prediction model

The proposed model performance is measured based on the values produced by the confusion matrix that is shown in Figure 6. The developed ACOM based segmentation with CNN-FOA based PCOS prediction system obtained the accuracy of 99% with the precision as 98.8%, Recall as 99.4%, Specificity as 99.4% and F1-score as 99.1%. All results presented in this paper represent the average values obtained from multiple experimental runs.

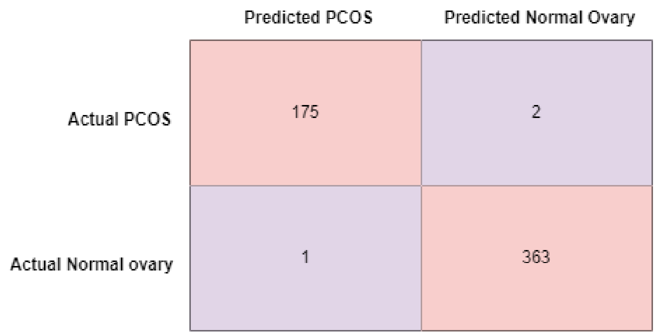

Figure 6. Confusion matrix – Proposed ACOM-CNN-FOA

4.2.1 Impact on cross validation

The over fitting issue of generating the prediction results for the particular pattern is handled by evaluating the proposed model using five folds cross validation shown in Table 2. The average metrics of accuracy is 98.88%, such as precision, recall, specificity and F1-score is 98.4%, 98.7%, 98.7% and 98.5% respectively.

4.2.2 Impact on number of samples

The evaluation based on varying number of samples to predict the PCOS using proposed model is shown in Figure 7. Varying number of images such as 200, 400, 600, 800 and 1000 images. As an average, the performance of the proposed model is 98.62%, 98.04%, 97.88%, 97.84% and 97.86% respectively. For the same number of images, the performance of standard deviation also computed and the results are 0.4868, 0.7021, 0.9471, 0.3578 and 0.5128 respectively.

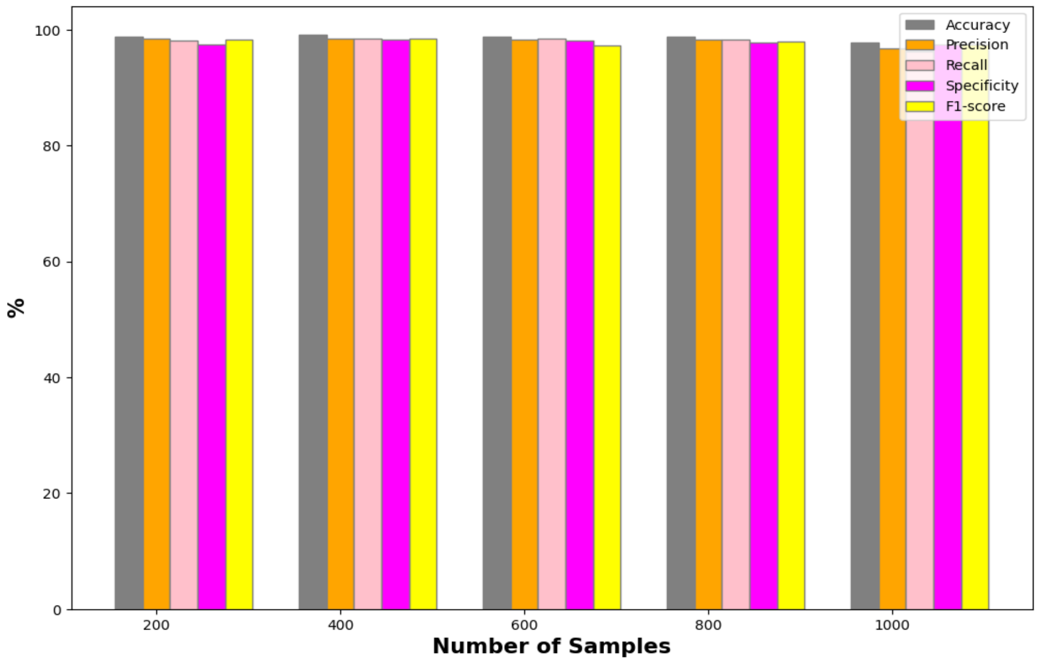

Figure 7. Performance of proposed model based on No. of samples

Table 2. Performance of proposed model based on 5-fold cross validation

Number of Folds	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
Fold 1	99	98.8	99.4	99.4	99.1
Fold 2	98.8	98.2	98.5	98.5	98.2
Fold 3	98.7	98.1	98.3	98.3	98.1
Fold 4	99	98.5	99.1	99.1	98.9
Fold 5	98.9	98.4	98.5	98.5	98.2
Average	98.88	98.4	98.76	98.76	98.5
Standard Deviation	0.1304	0.2739	0.4669	0.4669	0.4637

Table 3. Performance in terms of varying number of epochs

Number of Epochs	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
50	98.9	98.3	98	98.1	98.4
200	99.2	98.4	98.3	97.4	98.3
350	98.9	98.5	98.4	98.2	98.1
500	98.8	98.5	98.4	97.8	97.9
650	98.4	97.5	97.5	97.5	97.5
Average	**98.84**	**98.24**	**98.12**	**97.8**	**98.04**
Standard Deviation	0.2881	0.4219	0.3834	0.3536	0.3578

4.2.3 Impact on number of epochs

The evaluation in terms of varying number of epochs to predict the PCOS using proposed model is shown in Table 3. The range of epochs considered for this process is 50, 200, 350, 500 and 650. The average outcomes of the metrics using the proposed segmentation with classification of PCOS model is accuracy (98.84%), precision (98.24%), recall (98.12%), specificity (97.8%) and F1-score (98.04%).

4.3 Comparative analysis

Comparison can be made on the efficacy of the proposed method with the conventional methods of segmentation, classification of PCOS problems. The considered conventional PCOS prediction systems are Optimized Chi-Squared based feature selection with Gaussian Naïve Bayes PCOS prediction (CS-GNB), Artificial Neural Network with Improved Fruitfly Optimization based Classification system (ANN-IFO), Ensemble random forest classifier (ERFC) and PCA with gradient boosting decision tree (PCA-GBDT). The comparison of the result is shown in the Table 4. The ROC comparison of these models is shown in Figure 8 and the illustration shows that the proposed model secured the ROC value as 0.94. Table 5 shows the comparison of results in PCOS prediction with and without heuristic approach.

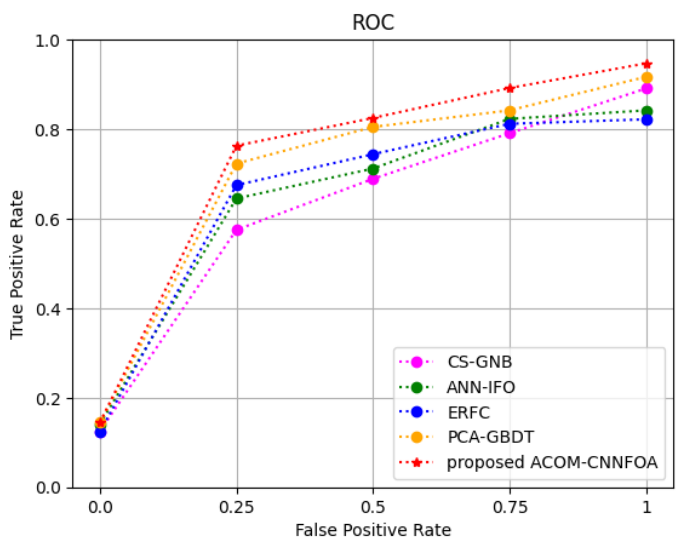

Figure 8. ROC comparison

Table 4. Performance comparison of existing and proposed Polycystic Ovary Syndrome (PCOS) prediction models

Literature	Classification Technique	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)	Training Time (s)	Testing time (s)
[15]	CS-GNB	98.4	98.3	98.1	98.1	98.2	0.0564	0.0625
[17]	ANN-IFO	97.5	94	93	93.4	92.1	0.0642	-
[12]	ERFC	98.2	98	97.8	97.8	97.5	0.3215	0.452
[13]	PCA-GBDT	95.2	94.3	95.1	95.1	94.9	0.0724	0.0631
[21]	PSO-ANN	96.7	-	96.7	96.7	-	-	-
Proposed ACOM-CNN-FOA		**99**	**98.8**	**99.4**	**99.4**	**99.1**	**0.0076**	**0.0081**

Table 5. Performance comparison of with and without heuristic approach Fruitfly Optimization approaches

Metric	Without Heuristic Algorithm (Initial)	With Heuristic Algorithm (Optimized)
Accuracy (%)	96.7	99
Precision (%)	95.3	98.8
Recall (%)	95.0	99.4
Specificity (%)	95.2	99.4
F1-Score (%)	95.1	99.1
Training Time (s)	0.065	0.0076
Testing Time (s)	0.063	0.0081

5. CONCLUSION

The prediction of PCOS disease using efficient follicles segmentation and deep learning-based classification model has been proposed in this paper. The proposed model is cascaded with the process of preprocessing, and then segmentation, feature extraction and finally classification are done by using the dataset collected from the hospitals. Input US images are preprocessed using image resizing, histogram equalization and noise removal to enhance the image to improve the detection process. The relevant features are selected using CS model which will increase the detection accuracy. From the preprocessed image, the follicles and the PCOS edges are segmented using the ACOM. The relevant features such as the location of follicles, area, perimeter are extracted from the segmented image using the first layer of convolution layer and the image is classified using CNN-FOA. Using the proposed Optimized CNN model, the follicles are classified based on its area, size, denseness and measurements.

The Fruitfly Optimization has been implemented to optimize the hyper parameters of the CNN which will increase the detection accuracy. The developed ACOM segmentation and CNN-FOA based prediction system is evaluated using the metrics in terms of number of samples, number of epochs, fivefold cross validation and ROC. Based on the result analysis, the proposed model is secured with improved performance about the accuracy of 99% than the all-other conventional methods. This model supports the medical professionals to automatically segment the follicles from the image and classified as PCOS affected ovary or regular ovary. In future, the model can be experimented with larger dataset and also incorporated with Internet of Things for real time monitoring.

REFERENCES

[1] Kyrou, I., Karteris, E., Robbins, T., Chatha, K., Drenos, F., Randeva, H.S. (2020). Polycystic ovary syndrome (PCOS) and COVID-19: An overlooked female patient population at potentially higher risk during the COVID-19 pandemic. BMC Medicine, 18(1): 220. https://doi.org/10.1186/s12916-020-01697-5

[2] Munjal, A., Khandia, R., Gautam, B. (2020). A machine learning approach for selection of polycystic ovarian syndrome (PCOS) attributes and comparing different classifier performance with the help of WEKA and PYCARET. International Journal of Scientific Research, 9(12): 59-63. https://doi.org/10.36106/ijsr/5416514

[3] Prapty, A.S., Shitu, T.T. (2020). An efficient decision tree establishment and performance analysis with different machine learning approaches on polycystic ovary syndrome. In 2020 23rd International Conference on Computer and Information Technology (ICCIT), DHAKA, Bangladesh, pp. 1-5. https://doi.org/10.1109/ICCIT51783.2020.9392666

[4] Aswathy, V.S., Vineetha, S.P. (2023). Comparative study on AI technology in PCOS diagnosis. International Journal for Research in Applied Science & Engineering Technology (IJRASET), 11(5): 846-848. https://doi.org/10.22214/ijraset.2023.51615

[5] Qayyum, A., Qadir, J., Bilal, M., Al-Fuqaha, A. (2020). Secure and robust machine learning for healthcare: A survey. IEEE Reviews in Biomedical Engineering, 14: 156-180. https://doi.org/10.1109/RBME.2020.3013489

[6] Garg, A., Mago, V. (2021). Role of machine learning in medical research: A survey. Computer Science Review, 40: 100370. https://doi.org/10.1016/j.cosrev.2021.100370

[7] Nasim, S., Almutairi, M.S., Munir, K., Raza, A., Younas, F. (2022). A novel approach for polycystic ovary syndrome prediction using machine learning in bioinformatics. IEEE Access, 10: 97610-97624. https://doi.org/10.1109/ACCESS.2022.3205587

[8] Nilofer, N.S., Ramkumar, R. (2021). Follicles classification to detect polycystic ovary syndrome using GLCM and novel hybrid machine learning. Turkish Journal of Computer and Mathematics Education, 12(7): 1062-1073.

[9] Gopalakrishnan, C., Iyapparaja, M. (2020). Active contour with modified Otsu method for automatic detection of polycystic ovary syndrome from ultrasound image of ovary. Multimedia Tools and Applications, 79(23): 17169-17192. https://doi.org/10.1007/s11042-019-07762-3

[10] Madhumitha, J., Kalaiyarasi, M., Ram, S.S. (2021). Automated polycystic ovarian syndrome identification with follicle recognition. In 2021 3rd International Conference on Signal Processing and Communication (ICPSC), Coimbatore, India, pp. 98-102. https://doi.org/10.1109/ICSPC51351.2021.9451720

[11] Nair, A., Devaser, V., Arora, K. (2024). Machine learning applications in the prediction of polycystic ovarian syndrome. In Generative Artificial Intelligence for Biomedical and Smart Health Informatics, pp. 565-589. https://doi.org/10.1002/9781394280735.ch27

[12] Isah, O.R., Usman, A.D., Tekanyi, A.M. (2017). A hybrid model of PSO algorithm and artificial neural network for automatic follicle classification. International Journal Bioautomation, 21(1): 43-58

[13] Kottarathil, P. (2022). Polycystic ovary syndrome (PCOS). https://www.kaggle.com.

[14] Agirsoy, M., Oehlschlaeger, M.A. (2025). A machine learning approach for non-invasive PCOS diagnosis from ultrasound and clinical features. Scientific Reports, 15(1): 33638. https://doi.org/10.1038/s41598-025-

10453-9
[15] Danaei Mehr, H., Polat, H. (2022). Diagnosis of polycystic ovary syndrome through different machine learning and feature selection techniques. Health and Technology, 12(1): 137-150. https://doi.org/10.1007/s12553-021-00613-y
[16] Zigarelli, A., Jia, Z., Lee, H. (2022). Machine-aided self-diagnostic prediction models for polycystic ovary syndrome: Observational study. JMIR Formative Research, 6(3): e29967. https://doi.org/10.2196/29967
[17] Sheikdavood, K., Bala, M.P. (2023). Polycystic ovary cyst segmentation using adaptive k-means with reptile search algorith. Information Technology and Control, 52(1): 85-99. https://doi.org/10.5755/j01.itc.52.1.32096
[18] Rajan, S.P., Davood, K.S. (2015). Performance evaluation on automatic follicles detection in the ovary. International Journal of Applied Engineering Research, 10(55): 1-5.
[19] Vora, K., Shah, A., Shah, N., Verma, P. (2023). Prediction of polycystic ovary syndrome (PCOS) using optimized machine learning classifiers. In Proceedings of 3rd International Conference on Artificial Intelligence: Advances and Applications: ICAIAA 2022, pp. 1-12. https://doi.org/10.1007/978-981-19-7041-2_1
[20] Alagarsamy, M., Shanmugam, N., Mani, D.P., Thayumanavan, M., Sundari, K.K., Suriyan, K. (2023). Detection of polycystic syndrome in ovary using machine learning algorithm. International Journal of Intelligent Systems and Applications in Engineering, 11(1): 246-253.
[21] Bedi, P., Goyal, S.B., Rajawat, A.S., Kumar, M. (2024). An integrated adaptive bilateral filter-based framework and attention residual U-net for detecting polycystic ovary syndrome. Decision Analytics Journal, 10: 100366. https://doi.org/10.1016/j.dajour.2023.100366
[22] Elmannai, H., El-Rashidy, N., Mashal, I., Alohali, M.A., Farag, S., El-Sappagh, S., Saleh, H. (2023). Polycystic ovary syndrome detection machine learning model based on optimized feature selection and explainable artificial intelligence. Diagnostics, 13(8): 1506. https://doi.org/10.3390/diagnostics13081506