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Polycystic Ovary Cyst Segmentation Using Adaptive K-means with Reptile Search Algorithm

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Polycystic ovary syndrome (PCOS) is a disorder in the female ovary caused because of reproductive age group hormonal changes. PCOS is a different follicle that is formed in the ovary and is termed an endocrine disorder. This disorder's effects are often linked with clinical symptoms such as arteries, acne, hirsutism, diabetes, cardiovascular disease, and chronic infertility. It is mainly associated with type 2 diabetes, obesity with high cholesterol. This must be diagnosed at an earlier stage for avoiding other related diseases. To ensure infertility, various kinds of ovulatory failures must be significantly diagnosed and recognized. The physicians manually determine the PCOS using ultrasound images, but it is inefficient to declare whether it is a simple cyst, PCOS, or cancer cyst. This manual detection is prone to trying errors. In this paper, PCOS detection is performed through a series of processes such as preprocessing, segmentation, feature selection, and classification. The speckle noise is removed in preprocessing, and the images are enhanced for further processing. The proposed improved adaptive K-means with reptile search algorithm (IAKmeans-RSA) has been utilized for cyst segmentation and follicles recognition. The relevant features from the segmented images are extracted using a convolutional neural network (CNN). Finally, the classification is performed using the Deep Neural Network (DNN) approach. The proposed system efficiently diagnosed PCOS through cyst detection from the input images. The algorithm's efficiency compared with existing methods shows that the proposed model is superior in segmenting and diagnosing PCOS.

KEYWORDS: PCOS, Deep Learning, Segmentation, Adaptive K-means, Convolution neural network (CNN), Deep Neural Network (DNN), Reptile Search Algorithm (RSA).

1. Introduction

The advancement in healthcare systems with effective methods together creates better services for the healthcare industry. Polycystic Ovary Syndrome (PCOS) is an endocrine disorder where a high level of estrogen is generated and creates PCOS problems. This affects majorly women during periods of adolescence. The PCOS condition is described as the mechanism of failure in the ovum to release from the ovary because of multiple follicular cysts formed in the ovaries. In 1935, the condition was initially narrated by Leventhal & stain. The PCOS-affected women are struggling to balance their hormone levels which creates various health issues including irregular menstrual cycle and problems getting pregnant. They are suffers from hormonal irregularity at the age of 15 to 40 years to bear a child. Based on the existing research, the PCOS vulnerabilities are about 4.8% for white Americans, 8% for Africans, 6.8% for Spain, and 31.3% for Asia people [13]. The PCOS suffered by women has the diseases such as cardiovascular diseases, hypertension, obesity, type 2 diabetes, hazardous pregnancy, and gynecological cancer. The hormone level is imbalanced due to the reasons of high blood pressure, acne problems, increased body weight and androgen hormone, irregular menstruation, and so on. Since PCOS holds back the follicle which affects the ovary's maturity level, it is considered a major cause of infertility.

The research from [2] shows that the higher risk of trimester miscarriage is because of PCOS. In the reproductive age group, 12-21% of women are suffered from PCOS, and among them, 70% of symptoms are not diagnosed. This can be changed and taken care of by the doctor under medication with a changed lifestyle such as birth control pills, anti-androgen medicines, tablets for diabetes, ultrasound scan, and fertility. The standard PCOS diagnosis and its test outcomes force doctors to give various clinical tests and irrelevant radio imaging courses which will affect the person's health further. The women having cysts in their ovaries does not mean they are having PCOS. The research studies suggested that 30 to 70% of women with PCOS are suffered from obesity and there is a bidirectional link between PCOS and obesity [13]. However, the improved secretion of several cysts in the ovary, androgens, and irregular menstruation are major facts to detect PCOS. These clinical characteristics with advanced technologies can be effectively used for the early detection of PCOS.

Recent advances in digital image processing, artificial intelligence, and computer-aided diagnosis system (CAD) assists clinicians to interpret medical images for early diagnosis. The CAD systems are majorly used to detect the region of interest in the images. The segmentation process automatically separates the region of interest from other areas of the images. These segmented images are used for the diagnosis process with segmented characteristics. Machine and deep learning algorithms are widely used for this segmentation and diagnosis process recently. Madhumitha et al., [14] developed a PCOS prediction system using Morphological operation-based follicle segmentation. For classification, machine learning algorithms such as Support Vector Machine (SVM), K nearest neighbor (knn), and Logistic Regression (LR) approaches are used. The combination of these approaches secured improved accuracy of 98% in detecting PCOS from a normal ovary. Oh, et al., [20] developed an automatic segmentation of pancreatic cyst dimension using endoscopic ultrasonography (EUS) images using Deep learning models such as U net and Residual U net.

1.1. Objectives

Using ultrasound images, the PCOS follicle is detected effectively using the automatic image analysis approach. This paper focuses to implement deep learning with a Meta heuristic algorithm for the segmentation of cysts in ultra-sound ovary images. So far, there are not many research papers are found the implementation of a Metaheuristic algorithm (MH) for follicle segmentation. This paper focuses to use the MH algorithm for Cyst location, size, and shapes in ovary ultrasound images. The regular thresholding and other edge detection approaches are not giving acceptable results when detecting the borders of follicle regions while it contains the artifacts such as shadow and reverberation. To take this as a motivation, this paper aims to develop deep learning with MH-based cyst segmentation and automatic prediction of PCOS with normal ovary images for earlier clinical diagnosis.

1.2. Contribution of the Work

The major contribution of the work is as follows:

- Segmentation: the follicles and the edges of the PCOS images are segmented using the proposed Improved adaptive K-means clustering optimized by Reptile search algorithm (IAKMeans-RSA)
- Feature Extraction: Using a deep learning model called convolutional neural network (CNN), the relevant features from the segmented images are extracted.
- Follicle Detection: This section identifies the appropriate follicle from the extracted characteristic based on follicle area, size, measurements, and denseness.
- Classification: the PCOS of the ovary is classified as 0 means PCOS and 1 means PCOS implication using Deep Neural Network (DNN).

1.3. Organization of the Paper

The remaining section of this paper is structured as follows: Section 2 discusses related works on the implementation of machine and deep learning algorithms for PCOS detection; Section 3 determines the proposed methodology representation and introduces the novel models with their architectures; Section 4 provides the experimented, evaluated and comparative analysis results; Section 5 concludes the proposed model with its remarks and future directions

2. Related Work

This section discusses the related research works for the detection of PCOS. Chen et al., [5] aim to develop a PCOS diagnosis system based on cardiovascular parameters such as radial pulse spectroscopy and blood pressure. They took 242 women's data suffered from childbearing age and obtain the measurement of the nonobtrusive radial pulse wave and blood pressure using the Fourier model. Their results show that there is no difference between diastolic blood pressure and systolic blood pressure between PCOS and non-PCOS women. Their study also shows that PCOS women have high body index than normal women and the C2 with a high body index is considered the significant factor for PCOS using logistic regression.

Property and Shitu [3] used machine learning algorithms and build an efficient classification tree. They used 542 women's data with 177 suffering from PCOS. Among the 31 features available, this paper selects 7 to 8 features as relevant features which includes irregular menstruation, BMI, HB in blood, pregnancy, respiratory rate, FSH, thyroid hormone, prolactin, endometrium, and anti-Mullerianhormone. They used SVM, KNN, Random Forest, and Naïve Bayes classifier. Among the classifiers, Random forest secured 0.93 accuracies. Bharati et al., [27] implement the classifiers such as Random Forest, Gradient Boosting, and Hybrid random forest and Logistic regression using the dataset from Kaggle. The results show that the hybrid model secured 91% more accuracy than other algorithms to detect PCOS at an early stage.

Xie et al., [19] developed hybrid ML models such as Artificial neural networks and random forests for the diagnosis of gene biomarkers. They collect the data from gene expression omnibus data consisting of 57 normal and 76 PCOS samples. The gene weights are computed using an artificial neural network with RNN. The obtained area under the curve score is 0.72. Madhumitha et al., [14] proposed an image segmentation model related to the region of interest in ultrasound images and also segment the background from the images. Morphological operation-based segmentation has been used to detect follicles. The ML approaches such as KNN, SVM, and LR were used for the classification of PCOS and normal ovaries.

Pulluparambil et al., [23] studied the prediction of PCOS with a systematic literature review. They discussed in detail the algorithms used for PCOS diagnosis and classification. Their study shows that most of the research on PCOS is done on clinical datasets and the hybrid methodologies produce better results in the diagnosis. Nilofer and Ramkumar [18] developed a hybrid model of an artificial neural network with an improved fruit fly optimization algorithm. The proposed hybrid model removes the noise and resizes the image with improved-quality of ultrasound images. To segment the follicles, the adaptive K-means algorithm was used and GLCM has been used for feature extraction. The hybrid model is trained with ANN to improve the classification results.

Gopalakrishnan and Iyapparaja [9] proposed an active contour-based modified Otsu thresholding model to extract the follicle from a PCOS ultrasound image.

This model is applied to binarize the image which is used for segmentation. Using this binary mask consisting of background and foreground regions effectively solves the contour issues. Based on the distributed gray level, the thresholding approach is infused with an ovary image to extract follicles. AZARUDIN et al., [4] reviewed the various automatic follicle identification systems for the diagnosis of PCOS. The methods with their performance measurements are compared and provide suggestions for future research directions.

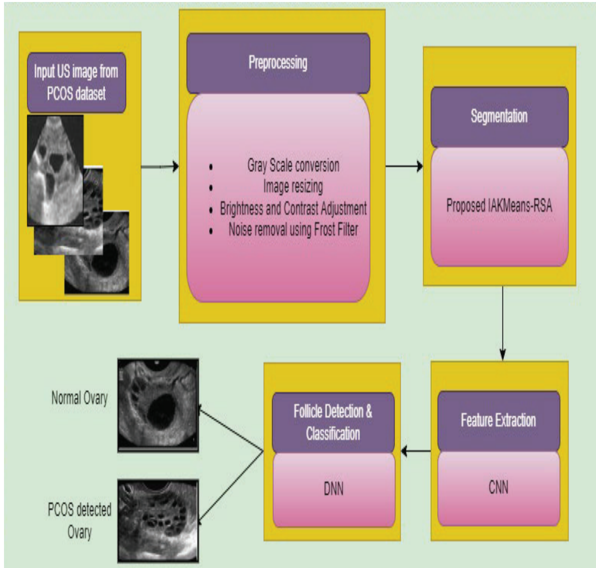
Isah et al., [10] developed an efficient hybrid approach using Particle Swarm Optimization (PSO) with ANN for the detection of follicles. Using the Lee filter, the input ultrasound images are preprocessed. PSO has been used to extract the features from the input image and it extracts 12 significant features. Multi-layer perceptron was used for classification. Richhariya et al., [21] efficiently detect the PCOS using machine learning algorithms such as KNN, LR, and SVM and proposed a hybrid model called XGBRF and cat boost approaches. The analyzed results prove that the hybrid model secured improved accuracy of 0.95than other algorithms for PCOS classification. Even though, many classification and segmentation approaches are studied, increasing detection accuracy with segmentation accuracy still need to be improved for better diagnosis.

3. Proposed System Process

The proposed PCOS diagnosis system using deep learning (DL) and Meta-Heuristic (MH) based cyst segmentation and classification is shown in Figure 1. The Ultrasound images of the ovary in the PCOS dataset are given as input which has the values such as body mass index, post-menstrual LH, length of cycle, and FSH values. Initially, the input images are preprocessed using Grayscale conversion, image resizing, brightness and contrast adjustment, and noise removal methods which increase the image efficiency. Second, image segmentation using the proposed Improved Adaptive K-means with MH approach called Reptile search algorithm (IAKmeans-RSA) is performed to segment the cyst location, size, and its measurements for better diagnosis. Third, the features from the segmented images are extracted using a DL

Figure 1

Overview of Proposed Cyst segmentation and PCOS classification system



algorithm called Convolution neural network (CNN). Among the extracted features, the most important and correct measurement of the follicle is selected and it is classified as a PCOS image or normal image using the Deep neural network (DNN) approach. These processes are explained in the following subsections.

3.1. Preprocessing

Preprocessing is a crucial stage to enhance the input data before it is analyzed. The preprocessing methods will improve the data quality, and important data will be stored in images. Various data preprocessing approaches are used for image enhancement, including histogram equalization, image bi-leveling, gray scaling, cleansing of data and inverting pictures, and so on. This paper uses preprocessing methods such as grayscale conversion, image resizing, brightness and contrast adjustment, and noise removal methods to enhance the quality of the input Ultrasound images.

- Gray Scale Conversion: Gray scaling is the process of covert the input color images to the grayscale images.
- Image Resizing: this will enhance the image using an object carving method that will reduce the artifacts and salience distortions using fast multi-operators [18]. To resize the images in dimensions,

the image height and width are resized separately with a more extended size.

- Brightness adjustment enhances the overall lightness and darkness of the image, providing proper brightness to the image. The contrast adjustment differentiates the brightness of the image region.
- Noise removal using frost filter: using the spatially varying kernel [8], this filter outputs the noise-free image. From paper [9], the frost filter enhances the image without noise and produces a good quality of image compared to other filters such as the median filter, Lee filter, Kuan filter, Gaussian, and wiener filters. Therefore, in this paper frost filter has been used for the noise removal process. Mathematically this filter is represented in Equation (1)

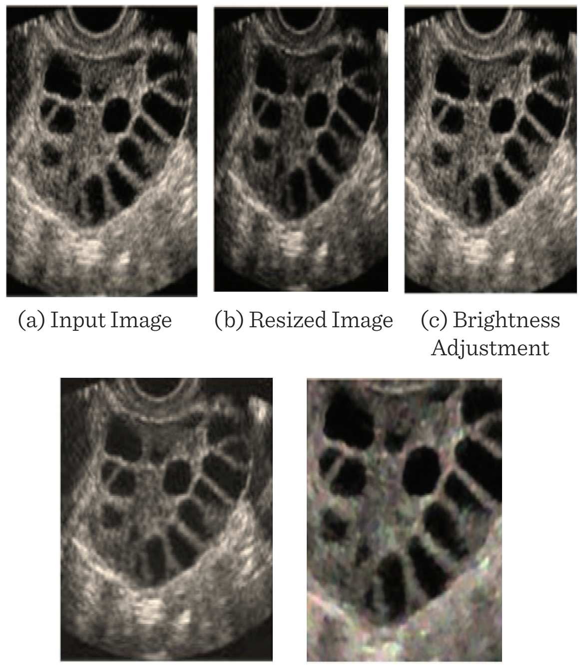
$$K(s,t) = g(s,t) * m(s,t), \tag{1}$$

where, the kernel m(s,t) is centered at (x_0, y_0) pixel location which is expressed in Equation (2)

$$m(s,t) = d_1 \exp\left(-dC_1^2(s_0,t_0)\left|s,t\right|\right), \tag{2}$$

where, d is the dampening rate which is chosen concerning the homogeneous region of the inhibited edges, the $|s, t|$ denotes the distance from each pixel of (s_0, t_0) and d_1 is the constant for the normalizing process. Figure 2 represents the preprocessing output of the input ultrasound image of the ovary.

Figure 2
The output of preprocessing phase



(a) Input Image (b) Resized Image (c) Brightness Adjustment (d) Contrast Adjustment (e) Noise removal using frost filter

3.2. Cyst Segmentation Using Proposed Improved Adaptive K-means Optimized by Reptile Search Algorithm (IAKmeans-RSA)

This paper proposed an improved AK means with an RSA algorithm for segmenting the cyst from ultrasound images for a better PCOS diagnosis. Compared to the standard K-means algorithm, two more features such as brightness and roundness are added in the segmentation process. The proposed model consists of three steps such as initialization, adaptive segmentation, and RSA optimization phases.

3.2.1. Initialization Phase

For the initialization, the objective function is determined through the implementation of the K-means algorithm for ten iterations. This entire phase is consideriteration one for the segmentation process. For new cluster formation, new centers are distributed. For the first iteration, the objective function estimation is carried and the average circularity of the objects called cysts is referred to as an objective function. The first feature called the roundness ratio is referred to as the ratio between the area of the ovary shape (S) and the area of the sphere consisting of an equal perimeter (P). It is mathematically denoted in Equation (3)

$$R = \frac{4\pi S}{P^2}. \tag{3}$$

The value of R is one of the shapes is a circle and for other shapes, it is less than one. In individual clusters, from the overall pixel count N, the area is derived. The objective function is denoted in Equation (4)

$$OF = \sum_{i=1}^{N} \frac{R_i * S_i}{S_i}, \tag{4}$$

where, R_i denotes the roundness ratio of ith object (cyst), S_i denotes the area of the ith object. Concerning increasing the values of larger objects and reducing the values of smaller objects, the R-value is multiplied by S.

3.2.2. Adaptive Segmentation Process

The objective function OF recalculation is performed using the feature-based computation process using Equation (5). Moreover, the value o the current F is compared with the value f the last off from the previous iteration. If the $OF_{current}$ have value lower than OF_{last} then the current state is retained by removing the previous iteration results. And If the $OF_{current}$ have subscription OF_{last} then new centers are generated to create the new clusters from the brightest two clusters.

$$distance\left(D\right) = X_i^j - C_j^2 . \quad (5)$$

The remaining clusters are modified using the D function which is used to determine the distance between cluster center C and data point X. using this process, the n data points' distances and their respective cluster centers are indicated using Equation (5). This process is repeated for several iterations until it converges based on two conditions such as (i) the best result is unchanged and (ii) the maximum number of iterations is reached. The novelty of this paper is added here with the implementation of the MH algorithm called RSA to enhance the objective function and also used to choose the best possible value of k for the number of clusters.

3.2.3. RSA Optimization Phase

The reptile search algorithm is the recent meta-heuristic algorithm proposed by Abualigah et al., [1]. It mimics the behavior of crocodiles in their nature habitat. In nature, the crocodiles are from the "Crocodlinae" family which lives in water and food-available environment. They have the capability of hunting in water and out of the water also. The crocodile living behavior characteristics are stated as follows:

- Crocodile vision: it has the ability of night vision that most animals lack to see. Compared to other animals, crocodiles have lower vision during night hunting.
- Eating behavior: crocodiles reside at the top of the food chain and are fed on surrounding environment foods including fish, cows, deer, baby elephants, zebras, and small crocodiles. The larger size of crocodiles also takes the food sources of sharks and cats. Without food, it has the ability to live long periods.
- Locomotion behavior: crocodiles swim, run and walk. They use their tails for swimming to steer and their legs to ignore. They use their legs to carry their body while walking and moving, tails were used to balance and steer. To attack prey, the crocodiles can able to run short distances and the energy is transferred from the tail to the body to move forward at high speed.
- Cognition: crocodiles can recognize the prey patterns like which animals come to the water to drink frequently.
- Hunting behavior: the crocodiles set the ambushes in the water to hunt the animals that came to the water to drink or dive. The crocodiles wait for the right moment and silently attack the prey in the water. While it catches the prey, it drags the prey into the water and drowns. At last, it cuts the prey into larger pieces and completely devours it. To share the prey, the crocodiles are fights each other frequently.
- Cooperation: the crocodiles are lives in groups and it cooperates to prepare the ambushes. For the predation task, everyone in the group has a role to help. These phases are explained as follows:

1. *Initialization of parameters:* at the initial stage, the control and algorithmic parameters are initialized. The control parameters are the number of crocodiles (N), and the maximum number of iterations (max). The algorithmic parameters are alpha and beta which are used to control the exploration and exploitation characteristics, respectively, during the searching process.
2. *Initialization of population:* initially, the set of populations is generated randomly using Equation (6)

$$X_{(i,j)} = X_j^{low} + r.(X_j^{upper} + X_j^{low})? \\ i = 1,2,3...N and ? j = 1,2,3,...d, \quad (6)$$

where, X_{ij} - decision variable of ith solution in jth position, X_j^{upper} and X_j^{low} is the upper and lower bound of jth position decision variable, r is the random variable in the range 0 to 1 and d is the total number of decision variables. The set of solutions for all N is generated and stored in X as in Equation (7) [14]

$$X \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d-1} & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d-1} & x_{2,d} \\ . & . & . & . & . \\ x_{N,1} & x_{N,2} & \cdots & x_{N,d-1} & x_{N,d} \end{bmatrix}, \tag{7}$$

where each row indicates ith position solutions.

3. *Fitness evaluation:* the fitness value of each solution is computed as $f(X_i)\,\forall i = 1,2,3,..N$.
4. *Encircling*: this is considered as an exploration attitude of crocodiles which is use to find the best solution with the exploration of new regions on the search space using two strategies such as high walking and belly walking denoted in Equation (8).

$$X_{i,j}(t+1) = \begin{cases} X_j^b(t) - \eta_{ij}(t) * \beta - Rs_{i,j}(t) * r, & t \le \frac{maxt}{4} \ (high\ walking) \\ X_j^b(t) * X_{r1,j}(t) * Es(t) * r & \frac{maxt}{4} < t < \frac{2maxt}{4} \ (belly\ walking) \end{cases} \tag{8}$$

where, $X_j^b(t)$ represents the best solution in the jth position at t iteration, t is the previous iteration, t+1 is the new iteration, η_{ij} represents the hunting variable of jth position of ith solution which is computed using Equation (5), β controls the exploration ability of high walking and it is set as 0 to 1, $X_{r1,j}$(t) is the decision variable of jth position in r1th solution at iteration ($r1 \in [1, N]$), $Rs_{i,j}$, is used to reduce the search area of jth position in ith solution computed using Equation (8), $Es(t)$ represents the probability of evolutionary sense which have decreasing random values from -2 to 2 computed using Equation (9)

$$\eta_i j = X_j^b(t) * p_{(i,j)}, \tag{9}$$

where p is the percentage difference of jth position decision variable of best solution and same position decision variable computed using Equation (6)

$$p_{i,j} = \alpha + \frac{X_{i,j} - avg(X_i)}{X_j^b(t) * \left(X_j^{upper} - X_j^{low}\right) + \varepsilon} \tag{10}$$

$$avg(X_i) = \frac{1}{d} \sum_{j=1}^{d} X_{i,j}, \tag{11}$$

where α is also used to control the exploration ability and set as 0.2, ε is the random number between 0 to 2.

$$Rs_{i.j} = \frac{X_j^b(t) - X_{r2,j}}{X_j^b(t) + \varepsilon} \tag{12}$$

$$Es(t) = 2 * r3 * \left(1 - \frac{1}{maxt}\right), \tag{13}$$

where r2 and r3 are random numbers in the range 1 to N and 0,1 or -1, respectively.

5. *Hunting stage:* this is considered as an exploitation attitude of crocodiles which is used to find the optimal solution based on two strategies such as hunting coordination and hunting cooperation as denoted in Equation (10).

$$X_{i,j}(t+1) = \begin{cases} X_j^b(t) - p_{ij}(t) * r & \frac{2maxt}{4} < t \le \frac{3maxt}{4} \ (hunting\ coordination) \\ X_j^b(t) * \eta_{i,j}(t) * \varepsilon - Rs_{i,j(t)} * r & \frac{3\ maxt}{4} < t < maxt (hunting\ cooperation) \end{cases} \tag{14}$$

The best solution from this optimization process is denoted as an objective function and k values for segmentation process. The cyst segmented image is shown in Figure 3.

Once the segmentation is over, the needed parameters such as cyst location, aspect ratio, size, perimeter, and solidity are measured to diagnose the PCOS using the cyst type, location, and size. The following table 1 represents the cyst information of input images. The workflow of the proposed cyst segmentation algorithm is shown in Figure 4. The process starts with the preprocessed ultrasound images given as input. Initially execute the standard K-means algorithm [12] for initial clusters. The upcoming process is repeated for n iterations until the stopping condition is met. The objective function is computed using the RSA algorithm. Suppose the value of the current objective function is less than or equal to the last value of the objective function. In that case, the present, accurate function value is retained, or the previous value is replaced with the current value. Once the n iterations are over, the segmented circular portion of cyst values is returned

Table 1
Cyst dimensions details

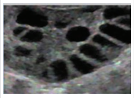
S. No	Input image	Kernel size	Area (sq. cm)	Perimeter (cm)	Aspect ratio	Extent	Solidity
1		(7,7)	58.54	14.73	1.54	0.573	0.792
2		(9,9)	38.82	8.78	0.871	0.634	0.941
3		(3,3)	3.92	4.21	1.238	0.92	1.12

Figure 3
Cyst Segmentation using proposed IAKmeans-RSA

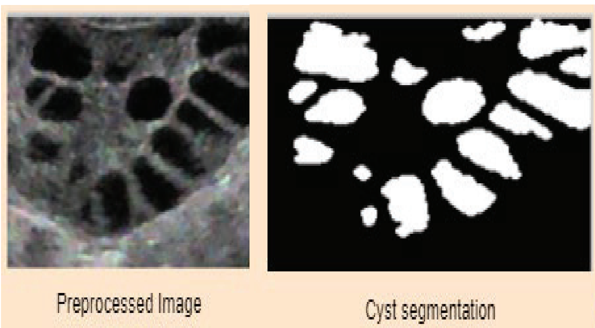
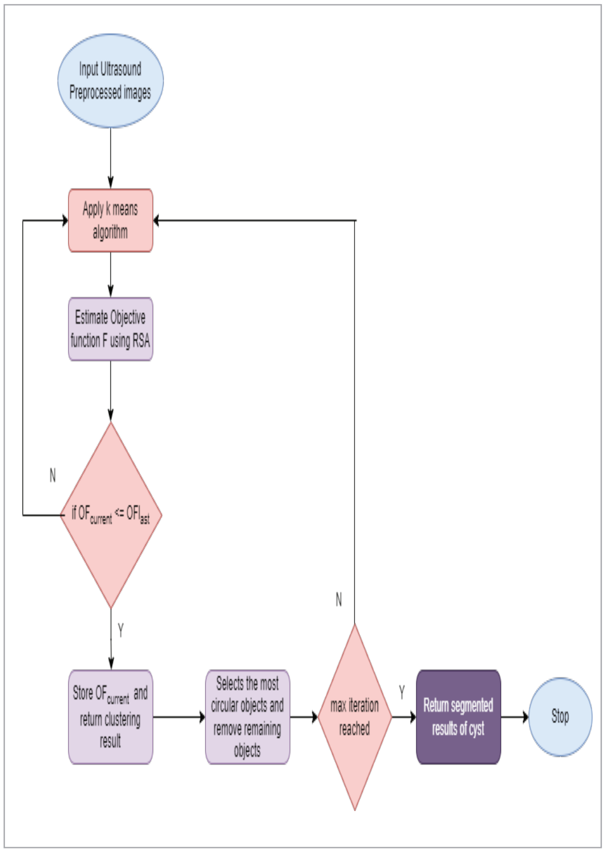


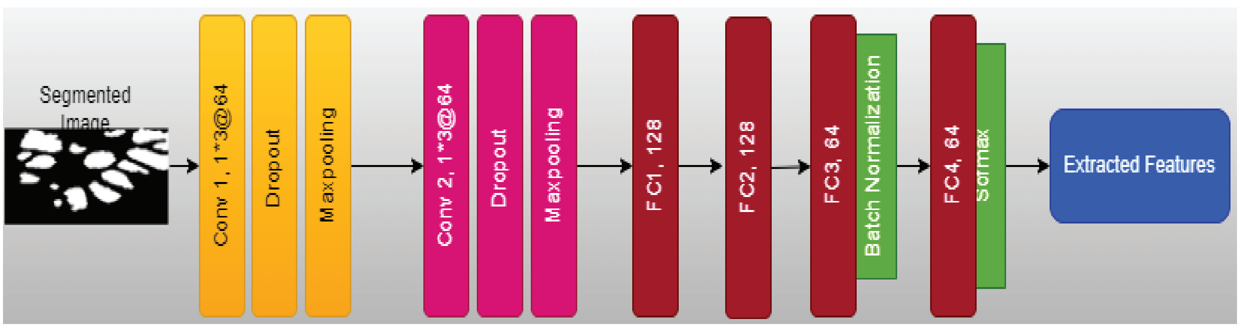
Figure 4
Workflow of proposed IAKmeans-RSA based cyst segmentation



3.3. Feature Extraction Using CNN

In feature extraction phase, the feature vector from data segmentation stage is used. Convolution neural network is the widely used feature extractor in variety of applications which includes image and text classification, speech recognition and so on [26, 11]. In this study, the architecture shown in Figure 5 is used for feature extraction and selection.

Figure 5
CNN architecture for feature extraction



The block conv1 -1*3 @ 64 denotes the convolution layer with filter size of 64 and each filter has 1*3 size with astride size of 1. The input data is one dimensional data. The major building blocks are convolution layer, fully connected layer, pooling layer and activation function. Based on the constructed data, the CNN learns complex feature representations [17]. The convolution operation used to learn the activation map from the input data. This simple CNN structure based feature extraction improves the classification accuracy. The best trained model based on its performance in test data is used to extract the features and selects the most relevant features. In Figure 5, the convolution is followed by the rectified linear unit (ReLU) [16] denoted in Equation (11) to avoid the negative and small values propagation. Pooling layer is used to reduce the dimensionality of the input data X.

$$ReLu\left(X\right) = \max\left(0, X\right). \quad (15)$$

Dropout layers are used to reduce the complexity and prevents from overfitting. The regularization rate for this dropout layer is 0.5 that can drop some neuron during training. The convolution operation on input data X^{l-1} of previous layer is declared in Equation (12)

$$X^{l} = w^{l} . X^{l-1} + b^{l}, \quad (16)$$

where w and b – weight and bias of l^{th} layer, respectively, and X^l - output. The extracted features after last pooling layers are given as input to fully connected (FC) layer. The layers FC1, FC2 and FC3 are used for feature extraction. FC4 is used for output using softmax activation function. Since, CNN is regularization method [24-25], batch normalization (BN) is used to normalize the features given input to FC4. The extracted feature vector from the layer FC3 is of size 1*64 which is given as input to the feature selection process. This will boost the classification performance with improved accuracy.

The taken database consists of 45 attributes including Follicle Number as left and right, skin darkening (yes or

no), hair growth (yes or no), weight gain (yes or no), Cycle (regular or irregular), fast food (yes or no), pimples (yes or no), Anti-Müllerian hormone(AMH) (ng/ mL), weight (kg), BMI, Hair loss (yes or no), Hip (inch), Waist (inch)and average Follicle size (left) (mm) and so on. Among the features, the most important ten features such as Follicle Simulating hormone (FSH), Luteinizing Hormone (LH), Follicle number (R), Follicle number (L), AMH, Cycle, avg follicle size,cycle length and BMI are selected for further processing.

3.4. Follicle Detection

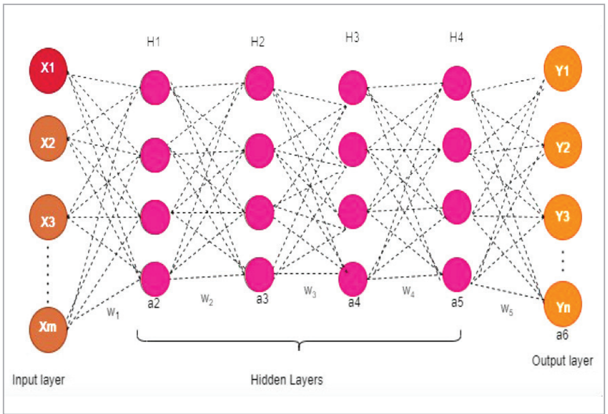
There are several features extracted in the feature extraction phase. The appropriate follicle from the identified characteristics is distinguished based on the follicle measurements, area, and denseness. The follicles are in the shape of spherical, and the area is about 4 to 80 mm2 for an ovary with PCOS and 314 mm2 for a normal ovary follicle. The bristles are ranged from 2 to 9 mm in diameter, which is affected by PCOS, and the normal ovary will be 20 mm in diameter. The freakiness of follicles is equivalent to origin levels, detected region zones, and similar strands.

3.5. Classification Using DNN

This section discussed the classification model called Deep neural network with optimized hyperparameter settings for detecting attacks in IoT. The detected follicle features are given as input to a fully connected deep neural network (DNN) for the classification of normal and PCOS data. The hyperparameters such as learning rate, epoch size, momentum, batch size, dropout regularization, and so on are selected to improve the model performance. A Random Search approach has been used to determine the hyperparameters for DNN. At each instance, the model is trained with the parameters chosen by the random search. It can improve the model performance after a fixed number of iterations of execution. A deep Neural network is a kind of Artificial Neural network (ANN) with more hidden layers. Each DNN has an input layer, multiple hidden layers, and one output layer. Each hidden layer consists of more neurons. Based on the received inputs, each neuron is fired or retained.

The DNN architecture is shown in Figure 6. X denotes the input feature, w indicates the weight of the link between neurons from Layer I to Layer i+1, Y is the output and a is an activation function which is used to fire the neuron based on the forward propagation computation. Each layer use different activation function for better computation. The hidden layer uses ReLu activation function and the output layer

Figure 6
Architecture of Optimized DNN



uses softmax activation function defined in Equations (13)-(14)

$$ReLU\left(a_i\right) = \max\left(0, a_i\right) \tag{17}$$

$$Softmax\left(a_i\right) = \frac{e^{a_i}}{\sum_{j=1}^{n} e^{a_i}}, \tag{18}$$

where, a_i- obtained output from neuron i in the output layer and n – number of classes in the output layer.

The DNN is comprised of two stages [15, 22] such as forward propagation and backward propagation. In forward propagation, the inputs are multiplied with the weights and bias which is assigned to each neuron to travel towards the hidden layer. The final predicted output is Y. Each hidden layer 'L' neuron calculates the following

$$a_l = w_l^L . H^{l-1} + b^l \tag{19}$$

$$H_l = a\left(H_l\right), \tag{20}$$

where a – activation function, H – hidden layer, w – weight and b – bias. The DNN has been trained by backpropagation which employs the gradient descent (GD) method for its weight updation. This will reduce the error between actual and predicted results. The gradient calculation computes the changes in the weight with respect to its expected output. The error between predicted and actual output stated in the output layer is computed and back propagated to the preceding hidden layers. Based on gradient values, the weight and bias are updated. The GD method is optimized using Adam optimizer which is the combination of gradient descent with momentum and RMS (Root Mean Square) prop approach. In the Momentum approach, the velocity and the gradient are calculated and RMSP uses the weighted average method on the second gradient moment (dw2). The Adam optimizer employs both past squared gradient (U), and past momentum (V) computed using Equation (17) and (18). The bias is added to U and V using Equation (19) and (20) and the weights are updated using Equation (21)

$$U = \beta_1 V + \left(1 - \beta_1\right) dw \tag{21}$$

$$V = \beta_2 V + \left(1 - \beta_2\right) dw2 \tag{22}$$

$$U = \frac{U}{1 - \beta_1^i} \tag{23}$$

$$V = \frac{V}{1 - \beta_2^i} \tag{24}$$

$$w' = w - \alpha \frac{U}{\sqrt{V + \epsilon}}, \tag{25}$$

where α - learning rate and β parameter [0, 1]. The DNN is trained and tested using the PCOS dataset with the hyper parameters for the prediction of PCOS data and normal ovary data.

4. Experimental Results

This paper used the public dataset from the Kaggle repository for experimentation and the dataset prepared by prasoon kottarathil called polycystic ovary syndrome [30]. The patient names and their file numbers are changed for privacy issues. It consists of 541 patient records with 45 attributes concerning clinical and metabolic characteristics, which help to detect PCOS. Among the 541 records, 364 patients are with average records, and 177 patients with PCOS. This data is gathered from ten various hospitals in Kerala, India. Since 45 features of data are tedious to process, the most relevant ten features are selected using Section 3.3, and the data is classified to detect the PCOS data from average data. The obtained data are in CSV format and implemented using Python programming. In Python, the packages such as Scikit learn, Matplotlib, Jupiter notebook, and anaconda are used for development.

4.1. Evaluation Metrics

To evaluate the PCOS prediction system using the proposed cyst segmentation and classification system, a confusion matrix is implemented. From the confusion matrix, the evaluation metrics such as accuracy, precision, recall, and F1-score are computed. Additional metrics such as ROC-AUC score and cross-validation accuracy were also computed. The confusion matrix template is shown in Table 2 and using the variables True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), the metrics are computed using the following Equations (22)-(27)

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \tag{26}$$

$$Precision = \frac{Tp}{Tp + Fp} \tag{27}$$

$$Recall = \frac{Tp}{Tp + Fn} \tag{28}$$

$$F1 - Score = \frac{2 * Tp}{2 * Tp + Fp + Fn} \tag{29}$$

ROC-AUC: It is computed using the true positive (TPR) and false positive rate (FPR) with various thresholds. Every threshold represents the plots in the graph and it is connected through a curve. A value closer to 1 means a better classifier.

Table 2
Confusion matrix

	Actual positive	Actual negative
Predicted positive	True positive (Tp)	False positive (Fp)
Predicted negative	False negative (Fn)	True negative (Tn)

$$TPR = \frac{Tp}{Tp + Fn} \tag{30}$$

$$FPR = \frac{Fp}{Fp + Tn}, \tag{31}$$

where, Tp- PCOS data in the dataset are correctly classified as PCOS ovary in the proposed model Tn-Normal ovary in the PCOS dataset is correctly classified as regular using the proposed model.

Fp- PCOS ovary in the dataset is wrongly classified as a normal ovary in the proposed model.

Fn- Normal ovary in the PCOS dataset is wrongly classified as PCOS ovary in the proposed model.

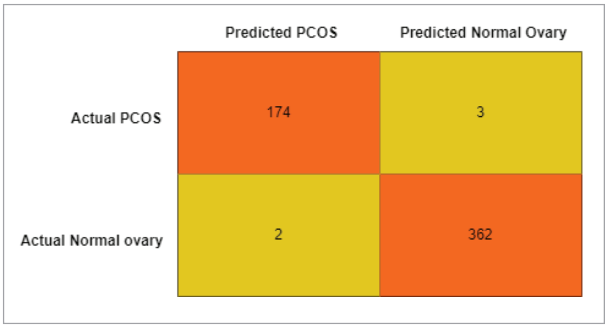
5. Results Cross-validation Accuracy: Randomly, the Set of Instances is Divided into k Groups

For our analysis, the k value of 10,20,30, and 40 have been chosen.

5.1. Evaluation and Comparison

The confusion matrix computation using the proposed model is shown in Figure 7.

Figure 7
PCOS prediction using the proposed model



Using Figure 5, the metrics results are shown in Table 3 for the proposed PCOS prediction based on cyst segmentation and classification system. From this table, the performance of the proposed deep learning with MH-based cyst segmentation and classification system is shown with an efficiency of 99.1% of accuracy and a ROC score of 0.9. This will prove that the proposed model effectively predicts the PCOS ovary of women and normal ovary data of the women.

Table 3

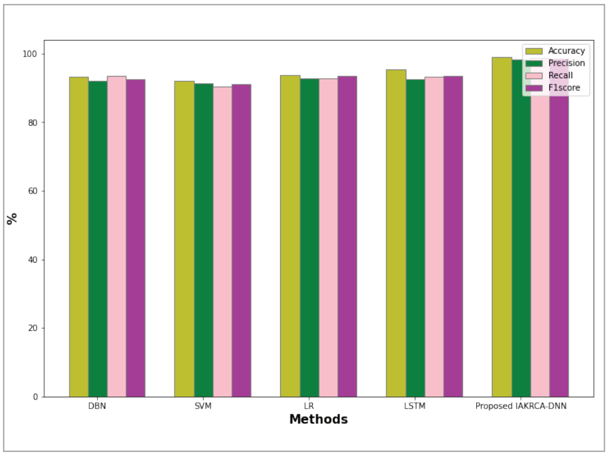
Performance of Proposed PCOS prediction system

Metrics	Results (%)
Accuracy	99.1
Precision	98.3
Recall	98.8
F1-score	98.5
ROC-AUC	0.9

The efficacy of the model is evaluated by comparing the proposed model results with conventional classification approaches such as Deep belief network (DBN), Support Vector Machine (SVM), Logistic regression (LR), and Long short-term memory (LSTM). The comparative analysis results are shown in Figure 8.

Figure 8

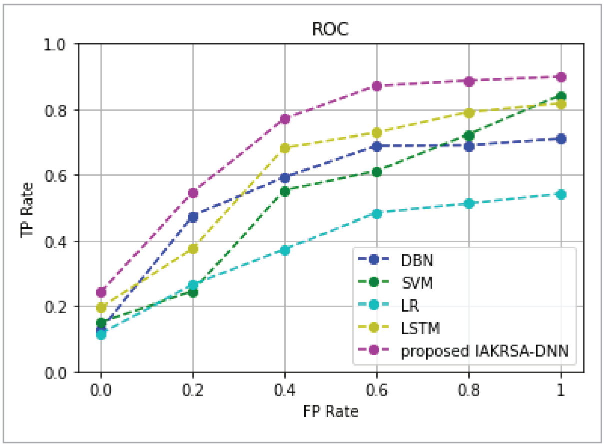
Comparative analysis of proposed classifier with existing classifiers



Compared to the existing classifiers such as DBN, SVM, LR, and LSTM, the proposed model performance is superior and efficient, with an accuracy of 99.1%, precision of 98.3%, and recall of 98.8%, and F1-score of 98.5%. Various other classifiers, such as DBN, secured the accuracy, precision, recall, specificity, and F1-score of 93.2%, 92.1%, 93.6%, and 92.5%, respectively. SVM secured 92.1%, 91.3%, 90.5%, and 91.2%, respectively. LR obtained 93.7%, 92.8%, 92.9%, and 93.4% sequentially and LSTM secured 95.4%, 92.6%, 93.3%, and 93.6%, respectively. The ROC of proposed vs. existing approaches is shown in Figure 9. Compared to the existing approaches, the proposed feature extraction, feature selection, and classification system secured the ROC value of 0.9.

Figure 9

ROC comparison results



The impact of the cross-validation accuracy of proposed and existing systems is compared, as shown in Table 4. This comparison based on different values of K folds such as 10, 20, 30, and 40 are used. The illustrated results show that the proposed model obtained improved accuracy for all the folds than other existing approaches. This will prove that the proposed model predicts PCOS more efficiently than different classifiers. Hence, the proposed model will help physicians with earlier and more accurate detection of PCOS for the patients' early treatment and diagnosis.

Table 4

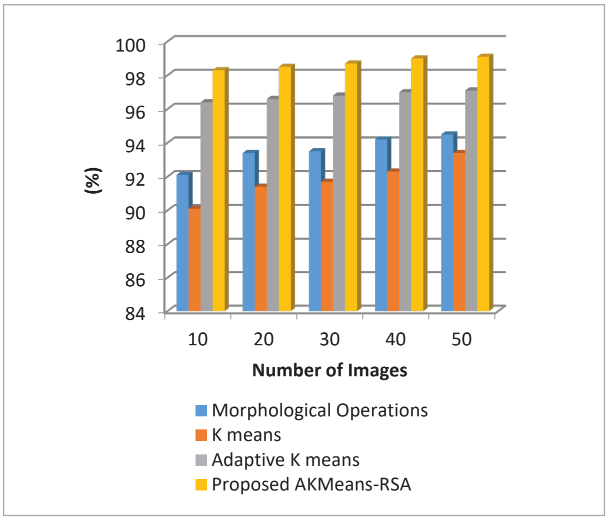
Cross (k fold) validation accuracy comparison

K-folds	Models				
	DBN	SVM	LR	LSTM	Proposed IAKR-SA-DNN
10	0.89	0.85	0.84	0.91	0.989
20	0.88	0.84	0.86	0.90	0.989
30	0.87	0.85	0.86	0.91	0.991
40	0.88	0.85	0.85	0.91	0.991

The efficiency of the proposed segmentation approach is evaluated with the segmentation accuracy in terms of the number of images. The proposed IAKmeans-RSA is compared with other cyst segmentation approaches such as morphological operations, K-means and standard Adaptive K-means approaches. The comparative results are shown in Figure 10. The accuracy of each method gradually increases while increasing the number of images. For the segmentation of cyst, the proposed Improved AK means with RSA algorithm proves its efficiency of 99% of accuracy and finds the cluster center which is superior than other approaches. The reason is the implementation of MH algorithm to choose the clusters and the clustering process with RSA identified the cyst correctly.

Figure 10

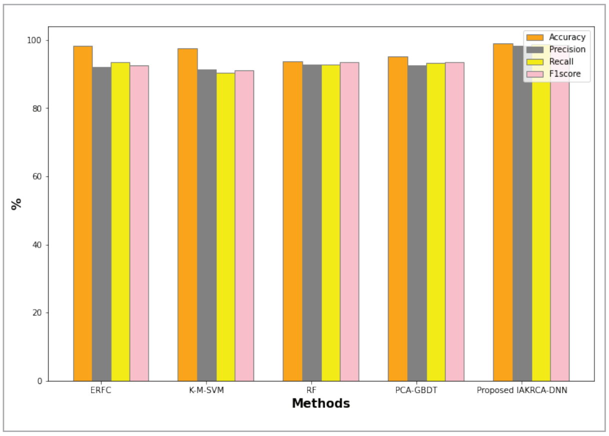
Segmentation Accuracy comparison of proposed segmentation and existing approaches



The efficacy of the proposed model has been experimented with recent PCOS detection systems such as Ensemble random forest classifier (ERFC) [30], K-means with LS-SVM (K-M-SVM) [6], Random forest (RF) [7], and PCA with gradient boosting decision tree (PCA-GBDT) [28]. The comparative results in terms of accuracy are shown in Figure 11. This illustration shows that the proposed model secured improved performance for the detection of PCOS than other approaches. The proposed model secured the improved accuracy of 99.1% than other approaches such as ERFC (98.2%), K-M-SVM (97.6%), RF (93.7%) and PCA-GBDT (95.2%). Hence, compared to the recent PCOS detection system, the proposed IAKRCA with DNN secured improved performance for the detection of PCOS.

Figure 11

PCOS detection comparison of Existing approaches vs proposed model



6. Conclusion

This paper proposes automatic early detection of PCOS using cyst segmentation using deep learning and Meta-heuristic algorithms. The input ultrasound image is preprocessed to enhance the appearance for further processing. The preprocessing such as Grayscale conversion, brightness and contrast adjustment, and speckle noise removal are performed. Second, the follicles and the edges of the PCOS images are segmented using the proposed improved adaptive K-means clustering optimized by the Reptile search algorithm (IAKMeans-RSA). This novelty detects the cyst characteristics such as size, area, and perimeter for better diagnosis. Third, the relevant features from the segmented images are extracted using a deep learning model called a convolutional neural network (CNN). Among the 45 parts, the most pertinent ten features are considered.

At last, the PCOS of the ovary is classified as 0 means non-PCOS, and one means PCOS implication using Deep Neural Network (DNN). The data from the Kaggle repository has been used for evaluation. The proposed PCOS diagnosis system experiments on confusion matrix, accuracy, precision, recall, F1 score, and ROC. The tested results are compared with existing segmentation and classification approaches to prove the performance of the proposed segmentation and classification system. With the analysis, the proposed model secured improved accuracy of 99.1%

in detecting the PCOS using cyst identification than other existing approaches. The deep learning-based cyst segmentation and classification process can efficiently assist the clinical diagnosis with the automatic identification of PCOS from Ultrasound images. The drawback of this approach is a smaller dataset of 541 records. In the future, the effective deep learning-based model will have experimented with a more significant number of datasets, and classification with optimization algorithms will be developed with reduced complexity.

References

1. Abualigah, L., Sumari, P., Geem, Z. W., Gandomi, A. H. Reptile Search Algorithm - A Nature-Inspired Meta-heuristic Optimizer, Expert Systems with Applications, 2022, 191, Article ID 116158. https://doi.org/10.1016/j.eswa.2021.116158
2. Amsy, D., Anitaraj, A., Maneeshram, C., Remya, G. I-Hope: Detection and Prediction System for Polycystic Ovary Syndrome (Pcos) using Machine Learning Techniques. In TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), 2019, 673-678. https://doi.org/10.1109/TENCON.2019.8929674
3. Aroni, S., Prapty, T., Tamanna, S. 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), 2020, 1-5. https://doi.org/10.1109/ICCIT51783.2020.9392666
4. Azarudin, A. A. Review on Automated Follicle Identification for Polycystic Ovarian Syndrome. Bulletin of Electrical Engineering and Informatics, 2020, 9(2), 588-593. https://doi.org/10.11591/eei.v9i2.2089
5. Chih, Y., Chen, C., Wei, C., Sheng, H., Wang, G., Chung, W. The Effects of Polycystic Ovary Syndrome on Cardiovascular System in Women of Childbearing Age. In BIBE 2019. The Third International Conference on Biological Information and Biomedical Engineering, 2019, 1-4.
6. Danaei, M. H., Polat, H. Diagnosis of Polycystic Ovary Syndrome Through Different Machine Learning and Feature Selection Techniques. Health and Technology, 2022, 12(1), 137-150. https://doi.org/10.1007/s12553-021-00613-y
7. Faris, N. N., Miften, F. S. An Intelligence Model for Detection of PCOS Based on K-Means Coupled with LS-SVM. Concurrency and Computation: Practice and Experience, 2022.
8. Frost, V. S., Stiles, J. A., Shanmugam, K. S., Holtzman, J. C. A Model for Radar Image & Its Application to Adaptive Digital Filtering for Multiplicative Noise, IEEE Trans Pattern Anal Mach Intell PAMI, 1982, 4(2),157-166. https://doi.org/10.1109/TPAMI.1982.4767223
9. Gopalakrishnan, C., Iyapparaja, M., Active Contour with Modified Otsu Method for Automatic Detection of Polycystic Ovary Syndrome from Ultrasound Image of Ovary, Multimed Tools Appl, 2020, 79, 17169-17192. https://doi.org/10.1007/s11042-019-07762-3
10. Isah, O. R., Usman, A. D., Tekanyi, A. M. S. A Hybrid Model of PSO Algorithm and Artificial Neural Network for Automatic Follicle Classification. International Journal Bioautomation, 2017, 21(1), 43- 58.
11. Kadry, S., Rajinikanth, V., Taniar, D., Damaševičius, R., Valencia, X. P. B. Automated Segmentation of Leukocyte from Hematological Images-A Study using various CNN Schemes, Journal of Supercomputing, 2022, 78(5), 6974-6994. https://doi.org/10.1007/s11227-021-04125-4
12. Kiruthika, V., Ramya, M. M. Automatic Segmentation of Ovarian Follicle using K-Means Clustering. In 2014 Fifth IEEE International Conference on Signal and Image Processing, 2014, 137-14. https://doi.org/10.1109/ICSIP.2014.27
13. Muhammad, S., Khan, I., Rubaiath, E., Ulfath, F., Irfan, A., Fateha, K., Bappee, R. H. Improved Sampling and Feature Selection to Support Extreme Gradient Boosting for Pcos Diagnosis. In 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), 2021, 1046-1050. https://doi.org/10.1109/CCWC51732.2021.9375994
14. Madhumitha, J., Kalaiyarasi, M., Ram, S. S. Automated Polycystic Ovarian Syndrome Identification with Follicle Recognition, 2021 3rd International Conference on Signal Processing and Communication (ICPSC), 2021, 98-102. https://doi.org/10.1109/ICSPC51351.2021.9451720
15. Mohammed, M. A., Ali, I. R., Obaid, O. I. Diagnosing Pilgrimage Common Diseases by Interactive Multimedia Courseware. Baghdad Scientific Journal, 2022, 19(1), 168. https://doi.org/10.21123/bsj.2022.19.1.0168

16. Nair, V., Hinton, G. E. Rectified Linear Units Improve Restricted Boltzmann Machines. In Proceedings of the 27th International Conference on Machine Learning (ICML-10), DBLP, Israel, June 2010, 807-814.

17. Nawaz, M., Nazir, T., Masood, M., Ali, F., Khan, M. A., Tariq, U., Sahar, N., Damaševičius, R. Melanoma Segmentation: A Framework of Improved DenseNet77 and UNET Convolutional Neural Network. International Journal of Imaging Systems and Technology, 2022.

18. Nilofer, N. S., Ramkumar, R., Follicles Classification to Detect Polycystic Ovary Syndrome Using Glcm and Novel Hybrid Machine Learning, Turkish Journal of Computer and Mathematics Education, 2021, 12(7), 1062-1073.

19. Ning, N., Xie, F., Fang, W., Jue, Z., Chang, L., Fan, Q. Establishment and Analysis of a Combined Diagnostic Model of Polycystic Ovary Syndrome with Random Forest and Artificial Neural Network, BioMed Research International, 2020, 1-13. https://doi.org/10.1155/2020/2613091

20. Oh, S., Kim, Y. J., Park, Y. T., Kim, K. G. Automatic Pancreatic Cyst Lesion Segmentation on EUS Images Using a Deep-Learning Approach, Sensors, 2022, 22, 245. https://doi.org/10.3390/s22010245

21. Prashant, R., Madhuri, N., Bharti, B., Anita, S., Pankaj, R. An Efficient Way of Detecting PCOS using Machine Learning, 2022, 32.

22. Priya, S. J., Rani, A. J., Subathra, M. S. P., Mohammed, M. A., Damaševičius, R. Ubendran, N. Local Pattern Transformation Based Feature Extraction for Recognition of Parkinson's Disease Based on Gait Signals. Diagnostics, 2021, 11(8), 1395. https://doi.org/10.3390/diagnostics11081395

23. Pulluparambil, S. J., Bhat, S. Medical Image Processing: Detection and Prediction of PCOS A Systematic Literature Review, International Journal of Health Sciences and Pharmacy (IJHSP), 2021, 5(2), 80-98. https://doi.org/10.47992/IJHSP.2581.6411.0075

24. Rahman, A. U., Saeed, M., Mohammed, M. A., Jaber, M. M., Garcia, Zapirain, B. A Novel Fuzzy Parameterized Fuzzy Hypersoft Set and Riesz Summability Approach Based Decision Support System for Diagnosis of Heart Diseases. Diagnostics, 2022, 12(7), 1546. https://doi.org/10.3390/diagnostics12071546

25. Rahman, A. U., Saeed, M., Mohammed, M. A., Krishnamoorthy, S., Kadry, S. Eid, F. An Integrated Algorithmic MADM Approach for Heart Diseases Diagnosis Based on Neutrosophic Hypersoft Set with Possibility Degree-Based Setting. Life, 2022, 12(5), 729. https://doi.org/10.3390/life12050729

26. Rajinikanth, V., Kadry, S., Nam, Y., Convolutional-Neural-Network Assisted Segmentation and SVM Classification of Brain Tumor in Clinical Mri Slices, Information Technology and Control, 2021, 50(2), 342-356. https://doi.org/10.5755/j01.itc.50.2.28087

27. Subrato, B., Prajoy, P., Rubaiyat, H., Mondal, M. Diagnosis of Polycystic Ovary Syndrome Using Machine Learning Algorithms. In 2020 IEEE Region 10 Symposium (TENSYMP), 2020, 1486-1489. https://doi.org/10.1109/TENSYMP50017.2020.9230932

28. Tiwari, S., Kane, L., Koundal, D., Jain, A., Alhudhaif, A., Polat, K., Althubiti, S. A. SPOSDS: A Smart Polycystic Ovary Syndrome Diagnostic System using Machine Learning. Expert Systems with Applications, 2022, 203. https://doi.org/10.1016/j.eswa.2022.117592

29. Zigarelli, A., Jia, Z., Lee, H. Machine-Aided Self-Diagnostic Prediction Models for Polycystic Ovary Syndrome: Observational Study. JMIR Formative Research, 2022, 6(3). https://doi.org/10.2196/29967

30. https://www.kaggle.com/prasoonkottarathil/polycystic-ovary-syndrome-pcos.