Follicles Classification To Detect Polycystic Ovary Syndrome Using Glcm And Novel Hybrid Machine Learning

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ABSTRACT: A complex endocrine disorder is Polycystic ovary syndrome (PCOS). Women's health is seriously affected by this. Female's fertile nature is hindered by this ad many more issues are caused by this. Ultrasound can be used for detecting Polycystic Ovaries. Females should be aware of this disease to leads to a good life. In general, around 70% of this cases are undiagnosed. Earlier, adaptive k-means clustering technique is used for follicile segmentation with ultrasound images, but follicles abnormal and normal classification are not focused. So, for follicles abnormal and normal classification, an artificial neural network (ANN) technique with Improved Fruit Fly Optimization (IFFOA) is proposed in this work and named as (IFFOA-ANN) that avoids those risks. In this technique, for enhancing image quality, input ultrasound images are resized and noise in it are removed. Then, adaptive k-means clustering technique is used for processing follicles segmentation. In addition, statistical GLCM is used for introducing feature extraction model. At last, for classification, ANN will be trained using these features. With respect to accuracy, recall and precision, proposed model's effectiveness is demonstrated in experimental results.

Keywords: Adaptive k-means clustering, classification, statistical and GLCM, artificial neural network, follicles segmentation, Improved Fruit Fly Optimization and Polycystic ovary syndrome.

1. INTRODUCTION

The development of sophisticated imaging devices coupled with the advances in algorithms specific to the medical image processing both for diagnostics and therapeutic planning is the key to the wide popularity of the image processing techniques in the field of medical imaging. Ultrasound imaging is one of the methods of obtaining images from inside the human body through the use of high frequency sound waves. The reflected sound wave echoes are recorded and displayed as a real time visual image. It is a useful way of examining many of the body's internal organs including heart, liver, gall bladder, kidneys and ovaries. The detection of follicles in ultrasound images of ovaries is concerned with the follicle monitoring during the diagnostic process of infertility treatment of patients.

PCOS (Polycystic Ovarian Syndrome) is disorder occur in females reproductive stage identified by formation of follicular cysts in the ovary. These follicular cysts are observed in ultrasound image which is obtained by scanning the ovary. This review provides information on the problem of PCOS in India, its pathophysiology, genetics and an overview of current management options to instigate further research in this field. Prevalence of PCOS in India ranges from 3.7 to 22.5 per cent depending on the population studied and the criteria used for diagnosis. Abnormalities in leptin-adiponectin (adipocyte biology), oxidative stress and autoimmunity are among the mechanisms studied regarding pathogenesis of PCOS [1]. The main cause of this disorder in females is due to menstrual problems, hirsutism, endocrine abnormalities, acne, obesity etc [2]. The detection of ovarian follicle is done using ultrasound images of ovaries. Object recognition in an ultrasound image is a challenging task which includes the detection of follicles in ovary, growth of the foetus, monitoring of proper development of the foetus and presence of tumor [3].

Now a days the diagnosis performed by doctors is to manually count the number of follicular cysts in the ovary, which is used to judge whether PCOS exists or not. This manual counting may lead to problems of variability, reproducibility and low efficiency. Automating this mechanism will resolve these problems. The objective of the present work is to propose an automated ovarian classification method for classifying an ovary as normal or not in an ovarian ultrasound image by using the IFFOA-ANN with GLCM based feature extraction. The experimental results demonstrate the efficacy of the proposed method.

The rest of the paper is structured as follows: The related work on PCOS classification and follicle detection in section 2. The proposed methodology is described in section 3. The experimental results and discussion are discussed in section 4. The conclusion and future work is given in section 5.

2. Related Work

For Polycystic Ovarian Syndrome detection, various techniques are reviewed in this section. In [4] propose an automated PCOS diagnostic system based on ultrasound images which consists of two major functional blocks such as preprocessing phase and follicle identification based on object growing. The object growing algorithm for follicle identification first computes a cost map to distinguish between the ovary and its external region and assigns each object a cost function based on the cost map. The object growing algorithm initially selects several objects that are likely to be follicles with very high probabilities and dynamically update the set of possible follicles based on their cost functions.

In [5], automated detection of PCOS is done by calculating no of follicles in ovarian ultrasound image and then incorporating clinical, biochemical and imaging parameters to classify patients in two groups i.e. normal and PCOS affected. Number of follicles are detected by ovarian ultrasound image processing using preprocessing which includes contrast enhancement and filtering, feature extraction using Multiscale morphological approach and segmentation. Support Vector Machine algorithm is used for classification which takes into account all the parameters such as body mass index (BMI), hormonal levels, menstrual cycle length and no of follicles detected in ovarian ultrasound image processing. 95%

The effective and automated method for the computer-aided diagnosis of PCOS using ovary ultrasound images is presented in [6]. The method is detecting the follicles using object growing. It consists of two major stages including preprocessing phase and follicle identification based on object growing. The speckle noise in the input PCOS ultrasound image is reduced using median filter. After reducing the speckle noise, the local minimum is extracted which represents the possible follicles using enhanced labeled watershed algorithm and the region of interest is selected to make the segmentation part an easier one. The object growing algorithm selects the objects that are likely to be follicles and thus the follicles are detected.

In [7] proposed an image clustering approach for follicles segmentation using Particle Swarm Optimization (PSO) with a new modified non-parametric fitness function. The new modified fitness function use Mean Structural Similarity Index (MSSIM) and Normalized Mean Square Error (NMSE) to produce more compact and convergent cluster. The proposed fitness function is compared to a non-parametric fitness function proposed by previous research.

In [8] designed an application to classify Polycystic Ovary Syndrome based on follicle detection using USG images. The first stage of this classification is preprocessing, which employs low pass filter, equalization histogram, binarization, and morphological processes to obtain binary follicle images. The next stage is segmentation with edge detection, labeling, and cropping the follicle images. The following stage is feature extraction using Gabor wavelet. The last stage is classification. It identifies the features of PCO and non-PCO follicles based on the feature vectors resulted from feature extraction. Here, three classification scenarios are designed: (1) Neural Network-Learning Vector Quantization (LVQ) method, (2) KNN - Euclidean distance, and (3) Support Vector Machine (SVM) - RBF Kernel.

In [9] proposed Gabor Wavelet as a feature extractor and a modified backpropagation used as a classifier. The modification of backpropagation algorithm which is proposed, namely Levenberg - Marquardt optimization and Conjugate Gradient - Fletcher Reeves to improve the convergence rate. Levenberg - Marquardt optimization produce the higher accuracy than Conjugate Gradient - Fletcher Reeves, but it has a drawback of running time. However, on those studies its feature extraction of the ultrasound image is still done manually. In [10], a solution where the feature extraction is also done automatically using Convolutional Neural Network is proposed.

In [11], a computational model for the detection of follicles of various sizes and extracting relevant features of the follicle and calculate the diameter and the number of follicles is proposed. The proposed model consists of pre-processing, speckle noise reduction, follicular segmentation, feature extraction, feature selection, and calculate the diameter of number follicles. The segmentation method uses active contour to divide objects base on the similarity of follicle shape feature so that it is more accurate in calculating the number and diameter of follicles.

The [12] focused on the data-driven diagnosis of polycystic ovary syndrome (PCOS) in women. Firstly, univariate feature selection algorithm is applied to find the best features that can predict PCOS. The ranking of the attributes is computed and it is found that the most important attribute is the ratio of Follicle-stimulating hormone (FSH) and Luteinizing hormone (LH). Next, holdout and cross validation methods are applied to the dataset to separate the training and testing data. A number of classifiers such as gradient boosting, random forest, logistic regression, and hybrid random forest and logistic regression (RFLR) are applied to the dataset.

Many researchers used Artificial Intelligence (AI) to classify ultrasound images automatically. AI is capable of “learning” features from very large amount of data through clinical practice to diagnosis the diseases. AI has the capability to remove unwanted data and to detect the disease with high accuracy and precision. In this work, applications of AI in the detection of PCOS such as segmentation of ultra sound images and classification are presented. By diagnosis the PCOS, AI has been proved as a best technology in the automated disease diagnosis of PCOS.

3. PROPOSED METHODOLOGY

PCO detection is still operated manually by a gynecologist by counting the number and size of follicles in the ovaries, so it takes a long time and needs high accuracy. In general, PCO can be detected by calculating stereology or feature extraction and classification. In this work, designed a system to classify PCO by using the feature extraction (GLCM method) and IFFOA-ANN. Initially the image preprocessing is done such as resizing and noise removal. After that, segmentation method is developed for follicle detection in ultrasound images using Adaptive k-means clustering algorithms. After segmentation, the GLCM based feature extraction and further ANN based classifier is used to identify the follicles in the ovary image. The proposed algorithm is tested on sample ultrasound images of ovaries for identification of follicles and with the IFFOA-ANN, the ovaries are classified into two, normal ovary and abnormal ovary. The overall architecture diagram of proposed methodology is shown in Fig.1.

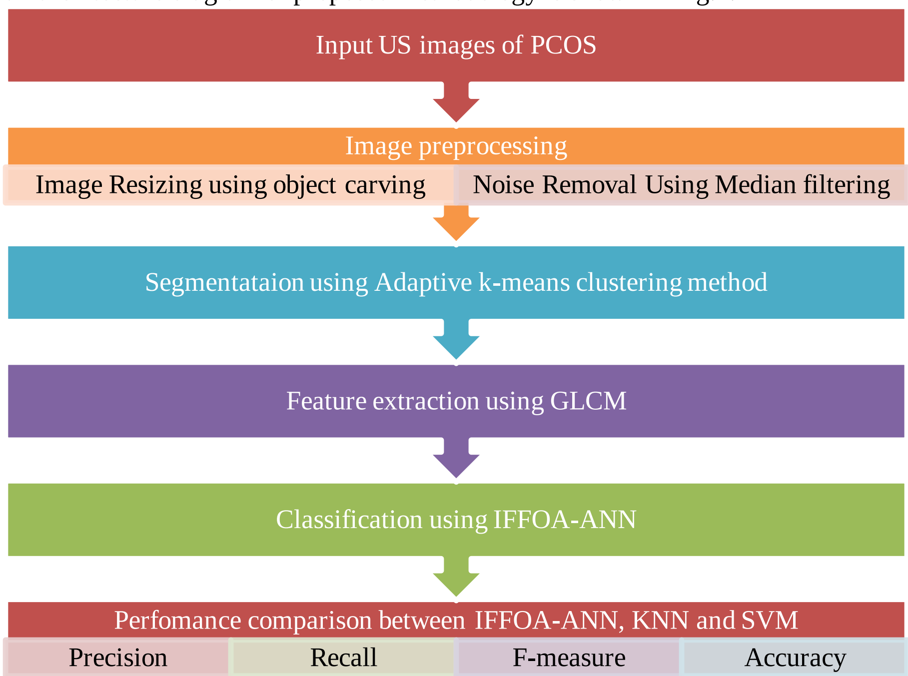

Figure 1. Overall Architecture of Proposed Model

3.1. Image Pre-Processing

Image Resizing using object carving

An enhancement is designed using Object carving. In results, for minimizing salience distortions and artifacts, this enhancement will coordinate with other resizing algorithms. Here, object carving carrier corresponds to fast multi-operators (F-MultiOp) image resizing technique. For image resizing, interactive performance is preferred by the users. Substantially faster performance is shown by this framework, when compared with original Multi-Op techniques and better results can be produced using this. If there is a need to resize both the dimensions, image height and width should be handled separately in this algorithm and there will be a resizing of longer dimension in the initial stages. The input image and corresponding resized image are shown in Fig.2.

Input image **Resized image**

Fig.2.The input image and corresponding resized image

Noise Removal Using Median filtering

In this phase, for denoising, input image corresponds to resized US images. A statistics based nonlinear signal processing technique is median filter. Computed neighbourhood's median value is used for substituting digital image's noisy sequence or value. Based on the gray levels of pixels in the mask, they are sorted and noisy value is substituted by sorting the median value in this group. The median filtering output is $(x,y) = med\{ f\ (x - i, y - j), i, j \ \ni W\}$, where actual image is given by $f\ (x,y)$, output image is represented as $g(x,y)$, two-dimensional mask is represented as W and its size is given by : $n \times n$. In general, odd values like 3 ×3, 5 ×5 is assigned to this. This mask may be of cross, circular, square and linear shapes [13, 14]. The noise removal using median filter is given in Fig.3.

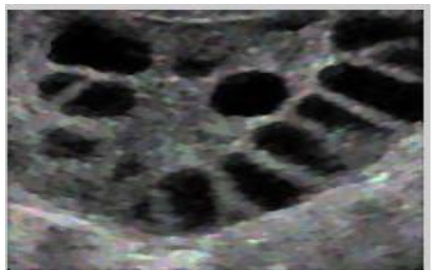

Fig.3.Noise removed image

3.2. Segmentation using adaptive k-means clustering

The adaptive k-means segmentation methodology is employed in this research work to segment follicle US images for diagnosing PCOS in women. In addition to the features in conventional k-means, two more features called roundness and brightness are involved in this during segmentation. The major reason behind this is, it is easy to detect highly spherical and brighter objects as follicle.

Initialization phase: Through image clustering process, estimated the objective function. For a least iteration count n (around 8), k-means is applied. In this proposed adaptive segmentation strategy, this entire phase is assumed as a first iteration. New centers are distributed for generating new clusters. For the first time, objective function is estimated during this iteration.

Where, objective function corresponds to overall obtaining objects average circularity (follicle). Roundness ratio corresponds to the ratio between area of shape (ovary) Ato area of a sphere with equal perimeter Pr. It is expressed as,

$$f_o = \frac{4*\pi*A}{Pr^2} \qquad (1)$$

For circle, value of f_o function is one and for all other shapes, its value will be less than one. In each cluster, through overall pixels count n, derived the area. The objective function F's estimation is expressed using subsequent expression.

$$F = \sum_{i=1}^{n} \frac{f_{o_i} * A_i}{A_i} \qquad (2)$$

Where, A_i indicates the ith object (follicle) area and f_{o_i} indicates the ith object (follicle) roundness ratio. Object area is multiplied with object's roundness ratio to minimize small objects values and to maximize large object values.

Adaptive segmentation phase: Primary part of this proposed algorithm is this adaptive segmentation phase. In further n iterations, k-means is applied which begins from previous initialization phase's final iteration. Expression (2) is used for re-computing F in a feature based computation manner. Subsequently, previous iteration's F_{last} is compared with current $F_{curremt}$.

If the new $F_{current}$ has the lower value than the previous one, current state is maintained and previous results are eliminated. New centers generation is initiated if there is a poor current goodness (new goodness value is greater than previous one) and using two brightest clusters called target objects, new clusters are created and remaining clusters are archived which are deprived of modification using distance(d) function. Between cluster center C and data point x, distance is estimated using this function.

Within n data points, distance and its respective cluster centers are indicated using this process and it is expressed as,

$$d = \left\| x_j^j - C_j \right\|^2 \qquad (3)$$

Until convergence, entire process is iterated with either one of the two following conditions, until reaching maximum iterations count n or until obtaining stable results. Ultimately, highly circular objects with circularity ratio near to 1 are identified using object selection process. In the suggested adaptive segmentation algorithm, involved steps are defined in Algorithm 1 and segmented result is shown in Fig.4.

Algorithm: 1. Proposed adaptive k-means segmentation algorithm

Input: US images
Output: segmentation outcome of follicle
Activation step
Call k-means clustering [15] for n iteartions
for all connected object (US images) proceed
Using eq.(1), roundness ratio is identified
End for
Using eq.(2), objective function F is computed
Replicate
Call k-means technique starting from last clustering result for n iteartions
Using eq.(2), objective function F is computed
If $F_{new} \leq F_{last}$tehn
Archive$F_{current}$ as new F
Segmentation's optimum clustering results are achieved and is depicted in Figure 5.
Else
Using eq.(3), new centre creation is called
End if
Until the convergence of n, entire process is iterated
For every resulted US images proceed
Using eq.(1), roundness ratio is computed
If roundness ratio is not equal to 1
other objects are eliminated
Else
Segmented follicle result's most circular object outputs are taken and are represented in figure 6 and 7.
End if
End for

Fig.4. Segmented follicles part using adaptive k-means clustering

3.3. Feature Extraction Using GLCM

For enhancing classification performance, GLCM is used in this phase to extract segmented follicle's features. The image characteristics having association with second-order statistics can be estimated using Grey-Level Co-occurrence Matrix (GLCM)) [16]. Using following expressions, texture features are computed.

Energy: In mammographic image, observed uniformity is indicated using Energy. From mean squared signal value, energy value is computed in general and is given by,

$$\text{Energy} = \sum_{i,j=0}^{n-1} p(i,j)2 (4)$$

Contrast: In vicinity, between highest and least pixel set values, difference measure is provided by contrast. In image, amount of available local difference is computed by this.

$$Contrast = \sum_{i,j=0}^{n-1} (i-j)^2 \; p(i,j) \qquad (5)$$

Correlation: Over entire image, pixel's correlation with its neighbor is measured using correlation and is given by,

$$Correlation = \sum_{i,j=0}^{n-I} \frac{(i \times j)p(i,j) - u_i u_j}{\sigma_i \sigma_j} (6)$$

In associations, all reference pixels intensity variation, which made its contribution to GLCM is represented as σ2 and it is given by,

$\theta^2 = \sum_{i,j=0}^{N-1} p_{i,,j}(\text{i-u})$ (7)

Homogeneity, Angular Second Moment (ASM): To measure image homogeneity, ASM is used.

$Homogeneity = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\{p(i,j)\}^2$(8)

Entropy: In an image, available complexity or irregularity is measured or specified using this Entropy. Even distribution of P (i, j) throughout the entire matrix will leads to high value of entropy. There exist a high inverse correlation among Energy and Entropy.

$Entropy = -\sum_{i,j=0}^{n-1} p(i,j)\log p(i,j)$ (9)

Where, GLCM matrix rows are represented as ‘i’, its columns are represented as ‘j’, gray levels count is represented as ‘n’ and cell which is represented by the GLCM matrix’s row and column is referred as P(i, j). Computed the texture features based on these assessments.

3.3. Follicles classification using Hybrid artificial neural network with Improved Fruit Fly Optimization

This section introduces the Levy flight (LF) strategy to update the positions of fruit flies to further improve its convergence speed, while reducing the probability of FFOA falling into the local optimal. The principle of LF strategy can ensure the diversity of algorithms in the process of optimization and improve the convergence rate. In this work, the improved FOA method, LFFOA, was utilized to optimize the two key parameters pair including weight and bias in ANN method and obtain the optimal model (IFFOA-ANN).

Artificial Neural Network (ANN): For follicles classification, artificial neural network is used in this work and Polycystic ovary syndrome (PCOS) is detected using this. A type of data processing system is an artificial neural network, where simple processing elements termed as neurons are highly interconnected. Within the network, in layers, arranged the neurons in ANN. Artificial Neural Network (ANN) is adopted from the biological complex system, the human brain, which consists of a huge number of highly connected elements called neurons. ANN tries to find the relationships between input-output data pairs. In general, the collected features of US image data were randomized and split into two groups; Training (70% of the image data) and Testing (30% of the image data). The training image datas used to learn the ANN based on finding the relationship between input and out pairs by adjusting the weights and biases using back-propagation algorithm. However; through learning process, there is a probability of the neural network to over-fit or over-learn the input-output image data.

This problem will generate a weak mapping between input-output especially for unseen image data. Once over-fitting occurs, the validation image data is used through learning process to guide and stop training if the validation error begins to rise. The prediction evaluation of the developed ANN model is done after finishing training phase though testing image data [17]. Artificial neural network have been successfully applied to solve hard and complex problems in the field of industry and research. A huge number of publications have proved the strength of ANN in the medical field [18].

An ANN is a network of highly interconnecting processing elements here referred as features (neurons) operating in parallel. These features are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s). Figure 5.1 represents the typical artificial neural network. This can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

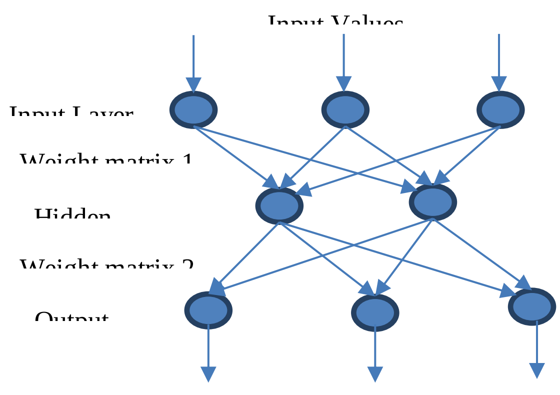

Figure 1. A typical artificial neural network

The neurons of the input layer take the input image data from the real environment. The input vector (x_i) in image dataset D is transmitted using the connection that multiplies its strength by a weight (w) to produce the product (w_{ij}). Each neuron has a biases (b_i). The output of the neuron is generated by $f(.)$ and $a(.)$, which is a summation function and activation function. An activation function consists of two algebraic formulas linear and non-linear ones. These two functions enable the neural network to find the relationships between input $(on_j)$and output (on_k). The outputs either send to other interconnected neurons or directly to the environment. The difference between the output and neural network output is considered as error. The steps of ANN are given as follows:

Step 1 – Image pre-processing of US image data.

Step 2 – Input the image data for training, the interrelated values of input and output execute for training using feed forward back propagation neural network algorithms.

Step 3 – Initialize weights and biases plays an important role in determining the final model of follicle detection

Step 4 – Calculate the neurons of output, every neuron output data calculated using

$$on_j = \sum_{i=1-m} w_{ij} x_i + b_j$$

where on_j and $w_{ij}$are output neurons and connection weight neurons, respectively, while x_i and b_j are the input data, and bias neurons. The sigmoid function or logistic function, also called the sigmoidal curve (Seggern, 2016), was used for netj and every neuron of ten hidden layers.

Step 5 – data of output layers' calculation using,

$$on_k = TV_k + \delta_K^L$$

where TV_k is target value of output neurons and δ_K^L is the error of neuron.

Step 6 – Compute the error E of neuron k and step 3 and step 6 were repetitive until network was congregated, and the error was computed using,

$$E_j = on_j(1 - on_j) \sum_k E_k w_{jk}$$

Improved FFOA (IFFOA): Levy's flight is characterized by short steps and random directions. This feature can effectively avoid the whole population falling into local optimum, thus enhancing the global detection ability of the algorithm. In this work, the LF strategy introduced into to FFOA to explore the search space more efficiently. The new position is updated according to the following rule.

$$X_i^{Levy} = X_i + X_i \oplus \text{Levy(s)}$$

$$\text{Levy(s)} \sim |s|^{-1-\beta}, 0 \leq \beta \leq 2$$

Where β represents an important Levy index to adjust the stability, s is the step length, X_i^{Levy} is the new position of the ith search agent X_i after updating.

Proposed IFFOA-ANN model: This study proposes a novel ANN that adopts the IFFOA strategy, and the resultant IFFOA-ANN model can adaptively determine the two key hyper-parameters for ANN. The general framework of the proposed method is demonstrated in Fig.2. The proposed model is primarily comprised of two procedures: the inner parameter optimization and the outer classification performance evaluation. During the inner parameter optimization procedure, the ANN parameters are dynamically adjusted by the IFFOA technique. Then, the obtained optimal parameters are fed to the ANN prediction model to perform the classification task for follicle diagnosis. The classification accuracy was used as the fitness function.

$$fitness = \frac{(\sum_{i=1}^{K} ACC_i)}{k} \tag{10}$$

Where ACC_i represents the average accuracy achieved by the ANN classifier. The main steps conducted by the IFFOA-ANN are described in detail as follows and The pseudo code of ANN is given in Algorithm 1.

Step 1: Initialize the input parameters for IFFOA such as include population size, maximum number of iterations, upper bound of the variables, and lower bound of the variables, the dimension of the problem with the ANN parameters such as weight and bias.

Step 2: Randomly generated the position of the fruit fly swarm based on the upper and lower bounds of the variables.

Step 3: Generate initial population for IFFOA based on the position of the fruit fly swarm.

Step 4: Evaluate the fitness of all fruit flies in population by ANN with the position of fruit fly as parameters.

Step 5: Take the position of the best fruit fly as the position of the fruit fly swarm (global optimum).

Step 6: Update the position of each fruit fly in the swarm with Levy-flight mechanism and evaluate the fitness of the fruit fly.

Step 7: Update global optimum if the fitness of the best individual in the fruit fly population is better than the global optimum.

Step 8: Update iteration t, $t = t + 1$. If t larger than maximum number of iterations, go to step 6.

Step 9: Return the global optimum as the optimal ANN parameter w and bias and follows the steps of ANN.

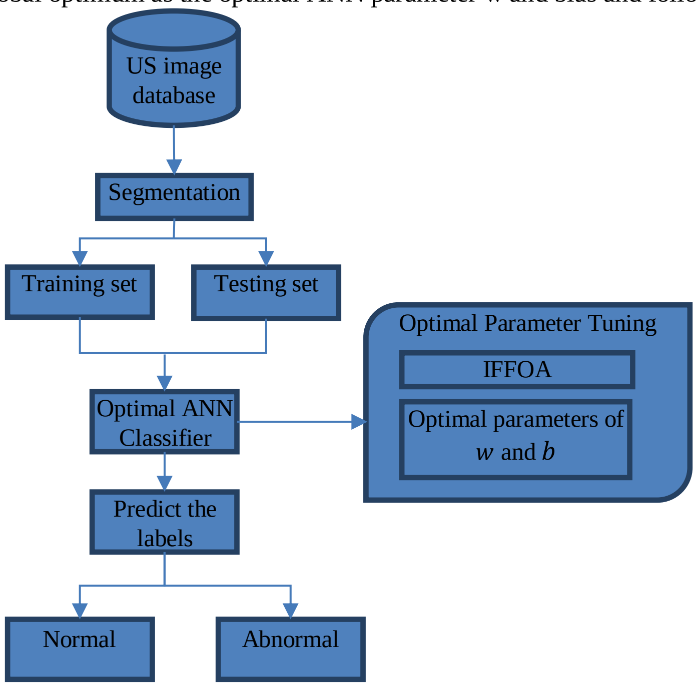

Fig.2.The process of IFFOA-ANN approach

Algorithm 1: The pseudo code of IFFOA-ANN for follicle detection

Input: D, a US image data consisting of the training samples and their associated target values; l, the learning rate; network, a multilayer feed-forward network, weight and bias

Output: A trained neural network for follicle detection.

1. Initialize the input parameters for IFFOA and do IFFOA procedure for getting w and b
2. {
3. Generate initial population for IFFOA
4. Evaluate the fitness
5. Take the position of the best fruit fly as global optimum solution
6. Update the position of each fruit fly with Levy-flight mechanism and do step 5
7. Update global optimum if the fitness of the best individual in the fruit fly population is better than the global optimum.
8. Update iteration t, $t = t + 1$
9. If t larger than maximum number of iterations, go to step 7.
10. Return the global optimum as the ANN parameters such as w and b
11. Initialize all weights (w) and biases (θ) in ANN structure
12. while terminating condition is not satisfied {
13. for each training US image sample X in D { // Propagate the inputs forward:
14. for each input layer unit j {
15. $on_j = on_k$; // output of an input unit is its actual input value
16. for each hidden or output layer unit j {
17. $on_j = \sum_{i=1-m} w_{ij} x_i + b_j$; //compute the net input of unit j with respect to the previous layer, i
18. $on_k = TV_k + \delta_K^L$}; // compute the output of each unit j
19. // Backpropagate the errors:
20. for each unit j in the output layer
21. // compute the error E for each unit j in the hidden layers, from the last to the first hidden layer
22. $E_j = on_j(1 - on_j) \sum_k E_k w_{jk}$; // compute the error with respect to the next higher layer, k
23. for each weight w_{ij} in network {

24. $\Delta w_{ij} = (l)E_j on_k$// weight increment
25. $w_{ij} = w_{ij} + \Delta w_{ij}$}; // weight update
26. for each bias θ_j in network {
27. $\Delta\theta_j = (l)E_j$ // bias increment
28. $\theta_j = \theta_j + \Delta\theta_j$}; // bias update } }
29. Return the results of ovary detection whether normal or abnormal

4. RESULTS AND DISCUSSION

Implementation Details: This work investigates the prediction of follicle in US image dataset using the proposed IFFOA-ANN. The output of the KNN [8], SVM [5] and IFFOA-ANN with the performance metrics of sensitivity, specificity and accuracy. If the sample is positive and it is detected by IFFOA-ANN as positive, i.e., correctly disease predicted positive sample, it is counted as a true positive (TP); if it is predicated disease as negative, it is considered as a false negative (FN). If the sample is negative and it is predicted as negative it is considered as true negative (TN); if it is predicted as positive, it is counted as false positive (FP).

Recall: Recall quantifies the number of positive class predictions made out of all positive examples in the image dataset as given below

$$Recall = \frac{TP}{TP + FN}$$

Precision: Precision quantifies the number of positive class predictions that actually belong to the positive class and it is estimated as follows

$$Precision = \frac{TP}{TP + FP}$$

F-measure: F-Measure provides a single score that balances both the concerns of precision and recall in one number and it is estimated as follows:

$$F - Measure = \frac{(2 * Precision * Recall)}{(Precision + Recall)}$$

Accuracy: It is one of the most commonly used measures for the classification performance, and it is defined as a ratio between the correctly segmented samples to the total number of samples as follows

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Utilizing the above expressed KNN, SVM and IFFOA-ANN algorithms is utilized for forecast the follicle in US image, the quality arrangement of the PCOS is dissected utilizing MATLAB 7.10.

4.1. Precision Result comparison

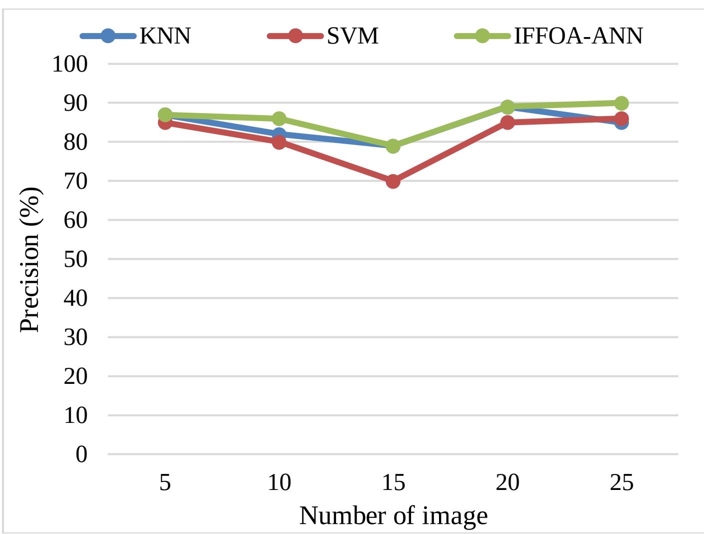

Figure 5.5. Precision performance comparison

Figure 5.5 shows that the precision comparison results between proposed IFFOA-ANN, and existing KNN and SVM. From the figure, the proposed method can obtain high precision rate when compared to existing methods. It is an effective way of getting the follicle detection exactly with the high precision rate of 90%. When comparing the precision among the existing methods such as KNN and SVM are providing good precision rates of 85% and 86% respectively which is lower than the IFFOA-ANN. Moreover, the precision of the training functions of IFFOA-ANN with back propagation algorithm were compared to select the best training function and thus leads to attain better precision rate.

4.2. F-measure Result Comparison

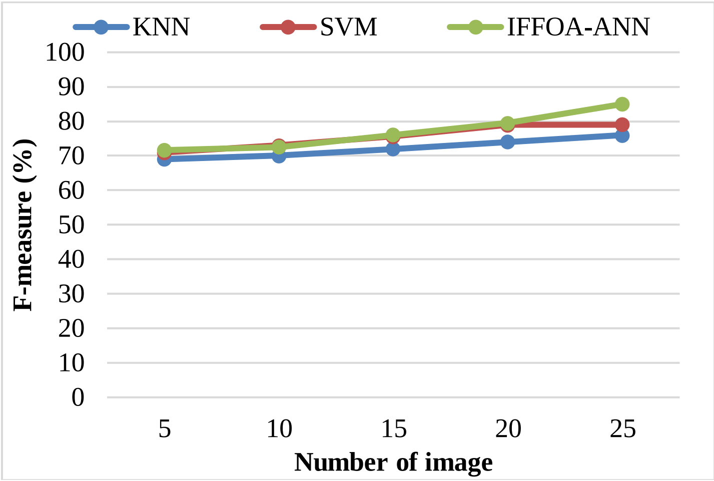

Figure 5.6. F-measure performance comparison

Fig.2 shows that the F-measure comparison results between proposed IFFOA-ANN, and existing KNN and SVM. From the results, it is well know that proposed IFFOA-ANN obtain high F-measure rate of 85%. When comparing the F-measure rate among the existing methods KNN and SVM are providing fewer rates of 76% and 79% respectively, which indicates the proposed work can give better follicle detection results than the existing methods. The reason is that the IFFOA-ANN usually much faster to train network than KNN and SVM.

4.3. Recall Result Comparison

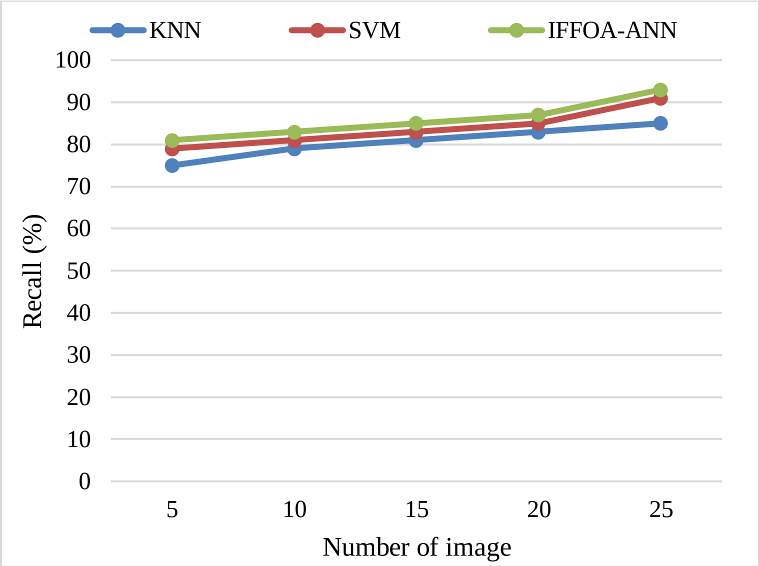

Figure 5.7. Recall performance comparison

Figure 5.7 shows that the recall comparison results between proposed IFFOA-ANN, and existing KNN and SVM. The proposed method has high value of recall rate of 93%. From the results, it is well know that proposed IFFOA-ANN obtain high recall rate value indicating the good cardio vascular disease detection rate. Because, the proposed scheme is reduced the size of the stored model and thus the training time will be reduced with good prediction model. When comparing the recall rate among the existing methods KNN and SVM providing recall rate of 85% and 91% respectively, which shows the proposed work can give better follicile detection results than the existing methods. The reason is that it uses one or two hidden layers and the main advantage is they can be used for difficult to complex problems which leads to attain better recall rate.

4.4. Accuracy Result Comparison

4.5.

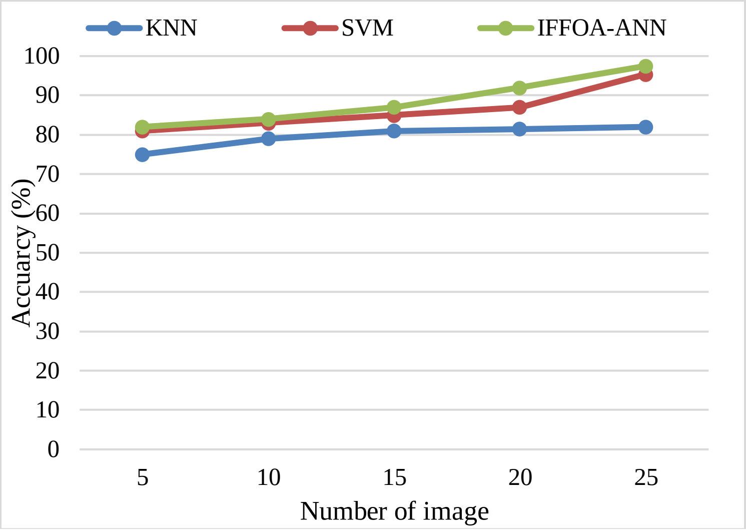

Figure 5.8. Accuracy performance comparison

From the above Figure 5.8, the graph explains that the accuracy comparison for prediction of follicle. The methods are executed such as KNN, SVM and IFFOA-ANN Classifier. When number of images increased according with the accuracy value is increased linearly. IFFOA-ANN is an effective way of getting the prediction accurately with the high accuracy rate of 97.5%. When comparing the accuracy among the existing methods such as KNN and SVM providing less rate of 82% and 95.39% respectively. Thus the output explains that the proposed IFFOA-ANN algorithm is greater to the existing algorithms in terms of better follicle detecting results with high accuracy rate. IFFOA-ANN learning methods are quite robust to noise in the training data. The training examples may contain errors, which do not affect the final output and thus leads to attain better accuracy rate.

5. CONCLUSION AND FUTURE WORK

In this work, proposed IFFOA-ANN method for ovarian classification and adaptive k-means method for follicle detection in ultrasound images of ovaries. Further, after detecting the follicles, the GLCM based feature extraction is done and IFFOA-ANN classifier is used to determine whether the ovary is normal or abnormal. The experimental results are in good agreement with the manual detection of the ovarian classes by medical experts and, thus, demonstrate efficacy of the proposed method. The ovarian classification performance is 97.5% in case of IFFOA-ANN classifier. Hence, the proposed method serves as the effective basis for the automatic classification of ovaries during entire female cycle. It helps to study the ovarian morphology of the patients and also significantly improves the quality of diagnosis and treatment of infertile patients. In addition to the performed research, there are also some alternative future works planned by the author. Briefly, the system will be used for alternative medical data and the effect of different parameters will be evaluated. Finally, there will also some efforts to use other soft computing methods for different parameter optimization of the ANN.

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