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An Intelligent Machine Learning Approach for Ovarian Detection and Classification System using Ultrasonogram Images

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Abstract

Ovulatory disorders contribute significantly for female infertility. Intelligent ovarian detection and classification is required for diagnosing and treating ovulatory disorders. Normal and cystic images reveal similar image characteristics which makes it challenging to classify among the two. In this paper, a suitable machine learning algorithm is identified for intelligent ovarian classification. Input to classifiers is a combination of image characteristics: intensity, texture features, demographic and diagnostic features. Diagnostic and demographic features are used with a view to develop a diagnostic algorithm with better accuracy. Standard machine learning techniques like Artificial Neural Network, Support vector machine and Linear Discriminant Analysis have been investigated to analyze its performance in ovarian classification. Support vector machine was identified as the best classifier in achieving the ovarian classification with an overall average accuracy of 98%, sensitivity of 96% and specificity of 95.66%. The region of convergence also depicted a better classification of ovaries with the support vector machine classifier. The developed intelligent ovarian classification system with high accuracy will serve as a preliminary investigating technique in diagnosis of infertility and will support clinicians in decision making.

Keywords: Texture features; Artificial neural network; Support vector machine; Discriminant classifier; Ovarian classification.
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1. Introduction

In the recent years, infertility has become a serious concern in the reproductive age group. According to a study conducted on 8500 infertile couples by World Health Organization, it was found that infertility due to male, female and a combination of both contributed to 8%, 37% and 35% respectively. Moreover 5% of the couples had unexplained infertility and 15% of the couples became pregnant during the study. The factors contributing for female infertility are ovulatory dysfunction (25%), unexplained infertility (20%), endometriosis (15%), fallopian tube problems (22%), pelvic disorders (12%) and hyperprolactinemia (7%).[1] Among the recognizable causes, ovulatory disorders are a main cause of female infertility arising in majority of the infertile women. Diagnosis of follicle/cyst is made in terms of shape, size and number which is of prime importance in infertility treatment. Ultrasound technology offers real time assessment of organs in the pelvis.[2] Transvaginal ultrasound is used in ovarian diagnosis and classification.

Manual analysis and interpretation of ovarian ultrasound images is laborious and not reliable. Moreover, quality and interpretation greatly relies on the expertise of the clinician performing the scan. However, such expertise is available only in multi-speciality hospitals in urban areas. Inter-observer variation and probability of false diagnosis are more leading to incorrect opinion and misinterpretation. People in rural areas need to travel to urban areas to avail expert opinion. Availability of an automated system will facilitate easy diagnosis and support the medical expert in decision making. So, automatic detection of ovarian follicle and follicular cysts support the radiologist to take a clear decision about the appearance of the follicle by visual inspection of ultrasound images.

Apart from detection, classification of ovarian images

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forms a vital part in infertility treatments. Classification of the ovary as cystic, polycystic and normal is indispensable for the medical expert during diagnosis and treatment. Ovulatory disorders can be efficiently diagnosed using a combination of ultrasound scans and appropriate blood tests.

Rate of misclassification is high when medical experts perform diagnosis based on ultrasound images alone. During ultrasound image-based diagnosis, interfollicular regions are difficult to be recognized and at times the normal ovarian follicle or cystic images share similar characteristics as their background and cause misinterpretation. This creates ambiguity during ovarian classification. The accuracy of human diagnostics rely not only on the image interpretation but also on the diagnostic and demographic data of the patient. The medical experts do not give an opinion based on the image interpretation alone. The supporting blood tests and demographic information obtained from the patient are also considered during their diagnosis and subsequent treatments. To resolve this issue, there is a dire need to develop a methodology for Ovarian Classification using Machine Learning Algorithms (OCML). The objective of this study was to develop a predictive modelling approach called OCML that takes in a combination of image features and the selected demographic and diagnostic features for automatic detection and classification of ovaries as normal, cystic and polycystic. Identification of the impact of including demographic and diagnostic variables along with image features for ovarian classification has contributed to the novelty of this study.

Ovarian detection and classification methods were developed by some researchers. Edge based segmentation followed by Support Vector Machine (SVM) classification was performed for detection of polycystic ovarian syndrome (PCOS).[3] Classification of polycystic ovaries alone was performed using Competitive Neural Network (CNN) which resulted in an accuracy of 80.84%.[4] Fuzzy c-means clustering was used for detection of cysts.[5] Clustering techniques have been used to automatically segment and detect the presence of follicle or cyst. However, these systems do not help in ovarian classification.[6]

Classification algorithms have been extensively studied in medical image diagnostics. Classification of extra-axial intracranial hemorrhages on brain CT images into subdural hemorrhage and extradural hemorrhage was performed using Linear Discriminant Analysis (LDA) and SVM. SVM outperformed LDA in classification.[7] LDA was used for automatically classifying the multispectral magnetic resonance images into gray matter, white matter and cerebral spinal fluid. The classifier performed well in spite of the image being prone to noise.[8] Artificial Neural Network (ANN) is a feature-based algorithm that learns adaptively from the input training features and helps in classifying the given problem. The significance of ANN in early detection of breast cancer reveals that it has a primary role in detection of carcinogenic conditions in the breast using texture and shape-based image characteristics.[9] The proposed OCML system also requires the use of texture-based features as input for detection of ovarian follicle/cysts along with selected demographic and diagnostic features to the ANN for classifying the different ovulatory disorders. Ovarian ultrasound image helps in detecting the presence or absence of cyst/follicle. However, the classification relies upon diagnostic and demographic features as well.

Classification based on image characteristics in ovarian studies was explored. Recognition of ovarian cysts using a segmentation technique called region based active contour method without edges was performed. Here, K-Nearest Neighbourhood classified the ovary as normal or cystic based on the geometric features obtained by segmentation.[10] Ovarian cyst was classified as simple cyst and endometrioma cyst using SVM, based on geometric features.[11] Fuzzy inference system was used to perform classification as simple cyst, complex cyst and normal ovary. Here, fuzzy input variables, size and number of follicles were used as inputs.[12] A fuzzy inference system to detect the presence of follicle or non-follicle was developed which used active contour without edges method for segmentation. Geometric features were extracted using this method and was used as input to the fuzzy inference system.[13] The drawback of the above cited classification methodologies is that they did not classify the ovary as cystic, polycystic and normal. Such a type of classification is indispensable for the medical expert during diagnosis and treatment.[14]

Using SVM, the ovary was classified as cystic, polycystic, or normal. The active contours without edges method were used to segment the follicles in this instance. The SVM classifier received input of geometric characteristics, and the outcomes were improved.[15-18] But the demographic and diagnostic data were not used as input for classification.

The classifiers were fed with geometric features.[10,11,13,14] When the ovarian follicles or cysts are of a specific shape, geometric features perform better. The ovarian follicles/cysts, however, might occasionally have a variety of atypical shapes and boundaries. Geometric features might not perform better under such limitations. The segmentation of interfollicular areas could also be unclear. Therefore, if texture- and intensity-based features are employed for feature extraction, follicle/cyst detection may be improved.

It was concluded that ovarian classification based on texture and intensity (TIOC) had an average accuracy of 94%.[19] The development of an approach that uses ANN for automatic ovarian detection with rule-based classification resulted in an overall average accuracy of 96%.[20] Due to the similarities in image characteristics such as intensity and texture features, there was a chance of misinterpretation.

Classification based on image characteristics and demographic and diagnostic data was studied. An ANN model having seven input features such as age, gender, height, weight, serum creatinine with image characteristics such as texture parameter and mean of texture features was developed to classify the level of chronic kidney disease.[21] Demographic features like gender, age and body mass index were included along with the extracted tongue colour and texture features for diagnosing the presence or absence of diabetes using SVM and Principal Component Analysis.[22] These studies reveal that demographic and diagnostic information were also taken into consideration along with the image interpretation for diagnosis and decision making.

The identified research gap is that the existing ovarian classification methodologies are based on geometric features or active contour without edge method. Geometric features do not perform well if the borders of the follicles/cysts are uneven. Smaller follicles or cysts could not be detected using active contour without edge method. Most of the classification methodologies do not classify the ovaries as normal, cystic or polycystic which is inevitable in infertility treatment. Sharing of common features between normal follicles and cysts makes classification a challenging task. In ovarian diagnosis, medical experts take into account the demographic and diagnostic data along with the ultrasound image interpretation for their diagnosis and subsequent treatments as it supports their decision making. But inclusion of demographic and diagnostic features has not been addressed by any of the existing ovarian classification methodologies. Hence a generic framework enabling analysis and quantification of several features in ultrasound images to classify ovaries has also been developed in this research.

2. Proposed methodology

The OCML displays a way for dividing and categorising ovarian cyst and follicle images as shown in Fig. 1.

This study's technique included classifying the ovary as normal, cystic, or polycystic after automatically identifying the follicles and cysts. Preprocessing techniques like colour space transformation and wavelet transform were performed in order to reduce computational complexity and remove the speckle noise respectively. Intensity and selected texture features were used for feature extraction. ANN was used for automatic ovarian detection with inputs as intensity and selected texture features. An intelligent system was developed using three different classifiers such as ANN, Discriminant Classifier and SVM which takes in a combination of image features and the selected demographic and diagnostic features for automatic ovarian detection and classification.

2.1 Data collection

The information needed for this investigation included an ovarian follicle/cystic imaging database and the accompanying demographic and diagnostic characteristics. Retrospective dataset was collected from the Obstetrics & Gynaecology department, Chettinad Hospital and Research Institute. Since the study involves data of patients, an ethical clearance was obtained from Chettinad Hospital and Research Institute. The datasets were collected from July 2018 to December 2018. Entire work was carried out only on the collected datasets and no intermediate dataset was developed. The ovarian classification methodologies utilize ultrasound images of ovary and the results were validated by the medical expert. In this study, ovarian ultrasound images were used and the research problem focusses on classification of ovaries as normal, cystic and polycystic based on image, demographic and diagnostic features. Data was collected from patients with normal, cystic and polycystic ovaries. If features are extracted from only healthy scenario (normal patients) it will help to say whether the given test image is normal or abnormal. It will not help in classifying the given image as cystic or polycystic which is actually desired. Since the proposed study is a medical study and the data that is to be collected required an ethical clearance, the data from the local health centre or the images used by the other studies were not utilized here.

A three clustered sampling was performed in this methodology. The final results were validated by the medical expert. Table 1 shows the dataset distribution.

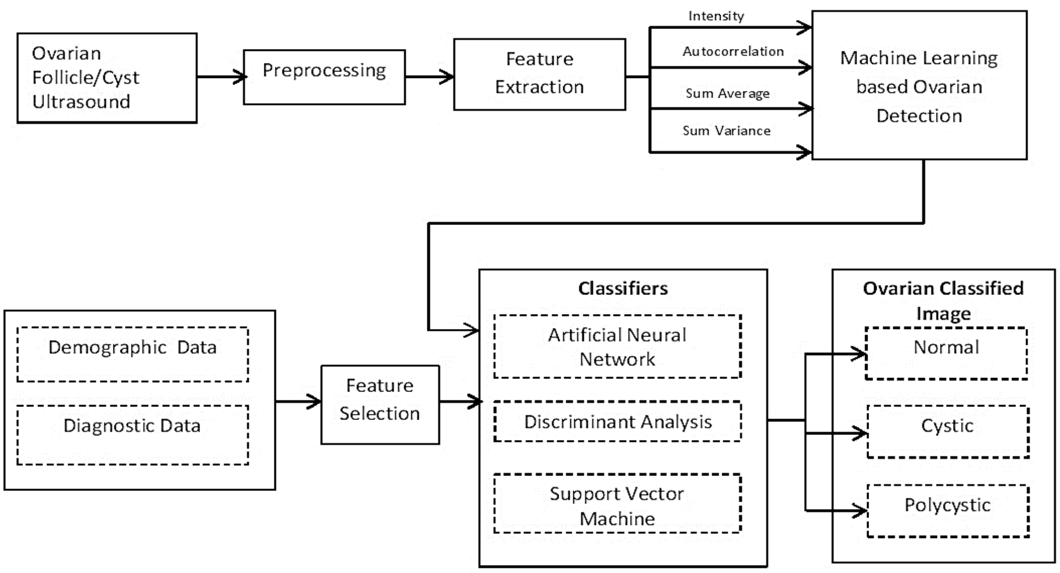


Fig. 1 Flow diagram of the OCML methodology.

Table 1. Dataset distribution.

Ovary Type	No of Datasets	
	Training	Testing
Normal Ovary	30	11
Polycystic Ovary	29	12
Cystic Ovary	23	10

Demographic and diagnostic dataset were also collected along with the ovarian ultrasound images. The sample demographic and diagnostic dataset in Table 2 correspond to the sample image dataset in Fig. 2.

A total of 115 datasets were collected out of which 10 datasets were found to be incomplete with the required data such as day of the cycle, value of FSH and LH. Hence these were taken as outliers and the total number of datasets considered for OCML was 105. Training efficiency was increased by taking multiple samples of the input. So, a total of 630 samples were used out of which 442 was used for training and the rest 188 for testing in a ratio of 70:30 respectively.

Fig. 2 Sample Dataset of (a) Normal ovaries, (b) Polycystic Ovaries and (c) Cystic Ovaries.

2.2 Pre-processing

The input ovarian follicle/cystic image was in RGB (Red Green Blue) colour space. To discriminate the colour information from the luminosity, L*a*b* colour space transformation was performed on the input image. This process reduced the computational time by 17% and improved the visualisation. Speckle noise is present in ultrasound images which make the specific and detailed information in the image difficult to be revealed.[2] Therefore discrete wavelet transformation was carried out on the luminosity (L*) component to eliminate the speckle noise. The approximation coefficient of the wavelet transformed image containing the low frequency information was fed as input for feature extraction using intensity and texture-based segmentation methods.

2.3 Feature extraction and selection

2.3.1 Intensity features

The intensity features were extracted using k-means clustering using equation (1).

$$J = \sum_{j=1}^{k} \sum_{i \in c_j^*} \left\| x_i - \mu_j \right\|^2 \quad (1)$$

where c_j denotes the jth cluster and μ_j denotes the centroid of the cluster c_j and $\left\| x_i - \mu_j \right\|^2$ is the Euclidean distance. This approach assisted to clearly separate the follicular, non-follicular, and interfollicular regions of the samples that had the same intensity. The ovarian follicle/cystic image needed to be divided into three clusters for the OCML approach, which had a predefined limit of three clusters: the germinal centres, the mantle zone, and the inter-follicular regions. Thus, intensity was chosen as one of the features.

Table 2. Sample demographic and diagnostic dataset.

Data	Ovary Type		
	Normal	Polycystic	Cystic
Age	30	24	23
Sex	Female	Female	Female
Education	<12th	UG	UG
Occupation	House Wife	Professional	Professional
Income	Nil	>20000	>20000
Weight	58kgs	80kgs	43kgs
Height	158 cm	156cm	140cm
Body Mass Index	23	32.87	22.12
Marital Status	Married	Married	Married
No of Children	0	0	0
Type of Family	Nuclear	Joint	Joint
Day of Menstrual Cycle	10	12	20
Number of follicles/cysts	5	8	1
Size of the follicles/cysts	2.1cm	1.03cm	3.2cm
Follicle Stimulating Hormone (FSH)	3.21	3.42	2.64
Luteinizing Hormone (LH)	4.36	5.12	5.69
Prolactin	10.26	10.23	16.24
Thyroid Stimulating Hormone (TSH)	1.14	3.14	3.13
Random Blood Sugar (RBS)	76	88	101
Blood Group	O+ve	O+ve	O+ve
Hemoglobin	10.2	8.9	9.6

2.3.2 Texture features

We employed the Haralick texture parameters[19] to distinguish the background information from the ovarian follicle/cyst with great clarity. Three of the fourteen Haralick texture features—autocorrelation, sum average, and sum variance—were chosen because they made it easy to discern between the follicular and cystic areas and the non-follicular and non-cystic areas, improving accuracy.

2.3.2.1 Autocorrelation

The gray tone linear dependencies in ovarian follicle/cystic image can be computed as given in equation (2).

$$AUTOCORRELATION = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{\{i\times j\}\times p(i,j)-\{\mu_x\times\mu_y\}}{\sigma_x\times\sigma_y} \quad (2)$$

σ_x, σ_y =Standard deviation of p_x and p_y respectively
μ_x, μ_y =Means of p_x and p_y respectively
G =Number of individual gray levels
p_x , p_y=Partial probability density function
i =Resolution cell with gray tone i and j respectively
$p(i, j) = (i, j)th$ entry in a normalised gray tone spatial dependence matrix.
The range of value is from -1 to 1. -1 shows maximum uncorrelation and 1 shows maximum correlation.

2.3.2.2 Sum Average

The average skewness pertaining to the ovarian follicle/cystic image can be measured by averaging the section-based skewness measures of the image using Sum Average as given by equation (3).

$$SUMAVG = \sum_{i=0}^{2G-2} ip_{x+y}(i) \quad (3)$$

i =Resolution cell with gray tone i
x, y = Row and column coordinates respectively in co-occurrence matrix
$p_{x+y}(i)$ =Probability of co-occurrence matrix coordinates summing to x+y.

2.3.2.3 Sum Variance

Heterogeneity between the follicular and non-follicular or cystic and non-cystic regions was measured using Sum Variance as indicated in equation (4). As the value of the gray level values differ from the mean, there is an increase in variance.

$$SUMVAR = \sum_{i=2}^{2G}(i-f_8)^2\, p_{x+y}(i) \quad (4)$$

Where f_8 is calculated using the equation (5)

$$f_8 = -\sum_{i=2}^{2G} p_{x+y}(i)\, log\{p_{x+y}(i)\} \quad (5)$$

These features enabled the removal of undesired regions of the image thereby highlighting the prominent attributes and interfollicular regions of the image. The selected features contributed an important role in differentiating between the follicular/cystic regions from the non-follicular or non-cystic regions.

But there is a need to automatically classify the ovary as normal, cystic and polycystic. The two major classes include normal and abnormal, where abnormal is further classified into polycystic and cystic to predict the level of malignancy. Each class has its own importance during its classification. Diagnosing the proper underlying cause is vital in infertility as the treatment given for each class completely varies.

A normal ovarian follicle indicates the healthy condition of the ovary. A healthy ovary does not necessitate any kind of treatment. A cystic ovary has one to large cysts which ramps the fertility cycle and causes abnormality. A cystic ovary with one or two cysts when misclassified as normal, it would not necessitate any treatment and may cause an ambiguity in diagnosis. In reality a cystic ovary may require medications or surgery. Similarly, a polycystic ovary has multiple cysts and enlarges the ovary disrupting its normal functionality. A polycystic ovary with multiple cysts if misclassified as cystic then the course of treatment given for the underlying cause totally differs. Sometimes a wrong diagnosis and treatment would trigger other abnormalities and complications too. Appropriate classification of each class is highly important in infertility diagnosis. So along with the image-based features, if the demographic and diagnostic features were included it would facilitate a better classification. So, it was proposed to include the demographic and diagnostic features also for classification.

2.3.3 Demographic and diagnostic features

Careful investigation was done in selecting the demographic and diagnostic features. Influence of each parameter in classification was thoroughly studied. Finally based on the study eight features were selected. The selected features were day of the menstrual cycle, size of the follicle, number of follicles, FSH, Prolactin, TSH, LH and RBS.

2.4 Machine Learning based Classification Algorithms

The OCML system requires an algorithm which should be simpler for deployment and implementation as its intended use is in rural areas. Moreover, as this system is used as a screening tool for patients in rural areas, it requires online and immediate processing of the patient data in order to facilitate further course of treatment or diagnostic opinion. This will also enable immediate attention. Deep learning algorithms require large amount of data and consume more time for their computational processes. But machine learning algorithms are computationally fast and learning is also very effective with definite datasets. So, in this system deep learning techniques are not suitable and machine learning algorithms were used for effective implementation. ANN, Discriminant classifier and SVM were developed and compared in the OCML methodology to identify the best performing classifier. The intensity variations in the follicle and cysts are more and hence decision tree algorithms which is rule based was not suitable here. Also, there is more likelihood between the normal follicles and cysts and so Naïve Bayes algorithm will not be effective. Moreover, in the current problem, there are more outliers in the boundary regions. Hence K-Nearest Neighbourhood algorithm which is more sensitive will end up with misclassification. The algorithm used in the proposed methodology is as follows.

***Step 1*:** Select the image, demographic and diagnostic features for the OCML system

Step 2: Determine the required hyperparameters for each classifier

Step 3: Estimate the lowest generalised error and highest accuracy for the classifier with the determined hyperparameters.

Step 4: Set the optimal hyperparameters for the network based on the desired accuracy
Step 5: Train the OCML network with the selected input features
Step 6: Employ 10-fold validation as k-fold cross-validation for testing the efficiency of the classifier.
Step 7: Determine the performance efficiency for each classifier and select the suitable classifier for the OCML system

In this study, ANN helped in successive weight updation resulting in minimization of error which helped in ovarian classification.LDA was useful to predict the linear combination of the image, diagnostic and demographic features for classification of ovary as normal, polycystic and cystic.SVM was used to develop a three-class classification. SVM helped to predict a correlation between the input features and find a hyperplane with largest margin to separate all the three classes by achieving higher accuracy. OCML methodology employed 10-fold validation as k-fold cross-validation for testing the efficiency of the classifier.

2.5 Ablation study

Ablation study was carried out in this research by excluding certain hyperparameters and testing the performance of the system. In ANN, the ablation study was performed by eliminating the hyperparameters such as learning rate, momentum and hidden neurons. It was observed that when learning rate was eliminated the network convergence was slow and significantly increased the time taken for learning. Similarly, when momentum was removed, optimization was not achieved and the network ended up in misclassification of ovaries. With respect to hidden neurons, when the number of neurons is decreased, minute features were missed and the accuracy was less. So, choosing of appropriate number of hidden neurons was important. In SVM, the ablation study was performed by eliminating the model parameters such as boxconstraint, outliers and solvers. When the boxconstraint value was eliminated the number of training errors increased contributing to lesser accuracy. Similarly, solvers had a significant role in optimizing the problem and reducing the processing time. On eliminating the solvers, optimization was not achieved resulting in lowered accuracy.

3. Results and Discussion

A single ovarian sample image from each cluster was chosen for presentation in this research. Fig. 2 displays a sample dataset for testing the OCML approach that includes images of normal ovarian follicles, polycystic ovaries, and cystic ovaries. The images a, b and c were of the sizes 107x119x 3, 54x113x3 and 132x 129x3 respectively. OCML was developed in MATLAB R2018a.

3.1 Evaluation of the proposed methodology

Denoising of the ovarian image was performed followed by the intensity- and texture-based segmentation. The interfollicular areas were improperly segregated during intensity-based segmentation. In order to improve the detection of follicles and cysts, it was intended to carry out texture-based segmentation and add those features that provide a better detection together with the intensity. An intelligent algorithm would improve the detection's effectiveness. Consequently, an ovarian detection system (MLOD) based on machine learning and ANN was implemented. The feedforward backpropagation neural network with hyperbolic tangent sigmoid neurons in the hidden layer and linear neurons in the output layer was used and the intensity as well as the three extracted texture features were chosen as inputs to the network. In this system, it was necessary to estimate the likelihood of a region being classified as follicular/cystic or non-follicular/non-cystic. Therefore, using sigmoid neurons was an optimal decision. In order to keep the model's operation within nominal parameters, linear neurons were employed. A thorough examination was made pertaining to the choosing of network hyperparameters. The classifier's performance was evaluated for different learning rates and momentum values ranging from 0.01 to 0.9 and 0.1 to 0.9, respectively. The final value for training was fixed at the value for which the lowest mean squared normalised error (MSE) was obtained. The lowest MSE was produced by a learning rate of 0.02 and a momentum of 0.2. By choosing the MSE with the lowest value, the number of hidden neurons in the hidden layer was fixed at 3. With a learning rate and momentum of 0.02 and 0.2, respectively, a classifier with four input neurons, three hidden neurons, and two output neurons was created.

The network's output was predetermined to be 0 for non-follicular/non-cystic regions and 1 for follicular/cystic regions. When the network's combined features were tested over all test images, the classifier produced an average testing accuracy of 96%. As illustrated in Fig. 3, the ANN assisted in automatically distinguishing between follicular/cystic and non-follicular/non-cystic regions. This output was used as one of the feature inputs for the ovarian classifier.

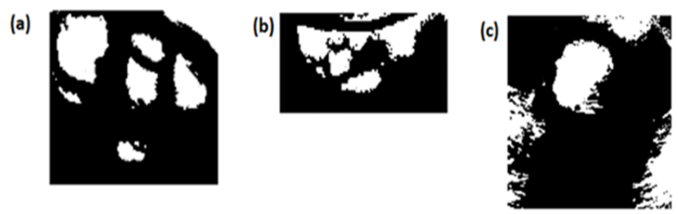


Fig. 3 Results of MLOD for (a) Normal ovaries, (b) Polycystic Ovaries and (c) Cystic Ovaries.

Ovarian classification was performed using three different machine learning algorithms such as ANN, Discriminant classifier and SVM. The input to train these classifiers include the output of the MLOD classifier along with the selected 8 demographic and diagnostic variables (discussed in section 2.3.3) which totally constitute as 9 inputs to each classifier. The 9 selected features are shown in Table 3.

Table 3. Features selected.

S. No	Selected Features
1	Day of the menstrual cycle
2	Size of the follicle
3	Number of follicles
4	FSH
5	LH
6	Prolactin
7	TSH
8	RBS
9	MLOD Classifier output

A 9 input, 3 hidden, and 3 output neuron ANN classifier with a learning rate of 0.02, momentum of 0.2, and gradient descent with momentum as the training function was created. The training algorithm's performance is displayed in Table 4.

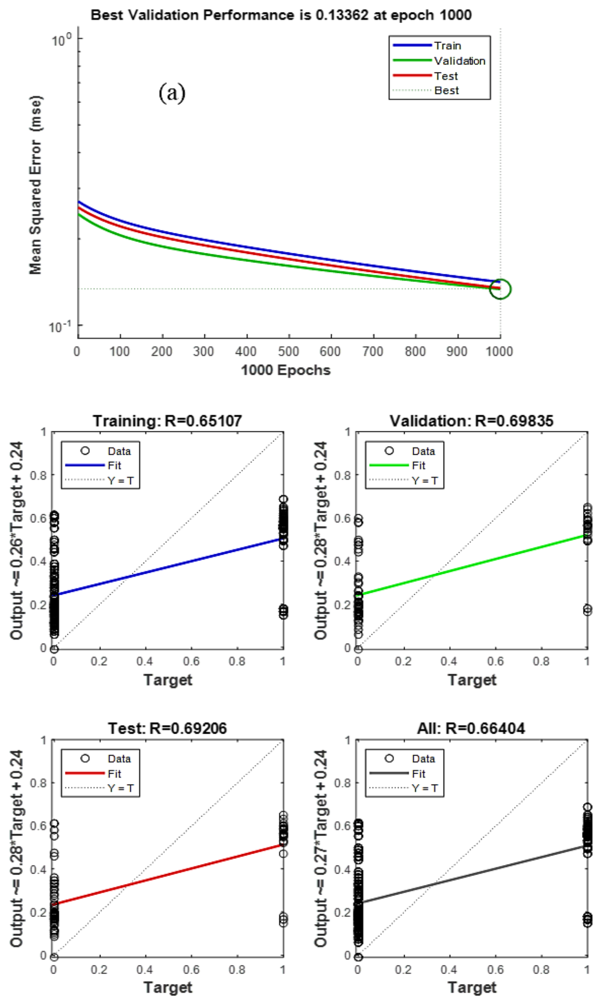
Table 4. Performance of ANN algorithm for OCML system.

Parameters	Value
Number of Epochs	1000
Learning Rate	0.02
Training time	0.01 seconds
Gradient	0.0529
Validation Performance	0.13362
Training Performance	0.141

The grouping of sigmoidal and the linear activation functions had prominent outcome in ovarian classification. In OCML, the probability of ovarian classification has to be predicted as an output which lies between 0 and 1. So, sigmoid neurons helped in classifying the ovary as normal, cystic and polycystic. The network training performance is shown in Fig. 4. Best validation performance is shown in Fig. 4(a) and training performance is shown in Fig. 4(b).

LDA classifier with the discriminant type 'pseuolinear' yielded a highest classification rate because the covariance matrix was singular for the fitted classifier. Gamma and delta are the two regularisation parameters in LDA for controlling regularisation and helping to identify and remove redundant predictors. Misclassification of ovary would occur if the redundant predictors were not removed. So, performance of the classifier was tested for various values of delta and gamma ranging from 0 to 1. Lowest generalised error and highest accuracy was obtained at a value of 0 for both gamma and delta. This is revealed from Fig. 5.

Classification was done using SVM. Trials were made in choosing model parameters such as kernel function, solver, boxconstraint, number of iterations and outlierfraction. With regard to kernel functions trials were made using linear, gaussian, polynomial and radial basis functions. Classification was highest using linear kernel function. Choosing of boxconstraint value plays a significant role because it aids in preventing overfitting. Increased boxcontraint value can lead



(b)

Fig. 4 Performance of ANN classifier for (a)Best Validation (b) Training.

to longer training time as well. Trials were carried out for various values of boxconstraint and outlierfraction ranging from 0 to 1. Maximum accuracy and lowest error were obtained at an outlierfraction value of 0 and a boxconstraint value of 0.5. The training time nor the training errors was increased with these values. Likewise, maximum classification accuracy was achieved at 1000 iterations. Fig. 6 represents the accuracy achieved with boxconstraint values.

Likewise, with regard to selecting of solvers, Sequential Minimal Optimization (SMO) and Iterative Single Data Algorithm (ISDA) were tried and tested. The study involves a three-class classification. Solver 'ISDA' works only for binary classification and so it cannot be used here. Similarly, the chance of misclassification of ovaries has to be reduced by minimizing the error function. But ISDA uses a gradient ascent technique and so it did not help in reduction of misclassification of ovaries. Kernel calculation time is reduced with SMO and its memory requirement is linear with respect to the training set size[24]. So, SMO solver was used in this study and it yielded highest accuracy. Hyperparameters used for the SVM classifier is given in Table 5.

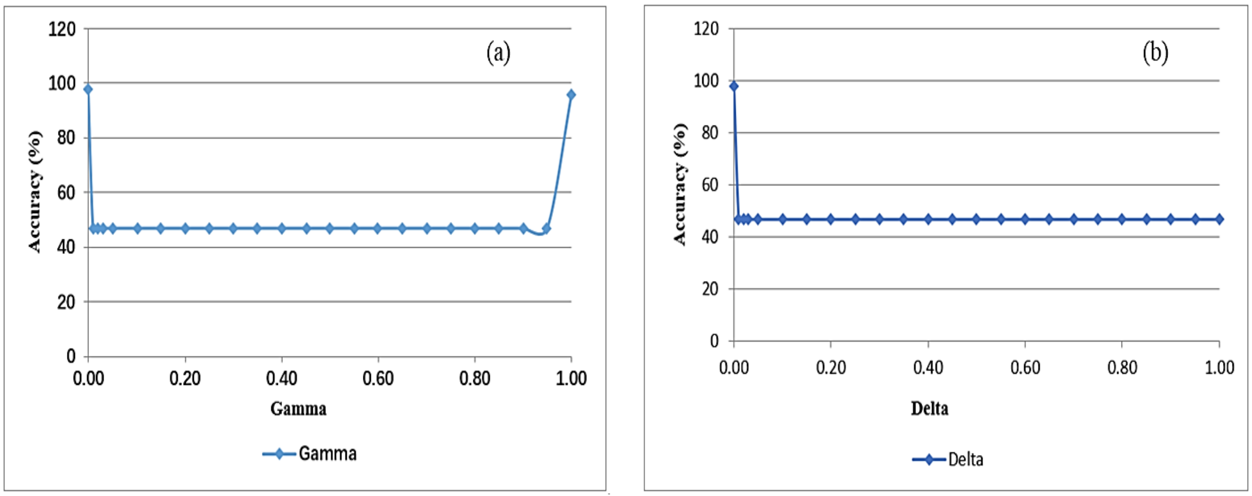


Fig. 5 Accuracy using (a) Gamma (b) Delta.

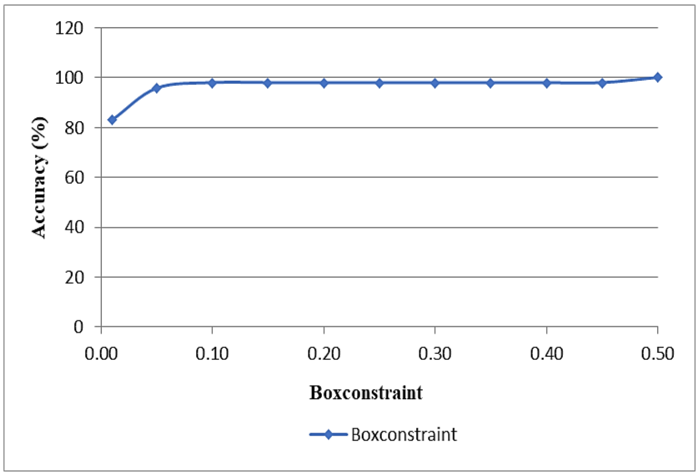


Fig. 6 Accuracy using Boxconstraint.

Table 5. Hyperparameters of SVM algorithm for OCML system.

Parameters	Value
Kernel function	Linear
Solver	Sequential Minimal Optimization
Boxconstraint	0.5
Outlierfraction value	0
Number of iterations	1000

3.2 Comparison of Classifiers

A confusion matrix was computed to compare the performance of the classifiers. It specifies the extent to which each classifier yields an accurate classification and helps to find the best performing classifier. Classification results of ANN, LDA and SVM classifiers are shown in Table 6.

From the confusion matrix, it can be inferred that the classifier accuracy accounted to 95% for ANN. An accuracy of 97.9% was obtained for LDA depicting a better classification. With respect to SVM, incorrect classification was not obtained for any sample thus yielding an accuracy of 100%.

The accuracy of each of the machine learning based ovarian classifier seems to be high. But in reality, the overall classification accuracy of the OCML system relies on the detection accuracy obtained from MLOD methodology also. A detection accuracy of 95%,97% and 97% was obtained from the MLOD methodology for normal, polycystic and cystic datasets respectively. This reduction in detection accuracy will definitely have an influence in the overall performance of the system. Hence this study requires the computation of the overall performance indices of the different classifiers by including the performance indices of the MLOD also.

The effectiveness of the classifier was demonstrated by comparing the results of the different classifiers using performance indices like sensitivity, accuracy, specificity, and precision, as well as F-measure, Mathew's Correlation Coefficient (MCC), and Receiver Operating Characteristic (ROC) curve. The performance indices were calculated using the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{6}$$

$$Specificity = \frac{TN}{TN+FP} \tag{7}$$

Table 6. Classification results.

Category		ANN		LDA		SVM	
		T	F	T	F	T	F
Normal Ovary	T	83(TP)	5(FN)	84(TP)	4(FN)	88(TP)	0(FN)
	F	4(FP)	96(TN)	0(FP)	100(TN)	0(FP)	116(TN)
Polycystic Ovary	T	72(TP)	0(FN)	72(TP)	0(FN)	72(TP)	0(FN)
	F	0(FP)	116(TN)	0(FP)	116(TN)	0(FP)	116(TN)
Cystic Ovary	T	24(TP)	4(FN)	28(TP)	0(FN)	28(TP)	0(FN)
	F	5(FP)	155(TN)	4(FP)	156(TN)	0(FP)	160(TN)

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{8}$$

$$Pr\,e\,cision = \frac{TP}{TP+FP} \tag{9}$$

$$MCC = \frac{(TP\times TN)-(FN\times FP)}{\sqrt{(TP+FN)(TP+FP)(TN+FN)(TN+FP)}} \tag{10}$$

$$F-measure = \frac{2\times Pr\,ecision\times Re\,call}{Pr\,ecision+Re\,call} \tag{11}$$

It can be said that the classifier performs well if its performance indicators, such as sensitivity, specificity, accuracy, precision, and F-measure are close to 100%. The formulae for sensitivity, specificity, accuracy, precision, and F-measure are given in equations (6), (7), (8), (9) and (11) respectively. If the value in relation to MCC shown in equation (10) is close to one, the classifier is performing well. This made it easier to find a suitable classifier for the problem of ovarian classification. The results of various performance indices are shown in Table 7.

Table 7. Performance comparisons of ANN, LDA AND SVM classifiers.

Performance Index	ANN			LDA			SVM		
	Normal	Polycystic	Cystic	Normal	Polycystic	Cystic	Normal	Polycystic	Cystic
Sensitivity (%)	91	97	82	92	97	95	96	97	95
Specificity (%)	89	96	95	93	96	98	93	96	98
Accuracy (%)	91	97	92	93	97	97	95	97	98
Precision (%)	89	96	81	94	96	98	94	96	98
F-measure (%)	90	97	81	93	97	96	95	97	96
MCC	0.80	0.93	0.76	0.85	0.93	0.94	0.89	0.93	0.94

It was inferred from Table 7 that all the performance indices are higher in SVM classifier when compared to ANN and LDA based classifiers. ROC curve was plotted to compare all the three methods to confirm the competence of the best performing classifier. SVM could be a more appropriate classification algorithm for the OCML methodology as depicted from Fig. 7.

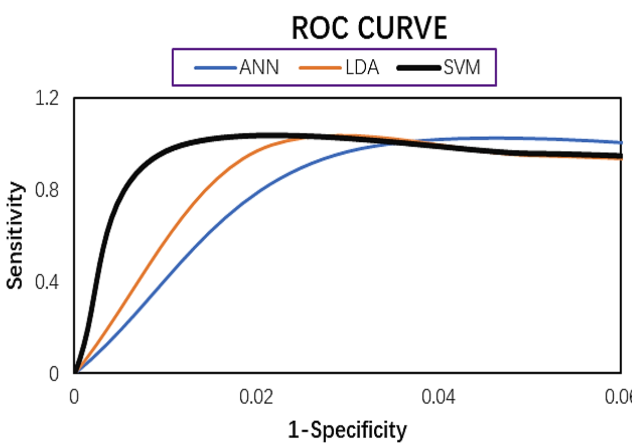


Fig. 7 ROC Curve for OCML methodologies.

The ovarian classifier using SVM has performed the classification of ovaries as normal, cystic and polycystic accurately. It has classified the ovaries as normal, cystic and polycystic accurately. ANNs can suffer from multiple local minima. In this study common features are shared by the ovarian follicles and ovarian cysts and ANN gets struck in exactly finding the variations between both of them resulting in lesser accuracy as compared to LDA and SVM. Similarly, LDA finds a linear combination of features to discriminate two or more classes. When there is some likelihood between the normal and cystic ovaries, it becomes difficult for LDA to find a linear combination of features and accurately classify them. When SVM is used in classification, it converges on a global minimum, has a greater search accuracy, allows a better tolerance and adapts even to the smaller variations between various classes yielding improved accuracy. The methods used in this study do not consider the shape or geometric features. They completely rely on features that help in discriminating the different classes of ovaries in a clear manner. The intelligent methods used in this study accommodates to changes depicting a better tolerance and accuracy. It has classified the ovaries as normal, cystic and polycystic accurately thereby successfully evading misclassification of ovaries.

Results obtained for detection (MLOD) and classification (OCML) was compared in Fig. 8. MLOD helped in efficient detection of follicular/cystic region and the non-follicular/non cystic region. OCML had classified the ovaries as normal, polycystic and cystic ovaries using the SVM classifier with an overall maximum classification accuracy of 98%. ANN was used in automatic detection of desired and undesired regions in the ovarian images. As similar features are shared between normal and cystic regions, ANN finds difficulty in differentiating. The outcome of ANN is also one of the inputs to the intelligent classifiers thus resulting in a lack of 2% accuracy. The results were validated by the medical expert of Department of Obstetrics and Gynaecology, Chettinad Hospital and Research Institute, Chennai. Time is an important computational trade off in the models that were developed. Computational time differed depending upon the size of the test image that is given to the classifier. The ratio of time taken between SVM and ANN is 1:3.25 and the ratio of time taken between SVM and LDA is 1:1.25. As an overall inference, the least amount of time was consumed by the SVM classifier, followed by LDA and ANN.

The existing ovarian studies either classify the ovaries as normal or cystic[10] simple and complex,[12] simple cyst and endometrioma cyst[11] or detect the presence or absence of the follicle.[13] But the developed intelligent system precisely classifies the ovaries as cystic, polycystic and normal evading the misclassification of ovaries with an accuracy of 98%.
Classification of ovary as cystic, polycystic and normal using SVM was performed where, only image characteristics were used as input to the SVM classifiers.[14] This study does not completely mimic the diagnosis procedure adopted by medical

experts for their decision-making process. The novelty of the work is the development of an intelligent system that combines the demographic, diagnostic and image information thus mimicking the decisions that would be taken by the medical expert in real time for infertility diagnosis. This novel system would serve as a decision support system with high accuracy. The study could be extended by analysing the influence of the ovulatory disorders in causing other abnormalities and exploring the impact of collected data for diagnosing other body dysfunctions.

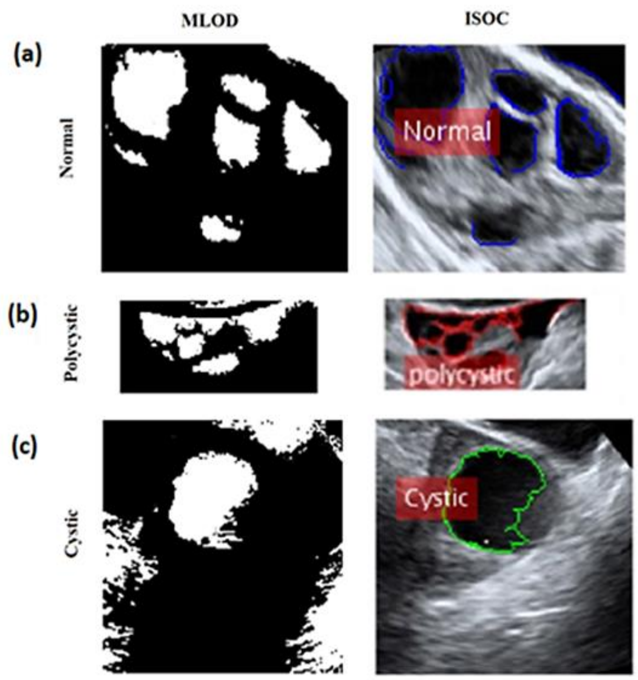


Fig. 8 Comparative results of MLOD and OCML methodologies for (a) Normal ovaries (b) Polycystic Ovaries and (c) Cystic Ovaries.

4. Conclusion

An intelligent algorithm for robust and accurate ovarian classification was developed using machine learning techniques in this study. ANN, LDA and SVM classifiers were developed for predicting a suitable classifier which attains the maximum accuracy. Optimization parameters for the classifiers were chosen properly as they played an important role in predicting the model performance. The extracted features include three texture features, intensity feature and eight features from the demographic and diagnostic data. Performance metrics confirm the efficiency of the classifiers. Out of all the three classifiers, effective classification of ovaries with an overall maximum accuracy of 98% was achieved by SVM. The major contributions of this study are co-training the machine learning algorithm with demographic and diagnostic features along with image characteristics. This co-training has increased the efficiency of the system by making it more robust, accurate and reliable. The developed intelligent ovarian classification system with high accuracy will serve as a preliminary investigating technique in diagnosis of infertility. It will support in investigating the underlying problem more clearly by reducing the possibility of misinterpretation and certainly serve as a decision support system.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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