

# Hybrid Textural Feature Descriptors for Ovarian Cyst Classification Using Machine Learning

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## Article History:

**Received:** 13-09-2024

**Revised:** 17-11-2024

**Accepted:** 27-11-2024

## Abstract:

A computer aided diagnosis system for classification of ovarian cyst is a crucial step towards treatment of women suffering from cysts in ovaries. Ultrasound or sonography is an efficacious technique that assists healthcare providers in diagnosis and therapeutics for cysts in ovaries. In this research, an automated ovarian cyst diagnosis system based on textural features from ultrasound images is designed. Local binary pattern and fractal dimension textural features are combined to deduce features related to texture from ultrasound images and these textural features are given as input to machine learning classifiers like, decision tree, logistic regression and support vector machine. This novel method assists healthcare providers to distinguish cystic ovaries from normal ovaries in ultrasound images. Evaluation metrics namely, precision, accuracy, recall, F1-score, specificity and receiver operating characteristics – area under curve are used to validate the efficacy of the classifiers. Decision tree, logistic regression and support vector machine classifiers furnished an accuracy of 83.42%, 89.12% and 91.19%, respectively on a dataset of 1203 ultrasound images procured from a medical diagnostic centre in India. Support vector machine has proved to be a better classifier in relation to accuracy (91.19%), precision (97.98%), F1-score (94.49%), specificity (90.90%) and area under curve (0.93) compared to decision tree and logistic regression. This computer aided diagnosis system helps healthcare providers in making efficient and accurate decisions towards treatment plan of patients.

**Keywords:** Ovarian cyst, machine learning, decision tree, logistic regression, support vector machine.

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## 1. Introduction

Ovarian cysts are minute saccules found inside or around the two ovaries of female reproductive system. They can befall at any age, but are most commonly found in women of reproductive age. These cysts differ in size from few millimetres to centimetres (greater than 10 centimetres) (Parekh & Shah, 2017). Most of the cysts in ovaries are non-cancerous, but few of them may result in soreness, pelvic ache, bloating or other symptoms that demand medical treatment. Healthcare providers diagnose cysts in ovaries through a series of procedures like physical examination, imaging tests like sonography or ultrasound, MRI and pathology tests to check various hormone levels.

Ultrasound is the most valuable and commonly used imaging test for detection of ovarian cysts. It works by producing images of the organs, tissues and blood flow of a human body with the help of

high frequency sound waves (Gupta & Fatima, 2023). Transvaginal or abdominal ultrasound scans give lucid view of ovarian cysts with the details like, shape, dimensions, texture, location, etc. and are employed to diagnose ovarian cysts. But still, identification of ovarian cysts is a complicated task as they may appear similar to the non-cystic or follicular regions in the ovary. Inter-follicular regions also look alike to the background in the ultrasound images. Henceforth, the interpretation of ultrasound scans entirely depends on the expertise of medical specialist performing the scans. An incorrect diagnosis may result in an erroneous treatment plan which may have adverse effect on patient's health. To avoid any such circumstance, computer aided diagnosis systems can act as a supportive decision tool to healthcare providers in the recognition of ovarian cysts with better accuracy and efficient results (Alzubi et al., 2023).

The research proposes a novel method to segregate ovarian ultrasound images into two classes – cystic and non-cystic or normal images. It combines two different texture features of ultrasound images as the basis for the classification. Once the texture features are extracted, machine learning algorithms like decision tree (Edwards., 1987), logistic regression (Cramer, 2003) and support vector machine (SVM) (C. C. Chang & Lin, 2011) are applied for classification.

Our contributions in this research are –

- After performing a comprehensive analysis of research articles related to ovarian cyst classification, it is found that most of the researches worked on a smaller number of ultrasound images taken mostly from various internet resources. This research caters an ultrasound dataset from a medical diagnostic centre with sufficient number of images.
- The research is based on the textural features of ultrasound images which is an essential parameter to differentiate cystic regions from ultrasound images.
- The research proposes a computer aided diagnosis system of cystic images from non-cystic images.

## 2. Literature Review

Many earlier research works have been accomplished for ovarian cyst classification. V. Kiruthika et al. developed a system to classify normal, cystic and polycystic ovaries using 105 ultrasound images taken from Chettinad Hospital and Research Institute, Tamil Nadu, India (Kiruthika et al., 2023). Intensity, auto-correlation, sum average, sum variance along with demographic and diagnostic data (size of follicle, number of follicles, prolactin etc.) are used as features for classification. The different classifiers used in the system are SVM, Artificial Neural Network and Linear Discriminant Analysis and SVM turned out to be the best classifier with an accuracy of 98%.

C. Gopalakrishnan and M. Iyapparaja designed PCOS detection and classification model (Gopalakrishnan & Iyapparaja, 2021). 90 ultrasound images are obtained from Nandhini Sri Diagnostic Center, Tamil Nadu, India in which 30 images are of normal ovaries, 25 images are cystic ovaries and 35 images are of polycystic ovary syndrome. Features like, area, perimeter, eccentricity, major axis and minor axis are given as input to SVM, Random Forest, LDA and Naïve Bayes machine learning algorithms which produced accuracies of 93.82%, 89.7%, 91.05% and 88.26%, respectively.

R. Benazir Begam along with other researchers proposed a classification system using Convolutional Neural Networks and differentiated three different types of ovarian cysts - dermoid, haemorrhage and

endometrioma (Benazir Begam et al., 2022). They used 80 ultrasound images, out of which 20 images were of normal ovaries and 60 images were of ovarian cysts. The accuracy achieved using the classification system is 94%.

A PCONet model is fabricated with fine-tuned Inception V3 network to identify polycystic ovaries from normal ovaries (Salman Hosain et al., 2023). Originally, Inception V3 model comprises of 42 layers; it is fine-tuned by adding 2 dense layers and removing top layers of the model. The number of neurons in the dense layer near the output layer is 512. The proposed model outperforms the original model with an accuracy of 98.12% over 96.56 %.

SVM, KNN and Logistic Regression are the classifiers employed by J. Madhumitha et al. to separate polycystic ovaries from normal ovaries in ultrasound images (Madhumitha et al., 2021). A hybrid system is generated using all the three machine learning algorithms with the dataset taken from <https://radiologykey.com> and produced an accuracy of 98%. The factors used as the basis of machine learning algorithms in this research are area, freakishness and denseness of images.

Anisah Nabilah along with other researchers worked on a decision tree model to segregate functional cysts from pathological cysts (Nabilah et al., 2020). 46 ultrasound images from Mother Child Hospital “Putri”, Indonesia are used in this research and an accuracy of 97.8% is accomplished. The selected features given as input to the decision tree are length and width of cyst along with papillary size.

Several researchers have worked on textural features of ultrasound images and used as a classification criterion of medical images. Maha Abdulameer Kadhim analysed and processed 80 medical images with the help of grey-level co-occurrence matrices (GLCM), fractal geometry and lacunarity (Kadhim, 2022). This research is performed using MATLAB and Microsoft Visual C++; and SVM as a classifier with 95% classification rate.

Hurst components are used as a classification feature in logistic regression, decision tree, SVM and KNN by Yen-Ching Chang and Jin-Tsong Jeng on 2D fractional Brownian motion images (Y. C. Chang & Jeng, 2023). Deep learning models like, AlexNet, GoogleNet and Xception are used that turn out to perform better than machine learning algorithms. They used chest X ray images from Kaggle with 127 x 384 as input size. It was found that their proposed model and Google Net performed well on the basis of maximum likelihood estimator, mean absolute error and mean square error. The classification rate which comes out to be the best for machine learning algorithms is 81.4% for 11 classes and 53.2% for 21 classes. In case of Deep learning models, the classification rates are 96% and 93.7% for 11 and 21 classes respectively.

Dmytro M. Bayzitov along with co-researchers worked on digital image classification of appendicitis and ovarian cysts with HAAR features cascade and AdaBoost classifiers (Bayzitov et al., 2023). Features are selected from images or frames of laparoscopic diagnostics using modified color local binary pattern (LBP). For training, 95 and 78 video images are used for appendicitis and ovarian cysts, respectively. 439 and 182 frames are utilized for testing of appendicitis and ovarian cysts. AdaBoost classifier achieved a better accuracy of 73.6% for appendicitis and 85.4% for ovarian cysts.

Mengwan Wei and other researchers combined texture and morphological features of 448 ultrasound images to differentiate non-cancerous and malignant breast tumour (Wei et al., 2020). They used local

binary patterns (LBP) (Ojala et al., 1996), grey-level co-occurrence matrices (GLCM) (Haralick et al., 1973) and histogram of oriented gradients (HOG) (Dalal & Triggs, 2005) under texture features. Non-cancerous tumours differ in morphology with the cancerous tumours like compactness, elliptical compactness and radial distance spectrum which are considered in this research. Their research combined multiple classifiers like, SVM and Naïve Bayes and achieved an accuracy of 91.11% with sensitivity as 94.34% and specificity as 86.49%.

Hybrid Convolutional Neural Networks (combination of Convolutional Neural Networks and LBP) are used for feature extraction in classification of medical images (Rocha et al., 2023). SVM, random forest, KNN, linear discriminant analysis and fully connected layer are employed as classifiers and their results are combined through ensemble method. The dataset comprises of jaw oral cysts – radicular cysts and odontogenic keratocysts. It produced 83.4% and 85.9% as an average accuracy in different combinations of oral cysts classification.

Xing-Xing Bao et al. aims to locate necrotic regions in the chronic spinal cord injury using MRI images of wistar rats (Bao et al., 2023). The features are extracted using LBP, Gabor texture features, GLCM, statistical features related to intensity and superpixel areas. SVM and random forest are used as a classification model in which SVM showed higher accuracy.

Many textural feature methods like LBP, local directional pattern (LDP) and local optimal oriented pattern (LOOP) are used in classification of ovarian cysts using KNN, SVM, Naïve Bayes, Decision Tree and ensemble classifiers (Sheela et al., 2020). The dataset used in the research consists of 100 ultrasound images, out of which 50 images are of normal ovaries and remaining 50 are of cystic ovaries. The comparative analysis of the three texture features proves that LBP is the most appropriate texture feature for ovarian cyst classification.

### **3. Materials and Methods**

#### **3.1 Data Acquisition**

The dataset used for experimentation comprises of transvaginal and abdominal ultrasound scan images that are collected from the “Skop” medical diagnostic centre located in Agra, India. The dataset is captured on a Toshiba Xario 100 ultrasound machine with probe frequency of 11MHz. The parameters of ultrasound machine are adjusted by the radiologist. The cases dealing with previous ovarian surgeries, pregnancy and inferior quality of images are discarded. Eventually 1203 ultrasound images of ovaries are used in the research. The dataset has been previously anonymized to ensure the privacy and confidentiality of the individuals depicted, and no identifiable information is associated with the images.

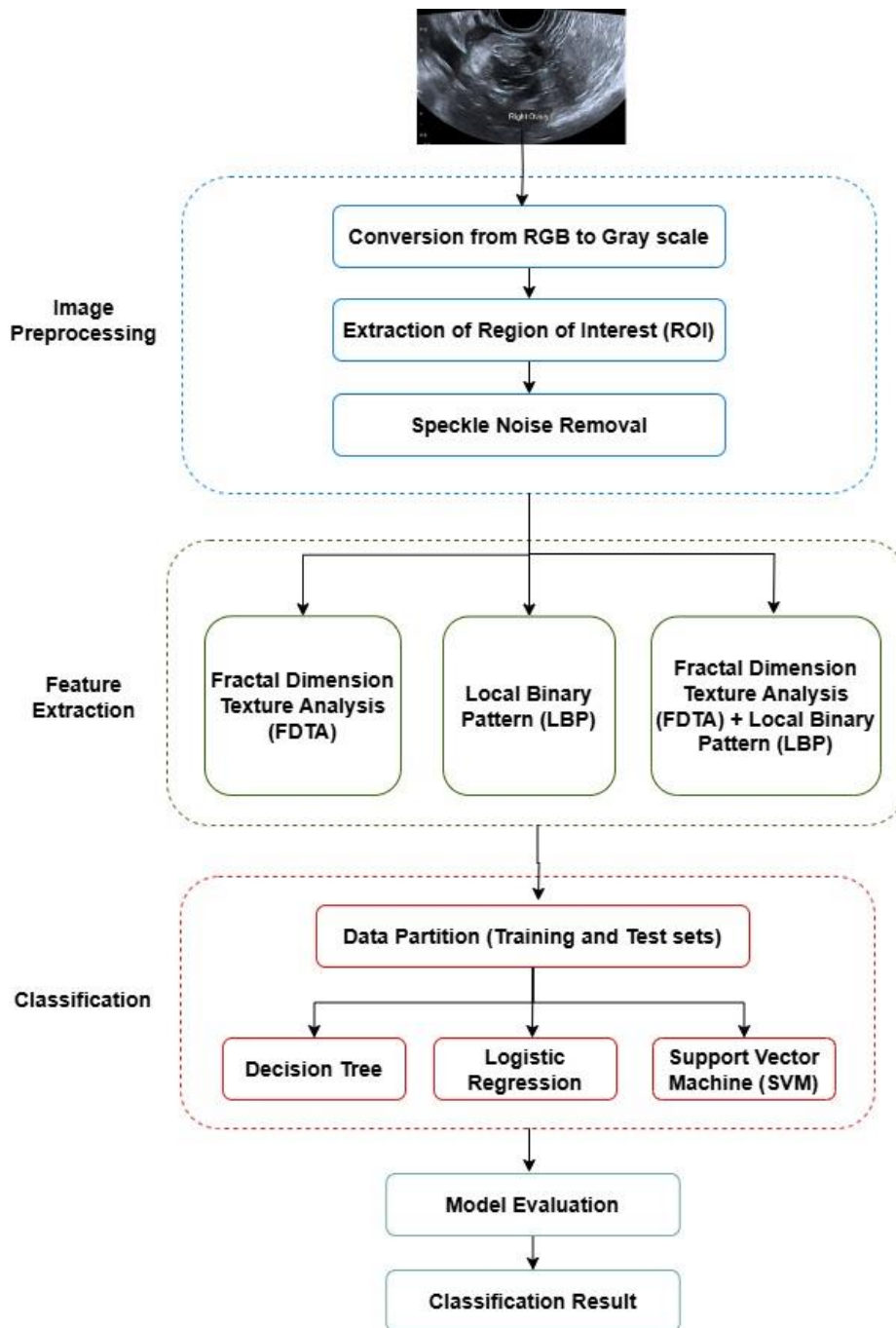
#### **3.2 Methodology**

The method of ovarian cyst classification comprises of number of steps which starts with preprocessing of input ultrasound images and finally ends in evaluation of the machine learning classifiers. The overall methodology is shown in Figure 1.

##### **3.2.1 Image Preprocessing**

Image preprocessing is the foremost step performed on the ultrasound images to enhance the quality and crucial features stored in them. Firstly, the ultrasound images are converted from RGB scale to grey scale images. Then, Region of Interest (ROI) is drawn out from the grey scale ultrasound images

by cropping the image to  $400 \times 300$ -pixel size to simplify the classification method. For further processing, the quality of the ultrasound images needs



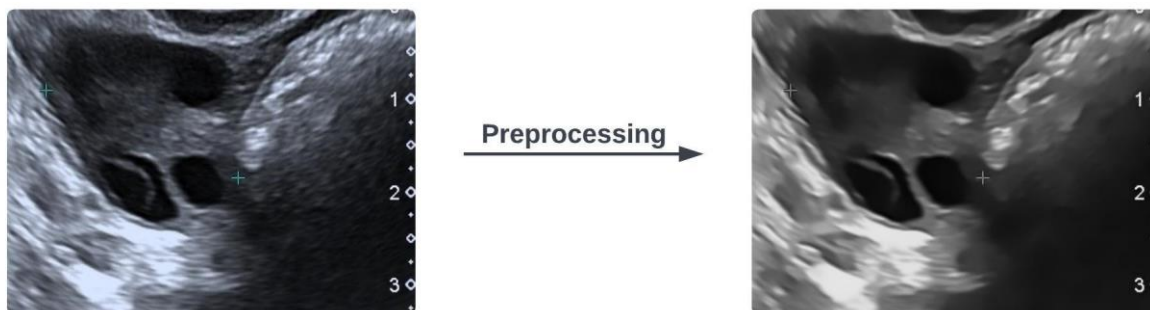
**Figure 1** Methodology.

to be improved by removing speckle noise from them (Pradeep & Nirmaladevi, 2021). Speckle noise is automatically added in the process of acquisition of the image; for instance, it is produced owing to the fact that head of the ultrasound machine is not moisture-laden. The task of removing speckle noise is performed by fast No Local-Means (NL) filter (Pang et al., 2009). The fast NL filter algorithm works on the similarity principle of spatially sampled pixels using equation (1). It produces better quality image in less processing time.

$$\begin{aligned}
 & \text{if } |v(i, j) - v(k, l)| < Th_u + 2\sqrt{2}\sigma_n \text{ and} \\
 & ((|v(i + 1, j) - v(k + 1, l)| < Th_u + 2\sqrt{2}\sigma_n) \text{ or} \\
 & (|v(i - 1, j) - v(k - 1, l)| < Th_u + 2\sqrt{2}\sigma_n) \text{ or} \\
 & (|v(i, j - 1) - v(k, l - 1)| < Th_u + 2\sqrt{2}\sigma_n) \text{ or} \\
 & (|v(i, j + 1) - v(k, l + 1)| < Th_u + 2\sqrt{2}\sigma_n)
 \end{aligned} \tag{1}$$

$N_{i,j}$  and  $N_{k,l}$  are similar neighbours, else  $N_{i,j}$  and  $N_{k,l}$  are unrelated

In equation (1),  $v(i,j)$  and  $v(k,l)$  represents the pixel values at the locations  $(i,j)$  and  $(k,l)$ ;  $\sigma_n$  refers to the variance related to noise,  $n(i,j)$ ;  $Th_u$  is the threshold for the absolute difference. Figure 2 shows an ultrasound image having speckle noise as left-hand side image and speckle noise free ultrasound image produced by fast NL filter as right-hand side image.



**Figure 2** Ultrasound with speckle noise (left), ultrasound with no speckle noise (right).

### 3.2.2 Feature Extraction

In the classification of medical images, unshattering of distinguishing features from the images is an essential and principal task. These features are given as input to the machine learning algorithms for training purposes. Thus, the goal of the feature extraction is to find out significant features that can assist in efficient diagnosis and prognosis of diseases.

Features based on textures in the ultrasound images play an important role in medical image classification as there are remarkable differences in echoes of a cyst and a normal ultrasound image (Humeau-Heurtier, 2019). The textural features draw out the surface characteristic along with dimension, density, etc. from the image. In this research, Fractal Dimension Texture Analysis (FDTA) (Pentland, 1984) and Local Binary Pattern (LBP) (Ojala et al., 1996) features are extracted from the ultrasound images.

Fractal dimension texture analysis is a procedure to measure the complexity of textures in images. It has its roots from fractals which mathematically represents intricate and self-similar patterns. Fractal dimension is computed by inspecting the details of texture with the changes in scale of observation. A complex and rough texture gives a higher fractal dimension in comparison with a smooth texture. Fractal dimension is calculated using fractional Brownian motion (fBm) model (Decreusefond & Üstünel, 1998). The fBm model computes the smoothness or roughness of textures in images. Hurst parameter (H) is a key factor in fBm and is utilized to identify the self-similarity characteristic of fBm

(Hurst, 1951). It is an important parameter in identifying similar or dissimilar textures in the image under study (Yakubu et al., 2019).

Ojala et al. first presented local binary pattern as an efficient texture descriptor (Ojala et al., 1996). LBP is a statistical textural descriptor with an advantage of unvarying grey and rotation values. It considers a circular neighbourhood around a pixel (either clockwise or anti-clockwise), comprising of P equidistant points with radius R. The P points are changed to a stream of binary values, depending upon the grey level of pixel is less or greater than the grey level of pixel in the center. The LBP codes are calculated using equation (2).

$$LBP(x, y) = \sum_{p=0}^{P-1} s(i_p - i_c)2^p \quad (2)$$

where p denotes the adjacent pixel number,  $i_c$  and  $i_p$  are the grey levels of center pixel (x, y) and adjacent pixel.

In equation (2), s(x) is a function defined as

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases} \quad (3)$$

Since LBP merges both statistical and structural approaches, it performs better in texture analysis. It is easy to implement and has less computational cost.

The research presents a novel technique for feature extraction from ovarian ultrasound images. It combines fractal dimension texture analysis with local binary patterns and provides an efficient and more robust computer aided diagnosis system for ovarian cyst classification.

### 3.2.3 Classification

The textural features extracted from the ultrasound images are given as input to the machine learning classifiers for training and evaluation purposes. In the research, decision tree, logistics regression and SVM are used as classifiers.

Decision tree is a hierarchical classification tree model in machine learning (Edwards., 1987). It is constructed on the input training dataset in which internal node performs a test on a particular feature; the branch rising from the internal node represents the result of test and every leaf node specifies to which class label or category it belongs. Decision tree targets to provide an optimal tree for classification. The final result of classification is depicted by the leaf nodes.

Logistic Regression is a machine learning algorithm that models the probability of occurring event by converting log-odds to probability (Cramer, 2003). The logistic function used is defined as:

$$f(p) = \frac{1}{1 + e^{-p}} \quad (4)$$

where  $p = w_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n$  is the linear combination of weights to their corresponding input features and  $w_0$  is the bias term. The likelihood function used in logistic regression is represented as:

$$L(w) = \prod_{k=1}^n f(z_k)^{y_k} (1 - f(z_k))^{1-y_k} \tag{5}$$

where n is the number of training dataset,  $y_k$  is the actual resultant for the k-th data, and  $z_k$  is the linear combination of weights to their corresponding input features for the k-th data. The key point of logistic regression is that it is very simple to implement and robust to multicollinearity.

SVM which is based on supervised learning, is one of the efficient predictive models (C. C. Chang & Lin, 2011). In case of linear classification, it tries to maximize the separation (margin) between two classes and establishes a hyperplane classifying the n data points ( $x_i, y_i$  where  $x_i$  is a p-dimensional vector such that  $x_i \in \mathbb{R}^p, y_i \in \{-1, 1\}$  and i ranges from 1 to n) into two classes. Support vector term is coined to specific data points that establish the maximum margin of the hyperplane to the data points. New data points are mapped into the class based on which side of the separation they fall. Consider a hyperplane is defined through w and b is the set of points such that  $H = \{x | w^T x + b = 0\}$ . The goal is to maximize margin defined as

$$\max_{w,b} \frac{1}{\|w\|_2} \min_{x_i \in D} |w^T x_i + b| \text{ such that } y_i (w^T x_i + b) \geq 0 \tag{6}$$

In case of non-linear dataset, SVM performs classification using the concept of kernel functions. The kernel functions transform the non-linear dataset to a high-dimensional feature space where the transformed dataset becomes more separable from the original dataset. Linear kernel, radial basis function (RBF) and polynomial kernel are some of the kernel functions to generate different types of classifying hyperplanes in SVM.

Linear Kernel  $K(x_i, x_j) = x_i^T \cdot x_j \tag{7}$

RBF Kernel  $K(x_i, x_j) = \exp(-\gamma |x_i - x_j|^2), \gamma > 0 \tag{8}$

Polynomial Kernel  $K(x_i, x_j) = x_i^T \cdot x_j + C^d \tag{9}$

where  $K(x_i, x_j)$  is kernel function,  $x_i, x_j$  are the i-th and j-th data, C is slack variable, d for degree of polynomial kernel function and  $\gamma$  is learning rate.

### 3.3 Evaluation Metrics

To assess decision tree, logistic regression and SVM algorithms, a confusion matrix as shown in Table 1 is generated with four parameters namely, True positive ( $T_P$ ), True Negative ( $T_N$ ), False Positive ( $F_P$ ) and False Negative ( $F_N$ ).  $T_P$  and  $T_N$  refer to the count of data that is correctly identified as normal ovary and cystic ovary in the proposed model.  $F_P$  and  $F_N$  are the count of data that is incorrectly identified as normal ovary and cystic ovary in the proposed model. Using these parameters, five evaluation metrics (accuracy, precision, recall, F1 score and specificity) are calculated as shown in Table 2 to analyse the efficiency of algorithms (Kalaiyarasi et al., 2020; Suganya et al., 2022).

**Table 1** Confusion matrix.

	<b>Real Positive</b>	<b>Real Negative</b>
<b>Predicted Positive</b>	True Positive ( $T_P$ )	False Positive ( $F_P$ )
<b>Predicted Negative</b>	False Negative ( $F_N$ )	True Negative ( $T_N$ )

**Table 2** Evaluation metrics.

Parameters	Formula
Accuracy	$\frac{T_N + T_P}{T_P + T_N + F_P + F_N}$
Precision	$\frac{T_P}{T_P + F_P}$
Recall	$\frac{T_P}{T_P + F_N}$
F1-score	$\frac{2 * Precision * Recall}{Precision + Recall}$
Specificity	$\frac{T_N}{T_N + F_P}$

Receiver Operating Characteristic curve (ROC) is also determined with area under the ROC curve (AUC) to evaluate the classifiers. It maps True Positive Rate (TPR) versus False Positive Rate (FPR) on different threshold values. TPR and FPR are computed using equations (10) and (11), respectively.

$$TPR = \frac{T_P}{T_P + F_N} \tag{10}$$

$$FPR = \frac{F_P}{F_P + T_N} \tag{11}$$

It is an important performance evaluation criterion that measures the effectiveness of a machine learning model. It specifies how capable the model is in classifying data and therefore, depicts the comprehensive performance of the model. A value near to 1 in AUC plot signifies that the model performs better in classification.

#### 4. Results and Discussion

The proposed system is assessed by comparing the results obtained through decision tree, logistic regression and SVM. These algorithms have utilized the textural features extracted from the ultrasound images using fractal dimension texture analysis (FDTA) and local binary patten (LBP). The confusion matrix computed for decision tree, logistic regression and SVM using FDTA and LBP as a single feature are displayed in Tables 3 and 4; and for combined textural features of FDTA and LBP are displayed in Table 5.

**Table 3** Confusion matrix for decision tree, logistic regression and SVM using FDTA.

	Real Positive			Real Negative		
	Decision Tree	Logistic Regression	SVM	Decision Tree	Logistic Regression	SVM
<b>Predicted Positive</b>	125	149	149	24	0	0
<b>Predicted Negative</b>	13	40	34	31	4	10

**Table 4** Confusion matrix for decision tree, logistic regression and SVM using LBP.

	Real Positive			Real Negative		
	Decision Tree	Logistic Regression	SVM	Decision Tree	Logistic Regression	SVM
<b>Predicted Positive</b>	123	143	141	26	6	8
<b>Predicted Negative</b>	16	19	16	28	25	28

**Table 5** Confusion matrix for decision tree, logistic regression and SVM using FDTA+LBP.

	Real Positive			Real Negative		
	Decision Tree	Logistic Regression	SVM	Decision Tree	Logistic Regression	SVM
<b>Predicted Positive</b>	129	145	146	20	4	3
<b>Predicted Negative</b>	12	17	14	32	27	30

Using confusion matrix parameters, the evaluation metrics are calculated for each of these three algorithms and are shown in Table 6. The table displays the performance metrics in relation to single feature FDTA and LBP separately, along with the combined textural features (FDTA + LBP). Using FDTA as a single feature, decision tree has given 80.83% as accuracy, 83.89% as precision, maximum recall as 90.58%, F1score as 87.11% and specificity as 56.36%. Similarly, logistic regression has secured 79.27% in accuracy, maximum precision and specificity as 100%, 78.83% as recall and 88.16% as F1-score. SVM outperforms decision tree and logistic regression in four metrics namely, accuracy (82.38%), precision (100%), F1 score (89.76%) and specificity (100%).

In case of LBP, decision tree has obtained minimum in all the five metrics, accuracy (78.24%), precision (82.55%), recall (88.49%), F1 score (85.42%) and specificity (51.85%). Logistic Regression has come out to be better in two metrics (precision 95.97% and specificity 80.64%). It has achieved 87.05% as accuracy, 88.27% as recall and 91.96% as F1score. SVM has reached 87.56% in accuracy, 89.80% in recall, 92.15% in F1 score as maximum values for LBP. It has attained 94.63% as precision and 77.78% as specificity.

**Table 6** Evaluation metrics for decision tree, logistic regression and SVM.

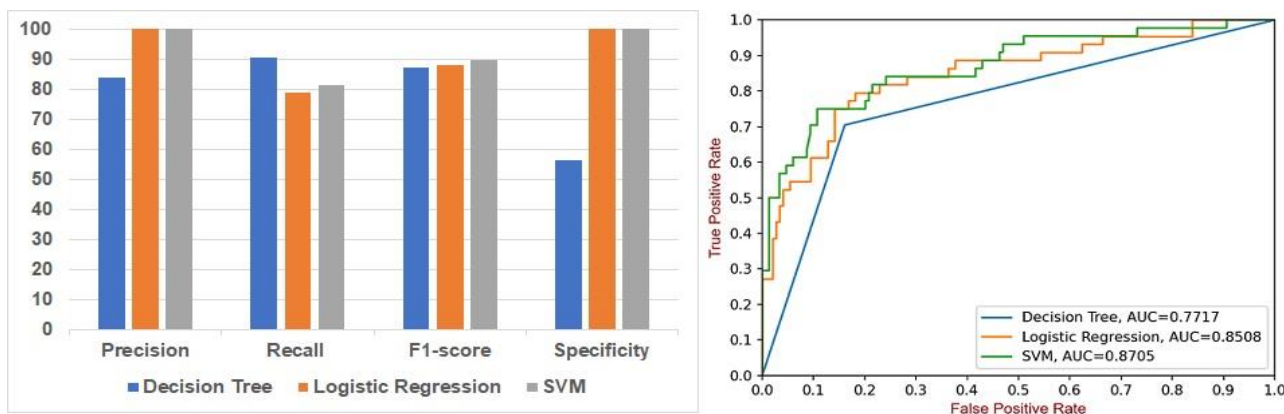
Evaluation Metrics (%)	Fractal Dimension Texture Analysis (FDTA)			Local Binary Pattern (LBP)			FDTA + LBP		
	Decision Tree	Logistic Regression	SVM	Decision Tree	Logistic Regression	SVM	Decision Tree	Logistic Regression	SVM
<b>Accuracy</b>	80.83	79.27	82.38	78.24	87.05	87.56	83.42	89.12	91.19
<b>Precision</b>	83.89	100	100	82.55	95.97	94.63	86.58	97.31	97.98
<b>Recall</b>	90.58	78.83	81.42	88.49	88.27	89.80	91.49	89.51	91.25
<b>F1-score</b>	87.11	88.16	89.76	85.42	91.96	92.15	88.97	93.45	94.49
<b>Specificity</b>	56.36	100	100	51.85	80.64	77.78	61.54	87.09	90.90

Multiple features yield a better method in identification of cystic ovaries from normal ovaries. Thus, the computer aided diagnosis system built on multiple features with one machine learning classifier is explored in detail. The result secured in combination of FDTA and LBP with SVM as classifier has achieved the maximum accuracy. Decision tree has obtained 83.42% as accuracy, 86.58% as precision, 91.49% as recall, 88.97% as F1-score and 61.54% as specificity. Logistic Regression has attained 89.12%, 97.31% 89.51%, 93.45% and 87.09% as accuracy, precision, recall, F1-score and specificity, respectively. SVM has secured 91.19%, 97.98%, 91.25%, 94.49% and 90.90% sequentially. It is evident that SVM has shown best performance in four evaluation metrics (accuracy 91.19 %, precision 97.98%, F1-score 94.49% and specificity 90.90%) and decision tree in one (recall 91.49%). Figure 3 depicts the accuracy performance metric for FDTA, LBP and FDTA + LBP models. The graph clearly delineates that combination of FDTA and LBP textural features performs better than single features. The comparative analysis of remaining performance metrics is represented graphically on left hand side for FDTA in Figure 4, LBP in Figure 5 and FDTA + LBP in Figure 6.

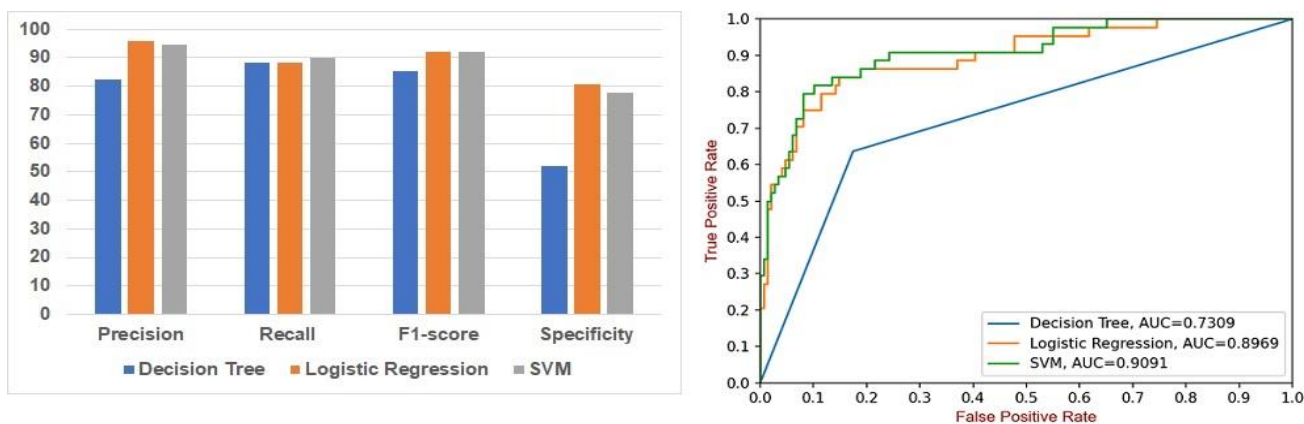


**Figure 3** Accuracy graph analysis for FDTA, LBP and FDTA + LBP.

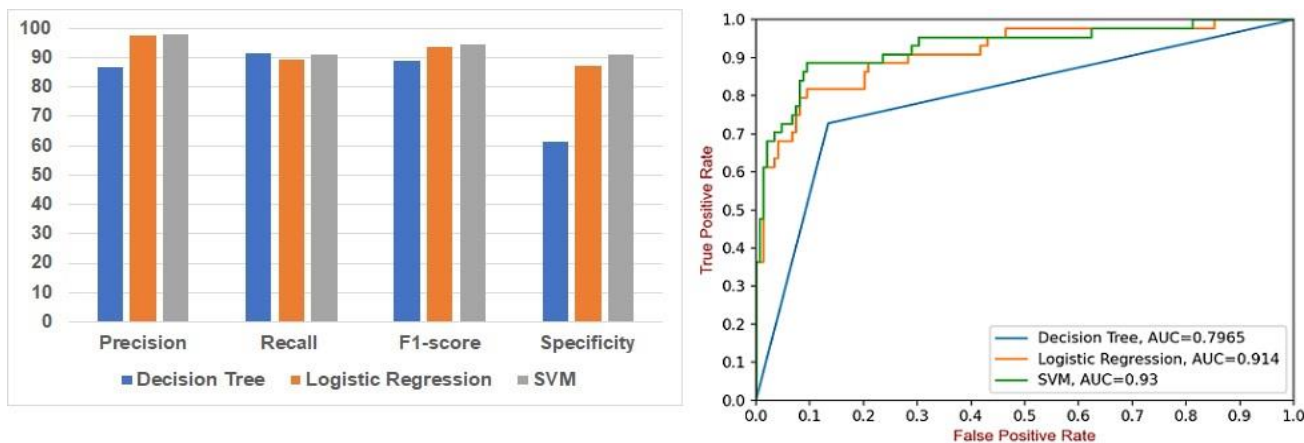
The ROC-AUC curves for decision tree, logistic regression and SVM for ovarian cyst classification for FDTA, LBP and combined feature of FDTA + LBP are shown on right hand side in Figure 4, Figure 5 and Figure 6. For FDTA, SVM has maximum area under curve with value of 0.8705. In case of LBP, the AUC value has increased for both logistic regression (0.8969) and SVM (0.9091) but reduced for decision tree (0.7309) as compared to FDTA value of 0.7717. For hybrid textural features (FDTA + LBP), the area under curve for SVM is 0.93 which is better than decision tree (0.7965) and logistic regression (0.914).



**Figure 4** Comparative analysis in terms of evaluation metrics and ROC-AUC curve for FDTA.



**Figure 5** Comparative analysis in terms of evaluation metrics and ROC-AUC curve for LBP.



**Figure 6** Comparative analysis in terms of evaluation metrics and ROC-AUC curve for FDTA + LBP.

Comparing the experimental results, it is obvious that SVM effectively classifies ovarian ultrasound images as normal and cystic with an accuracy of 91.19% and AUC score of 0.93 using multiple textural features of FDTA and LBP. It has proved to be a productive machine learning algorithm for classification of ovarian cyst from normal ovaries with precision, recall, F1-score and specificity as 97.98%, 91.25%, 94.49% and 90.90%, respectively. Thus, SVM is chosen as the compared machine learning model with other models.

This research further compares the SVM model results with the latest ovarian cyst classification machine learning models mentioned in the literature that considered textural features as a basis for classification in images. A summary of this contrast is shown in Table 7. Wei et al. extracted LBP, GLCM and HOG features from 448 images and achieved 91.11% as classification accuracy. Using ensemble model, Rocha et al. classified images with 85.9% accuracy by extracting features with the help of LBP and convolutional neural network. The SVM model proposed in this research outperforms all other models extracting textural features with an accuracy of 91.19% on 1203 ultrasound images.

**Table 7** Comparison between findings of proposed model with recent machine learning models.

References	Feature Extration	Models	Accuracy (%)
(Wei et al., 2020)	LBP, GLCM and HOG	SVM and Naïve Bayes	91.11%
(Y. C. Chang & Jeng, 2023)	Hurst exponent	Logistic Regression, KNN, Decision Tree and SVM	LR – 83.7%, KNN-81.3%, DT – 82.6%, SVM - 83.9%
(Bayzitov et al., 2023)	LBP	AdaBoost Classifiers with LBP	85.4%
(Rocha et al., 2023)	Hybrid Convolutional Neural Networks (combination of Convolutional Neural Networks and LBP)	Ensemble Model (SVM, Random Forest, KNN, Linear Discriminant Analysis)	85.9%
Proposed Model	FDTA and LBP	SVM	91.19%

## 5. Conclusion

The research suggests a computer aided diagnosis system for early detection of ovarian cyst using machine learning algorithms. The ultrasound images are pre-processed to improve the quality of images to achieve better classification model. They are transformed to grey scale images from RGB scale followed by region of interest extraction to remove complexities from computer aided diagnosis system. For further enhancement, speckle noise is discarded from ultrasound images with the assistance of fast NL filter. Then, 14 textural features are acquired from images using local binary pattern and fractal dimensions. The research has utilized three machine learning algorithms, namely decision tree, logistic regression and SVM to differentiate images having cystic ovaries from normal ovaries. Specificity, F1-score, recall, accuracy, precision and ROC-AUC curve are employed to check the performance of the algorithms. SVM has achieved better performance: accuracy (91.19%),

precision (97.98%), F1-score (94.49%), specificity (90.90%) and AUC (0.93) compared to decision tree and logistic regression. Thus, it can be utilized as a decision tool to help healthcare providers for the classification of ovarian cysts from ultrasound images.

In future, this research can be extended to ascertain similar types of diseases using ultrasound images with better accuracy. It can be additionally expanded by including a greater number of ultrasound images as input and verifying its effect on the overall performance of the computer aided diagnosis system. It may also classify different types of ovarian cysts found in women. This research is certainly beneficial to healthcare providers in providing accurate clinical diagnosis and medical care for patients.

### Acknowledgment

The authors express their gratitude to Dr. Pallavi Goyal for generously providing a collection of anonymized ultrasound images and for offering valuable insights into the medical interpretation of these images.

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