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Automated Detection of Polycystic Ovarian Syndrome Using Follicle Recognition

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***Abstract*—Polycystic Ovarian Syndrome (PCOS) is one of the most common hormonal disorder present in females in reproductive age group. Early detection and treatment of PCOS is important since it is often associated with obesity, type 2 diabetes mellitus, and high cholesterol levels. In this paper, 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. The results obtained are verified by doctors and compared with manual detection. The accuracy obtained for the proposed method is 95%.**

Keywords*—*Polycycstic Ovarian syndrome; Ultrasound Image Processing;Multiscale Morphological Approach; Support Vector Machine Algorithm

I. INTRODUCTION

Polycystic Ovarian Syndrome, or commonly known as PCOS, is one of the most common, complex, heterogeneous endocrine disorders among females of reproductive age. The syndrome was initially described by Stein and Leventhal in 1935[]. The exact cause behind occurrence of PCOS is still unknown but factors such as hormonal imbalance, having body-mass-index (BMI) greater than 24, central obesity or overall obesity are some factors contributing to it. The principal features are anovulation (i.e. absence of menstrual cycle), amenorrhea (irregular menstrual cycle), and ovulation-related infertility; excessive amounts or effects of androgenic (masculinizing) hormones, which results in acne and hirsuitism; and insulin resistance, which is often associated with obesity, type 2 diabetes and high cholesterol levels. The syndrome is generally diagnosed by ovarian ultrasound image showing ovaries having multiple cysts, but it is not the only requirement in all definitions of the disorder. Large variation in the symptoms and severity of the syndrome can be seen among affected women. There are mainly three criteria for diagnosis of PCOS. These are clinical, biochemical, and ovarian ultrasound imaging. The Rotterdam Consensus is currently the most important criteria in diagnosing this condition [6][7]. According to it, a patient may be diagnosed as suffering from PCOS if any two of the following three conditions are seen: (1) Chronic Anovulation or Oligo-ovulation characterized by irregular menstrual cycle, (2) Excess androgen activity characterized by occurrence of acne, hirsuitism, and elevated serum enzymes and (3) Presence of polycystic ovaries seen by gynecologic ultrasound[6].

In case of normal ovary, under influence of right levels of hormones FSH and LH (i.e. Follicle Stimulating Hormone and Luteinizing Hormone), only one follicle grows in size to about 20 mm in diameter, matures and becomes ready for ovulation. In PCOS affected ovary, due to reduced levels of FSH and LH and high levels of prolactine, follicles fail to grow and attain maturity. Thus, in ultrasound image of PCOS affected ovary, large number of small follicles (typically 12 or more and about 2-9 mm in diameter) can be seen distributed along the periphery of the ovary, classically described as ‘necklace formation’[6]. Moreover, the ovarian volume in such patients is typically increased over 10 cm^3 [6]. Figure 1 shows ultrasound image of normal ovary showing only one follicle ready for ovulation. Whereas, figure 2 shows numerous small follicles present along the periphery of the ovary.

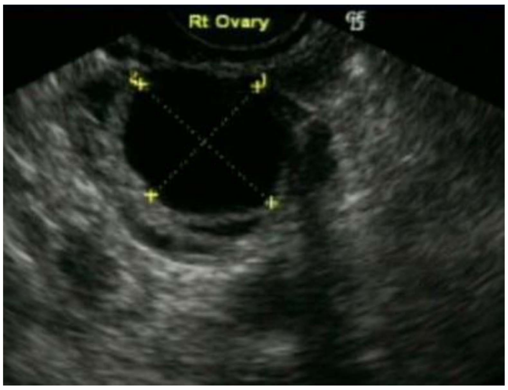

Figure 1: Ultrasound image of normal ovary showing mature follicle ready for ovulation

Figure 2: Ultrasound image of PCOS affected ovary showing large number of follicles distributed along the border of ovary

In this paper, automated detection of PCOS is addressed by combining all the three methods viz. clinical (BMI and cycle length), biochemical (FSH and LH levels) and imaging (calculating number of follicles present in the ovary).

II. Algorithm For Proposed Work

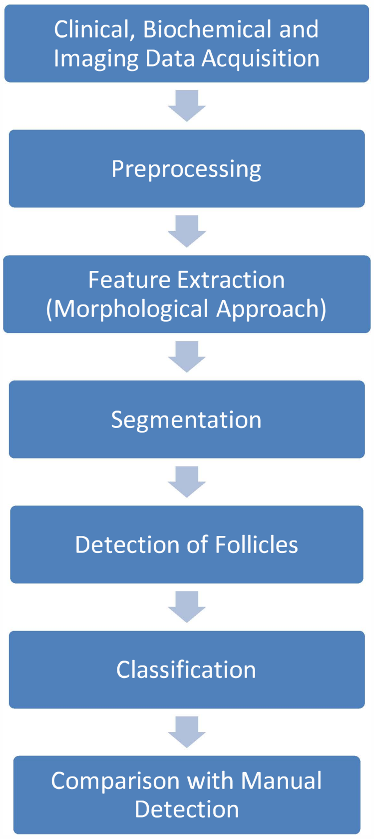

Figure 3: Schematic block diagram for automated PCOS detection

Data Collection is the first and foremost step in this process. Trans-vaginal ovarian ultrasound images of about 20 patients with or without typical PCOS symptoms are collected along with values for BMI, cycle length, post menstrual LH and FSH values. The transducer used for this process is 6 MHz ultrasonic transducer manufactured by General Electric (GE).

Patients having conditions such as Hyperthyroidism or Cushing syndrome are excluded from the study. To improve the quality of the images collected, preprocessing techniques such as contrast enhancement and filtering are applied. Feature extraction is done by multiscale morphological approach using Top-hat transform which extracts dark or bright features from the original image. Segmentation is done by canny edge detection technique. It gives large number of detected follicles from which desired follicles are separated using various threshold values such as maximum and minimum size of the follicle, area, eccentricity and compactness.

Based on number of follicles obtained in above process and clinical and biochemical data collected from doctors, classification is carried out using Support Vector Machine Algorithm (SVM). The results are then compared with that od manual detection to calculate accuracy of the proposed algorithm.

III. Methods and Materials

A. Preprocessing of Ovarian Ultrasound Image

The main disadvantage of medical ultrasonography is poor quality of images having low contrast and high noise content. This makes automated ultrasound image processing a difficult task [5]. Therefore it is necessary to improve contrast of the image and remove noise before further processing such as feature extraction, segmentation and follicle detection. Preprocessing of the input image involves improving quality of the image using contrast enhancement and filtering techniques.

The first step in preprocessing is contrast enhancement. Different global (Histogram Equalization) and local (Adaptive Histogram Equalization and Contrast Limited Adaptive Histogram Equalization) techniques can be used to improve contrast of ovarian ultrasound image. In this paper, Histogram Equalization technique is used. As it is a global contrast enhancement technique, it increases contrast of noise also along with desired features. To remove the additive and speckle noise present in the image, different linear filters such as mean or averaging filter, median filter, Gaussian filter and wiener filter are applied to contrast enhanced image and performances of these filters are analysed based on Signal-to-Noise ratio (SNR). The Signal-to-Noise ratio is calculated as given in equation 1.

$$SNR\ (in\ dB) = 10log_{10}\frac{\sigma^2}{\sigma_e^2} \qquad (1)$$

Where SNR is defined in dB, σ^2 is the variance of original image and σ_e^2 is the variance of enhanced image after filtering [5]. Other parameters such as mean square error (MSE) and root mean square error (RMSE) can also be used for analysis of performance of these filters. .

B. Feature Extraction

In ovarian ultrasound image, apart from follicles, endometrial blood vessels, lymph nodes, nerve fibers and stroma are seen. Therefore, to reduce false detection, feature extraction is done by using Multiscale morphological approach, in this case Top-hat transform. Dark and white features can be extracted from the image and then resulting image is subtracted from original image to get contrast enhanced image.

In this algorithm the Top-hat transformation helps in the extraction of bright (or dark) features from the background by using morphological opening and closing operation of a structuring element respectively[6][7]. The structuring element used in this case is a disk structuring element. The bright top hat transformation is defined as the difference between the input image and its opening by the structural element[13]. On the other hand, black top-hat transform is defined as the difference between closing by same structural element and input image. If $b(x)$ is a structuring element, then bright and dark top-hat transforms can be given as in equation 2 and 3 respectively [13].

$$T_w(f) = f - f \circ b(x) \tag{2}$$

Where '∘' denotes opening operation and f is the image obtained after filtering.

$$T_b(f) = f \bullet b(x) - f \tag{3}$$

Where '•' is the closing operation.

The size or width of the features that are extracted by the top-hat transform can be controlled by the choice of structural element $b(x)$. The bigger the structuring element, the larger the features that are extracted. But both transforms return images that contain only non-negative values at all pixels.

The image is then binarized by assigning pixel value 0 to dark features and 255 to white features. This gives black and white image resulting in clear demarcation of boundaries which is important for further processing such as segmentation and classification to yield accurate results.

C. Segmentation

Image segmentation is used to detect desired features so that the resultant image is easier to analyze. There are different techniques used for image segmentation like edge detection, thresholding, histogram-based methods and watershed transformation. For segmentation of ovarian ultrasound image, different edge detection techniques like Sobel, Prewitt and Canny edge detection can be used.

In edge detection technique, points in image are identified where image brightness changes sharply or has discontinuities, as in image we get after binarization. In binarized image, pixel values at certain points or regions change suddenly from 0 to 255 (i.e. dark to bright) and vice versa. All these points are organized into a set of curved line segments to detect the edges.

The method used here is canny edge detection technique. For this, pixel gradient in x-direction and gradient in y-direction is calculated at each point of the image. The total gradient at that point is a combination of both the gradients. If the calculated gradient is above the set threshold value, edge is detected at that point. On the other hand, if gradient is below threshold, edge is not detected. Deciding threshold value for the application is an important task. If lower threshold value is selected, it results into detection of unwanted false edges. Else is higher threshold value is selected; there can be loss of information.

D. Detection of Important Follicles

Large number of features are detected after binarization and edge detection. To separate out important follicles from detected features, criteria such as maximum and minimum size of follicles, area of follicles, eccentricity and compactness have to be added to the algorithm. As per studied literature, follicular size ranges from 2-9mm in diameter in PCOS affected ovary and about 20 mm in normal ovary [6]. So, considering follicles are circular in share, respective areas will be about 4-80 mm^2 for PCOS ovary and about 314 mm^2 for normal ovarian follicle. As it is assumed that the follicles are circular in shape, eccentricity is almost equal to 1. Considering all these values for threshold, area of each detected region or feature is calculated and number of important follicles detected is found out.

E. Classification

Deciding whether the patient is suffering from PCOS does not depend only on number of ovarian follicles but also depend on clinical and biochemical parameters such as BMI, cycle length, post menstrual FSH and LH. All these parameters along with number of follicles are considered for classification. The values of these parameters for normal and PCOS affected patients are given in table1 (as per data obtained from doctors).

TABLE 1: VALUES OF CLASSIFICATION PARAMETERS FOR NORMAL AND PCOS AFFECTED PATIENTS

Parameters	Normal	PCOS Affected
No. of ovarian follicles	1 Dominant follicle	>8-10
BMI (kg/m^2)	≤ 24	> 24
Cycle Length (Days)	28-32	>32
LH (IU/L)	2-8	>8
FSH (IU/L)	2-5	>5

The feature or parameter can be used for classification only if it has significantly distinct values for normal and PCOS affected patients. For this, kernel density plot (or box plot) is drawn and it is verified that mean values for both classes (normal and PCOS) is well separated and there is minimum overlap.The technique used for classification is Support Vector Machine (SVM) algorithm. In this method, the data points are classified into two groups (normal and PCOS) by a linear hyperplane. The hyperplane is optimized such that it is at the maximum distance (margin) from each data point. The data points/vectors which are closest to hyperplane are called support vectors. The data points/vectors which are greater than PCOS support vectors are classified as PCOS cases and those which are less than normal support vectors are classified as normal cases.

IV. EXPERIMENTAL RESULTS

Clinical, biochemical and imaging data is collected for 20 patients. Ovarian ultrasound images are obtained using 6MHz ultrasound transducer from General Electric. The image is cropped to get desired area. Then histogram equalization algorithm is applied to get a contrast enhanced image. For denoising, linear filters, viz. averaging filter, median filter, Gaussian filter and Wiener filter are applied one by one and signal-to-noise ratio is calculated for each filtered image by equation 1. Figure 4 shows original image along with its histogram and contrast enhanced image by application of histogram equalization algorithm. Figure 5 shows output images after application of different filters.

Signal-to-noise ratios (SNR) are calculated for original image and for each filtered image and results are obtained as shown in table 2. From this, we can deduce that wiener filter is the most suitable choice for reduction of noise in ovarian ultrasound image. The Wiener filtered image is used for further processing.

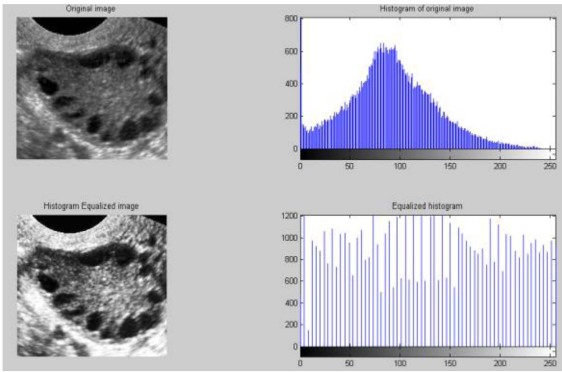

Figure 4: Preprocessing stage I- Contrast Enhancement

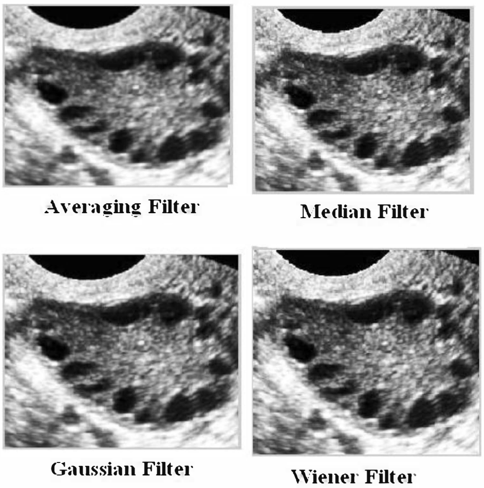

Figure 5: Output images after filtering

TABLE 2: PERFORMANCE ANALYSIS AND COMPARISON OF DIFFERENT FILTERS BASED ON SNR

Image/filtered image	Signal-to-noise ratio (SNR) in dB
Original image	1.9350
Averaging filter	4.0058
Median filter	4.2470
Gaussian filter	4.1546
Wiener filter	4.2597

Feature extraction by bright top-hat transformation is done followed by Binarization which results into clear demarcation of follicle boundaries. Edges of follicles are detected using canny edge detection algorithm which results into automated detection of follicles in an ultrasound image.

Area of each detected feature is calculated by counting the number of 1s in binarized image. This area is in pixels. It is converted to mm^2 and features or regions having areas less than 4 mm^2 are excluded. Further, Number of regions is calculated having area between 4 mm^2 to 80 mm^2 (PCOS follicles) and those having area greater than 340mm^2 (Normal follicles) as explained in section 3(D). Eccentricity and compactness is checked for all the follicles and verified that they are in the desired range. Figure 6 shows extraction of bright features by morphological approach, binarized image, and detection of important follicles.

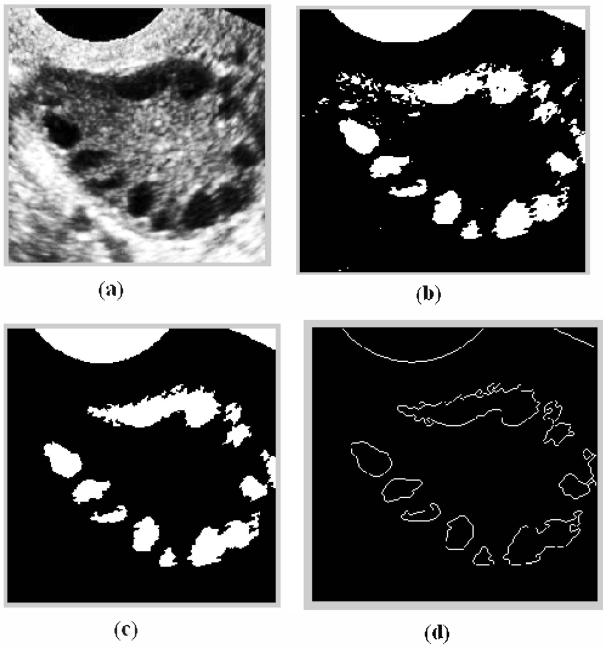

Figure 6: (a) Image obtained after feature extraction using bright top-hat transform (b) Image obtained after binarization (c) Image obtained for important follicle detection (c) Follicular boundaries detected after canny edge detection

For deciding whether BMI, cycle length, FSH and LH can be used for classification, kernel density plot for all the four parameters is drawn. It can be seen that mean values for both normal and PCOS cases are very distinct and overlap is minimum. Figure 7 and 8 shows representative kernel density plot of BMI and LH respectively.

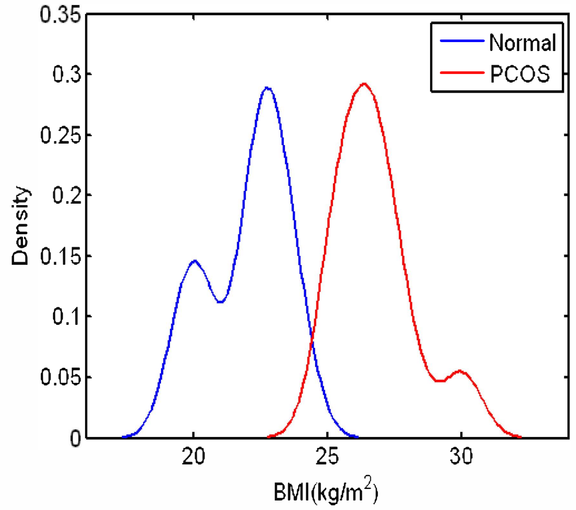

Figure 7: Kernel Density plot for BMI

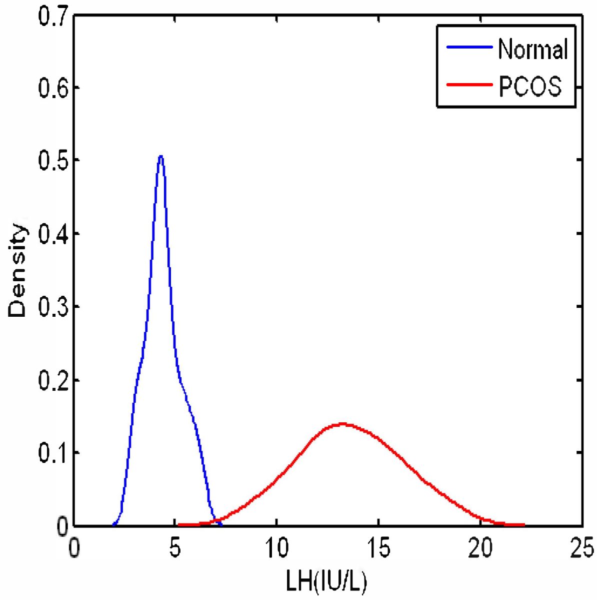

Figure 8: Kernel Density plot for LH

The clinical and biochemical data (BMI, cycle length, post menstrual FSH and LH values) and number of follicles detected in above process are used for classification using SVM algorithm. Figure 9 shows representative SVM plot for classification using BMI and LH values.

Among the data for 20 patients, data for first 15 patients are used for training the SVM algorithm and classification of next 5 data sets is done. The process is repeated for data set of all the patients and using different training sets, classification of each data set is carried out. The results obtained are compared with those obtained by manual classification and from doctors. It is seen that accuracy of this algorithm is about 95%. Table 3 shows results obtained for classification of data of patient no 16-20 when first 15 are used as training set.

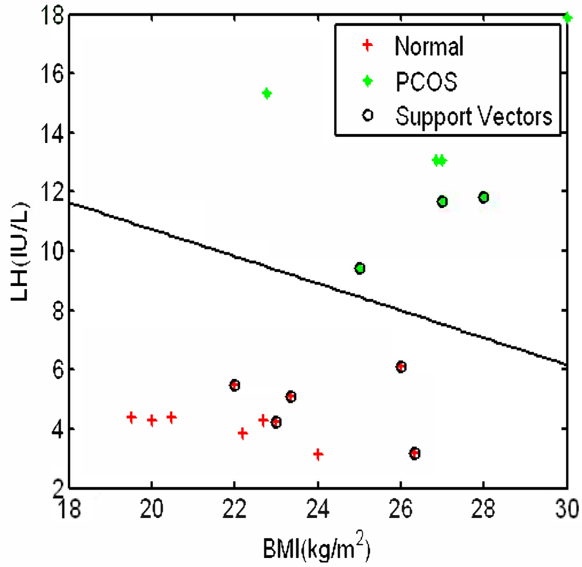

Figure 9: Classification using SVM

TABLE III: RESULT OF CLASSIFICATION

No.	BMI	Cycle Length	FSH	LH	Follicles	Result
1.	26.87	38	5.76	13.08	7	PCOS
2.	20.47	26	3.4	4.4	1	Normal
3.	26.34	32	3.98	3.18	2	Normal
.	22.69	28	1.78	4.28	1	Normal
5.	25.39	36	6.07	15.66	10	PCOS

V. CONCLUSION

In this paper, we have tried to develop an automated method for Polycystic Ovarian Syndrome (PCOS) detection using follicle recognition and classification using SVM. Image preprocessing (contrast enhancement and filtering) is used for improving quality of the image. Features are extracted using Multiscale morphological approach and bright top-hat transform. The image is binarized and segmented using canny edge detection technique. Important follicles are separated from other regions using area and eccentricity threshold. Classification of all the data (clinical, biochemical and imaging) is done using Support Vector Machine (SVM) algorithm. The results are compared with that obtained from manual classification and from doctors. Accuracy of the method is about 95%. Thus, this algorithm can be effectively used for automatic screening of PCOS patients.

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