Asian Journal of Engineering and Applied Technology
ISSN: 2249-068X (P) Vol. 7 No. 2, 2018, pp. 46-51

DOI: https://doi.org/10.51983/ajeat-2018.7.2.1008

Detection of Polycystic Ovarian Syndrome: A Literature Survey

A. Saravanan[1] and S. Sathiamoorthy[2]
[1&2]Assistant Professor, Division of Computer and Information Science,
Annamalai University, Annamalai Nagar, Tamil Nadu, India
E-Mail: sarancseau@gmail.com
(Received 6 June 2018; Revised 30 June 2018; Accepted 22 July 2018; Available online 30 July 2018)

***Abstract* - Polycystic ovarian syndrome is an endocrine issue attacking ladies at the age of reproduction. This indication has primarily found in ladies whose age is in the middle of 25 and 35. It is essential to diagnose and recognize diverse types of ovulatory failure that can add to infertility. There are numerous clarifications for ovulation failure. Without distinguishing the correct locality of the follicle, the risk seriousness of the patient can't reveal. In line with this, many of the researchers focusing their research interest in PCOS. In this paper, literature review on polycystic ovarian syndrome using machine learning and image processing has exhibited.**
***Keywords:* Polycystic Ovarian Syndrome, Machine Learning, Denoising, Segmentation, Threshold**

I. INTRODUCTION

The Polycystic Ovary Syndrome (PCOS) is a complicated heterogeneous endocrine issue [1-10] related with long haul absence of hyperandrogenism and ovulation, influencing 5-10% of ladies in the pubertal just as reproductive age. Most ladies with PCOS develop numerous little cysts with ovaries. The cysts lead to hormone lopsided characteristics. Side effects of PCOS incorporate hypertension, menstrual dysfunction, hirsutism, infertility, obesity and acne. Thus, PCOS has been accepted as territory of clinical need and as a general medical problem around the world. Still the reason for PCOS is not known but literature reports that genetic factor with gestational environment or lifestyle factors or both might be the reason for PCOS [11]. The polycystic ovary syndrome leads to infertility [12].

However, early determination and treatment can reduce the side effects and avert long term issues. The PCOS image is gained by ultrasonography or ultrasound imaging since ultrasound images are non-obtrusive and more affordable contrasted with other therapeutic imaging strategies. The morphology of PCOS is described by the nearness of at least 12 ovarian follicles and are in 2-9 mm, and/or total ovarian volume [3] of more than 10 cm.

Notwithstanding, manual recognizable proof of follicles may cause a few issues, for example, additional time is required for recognition of the follicles, intra and inter-observer fluctuation and some of the time they can disregard follicles of under 2mm sizes, which could truly influence ladies health. One of the main focuses of interest in image processing and computer vision is medical imaging. With an improvement of technology, along with increasing size and resolution of the images, volume of medical images also increased. Today three dimensional or four-dimensional images are also used in medical image analysis which insists the researchers that much more effort needs to be taken along this direction of research to accurately identify the diseases. Even minute textural variations in ovarian stroma, ovarian size and distribution of characteristic follicles patterns are playing vital role in the accuracy of diagnostic [13].

Researchers used Ultrasound imaging method [3] for the identification of PCOS as it is cheap and is so effective for cyst identification. However, an ultrasonic image may comprise noises due to lack of air gap or individual contact among body part and transducer. Noises can be produced through the beam forming process or signal processing. The noises may create the image dimmed and through evidence to poor segmentation. Therefore, researchers working in this domain also focus their interest on denoising techniques also. In common, image denoising, enhancement, segmentation, feature extraction and classification are the processes involved in follicle detection.

II. LITERATURE SURVEY

In [8], Sarty *et al.*, presented a technique for automatically identifying outer follicle wall boundaries in ultrasound ovary images. Prior knowledge about edge direction and strength, knowledge of follicle wall and typical follicle shapes are used for analysis of ovary image. In [8], the follicle in which the physician is interested is segmented then and features like size of follicle, root mean square deviations of fluid signal, or wavelet packet energy are calculated for the detection of disease.

Survey on ovary image analysis is reported by Singh et al., in [9] in which line analysis, spot analysis, mathematical modeling, wavelet packet texture analysis and region analysis methods have been discussed. The authors reported that aforesaid methods have drawbacks.

In [10], denoising using soft threshold method and contrast enhancement is performed. By employing fuzzy c-means clustering algorithm, denoised images are categorized to recognize the cysts.

In [12], a detailed review on identification of PCOS has been carried out. They also performed a comparative study and deep analysis on PCOS detection using the various combinations of techniques proposed in the literature. [12] reported that Adaptive morphological filter moderates the speckle noise by discouraging the fluctuations of pixel values and the morphological filter transforms the image size, and the region growing algorithm stretches a vibrant edge and gives good segmented result but it requires manual interaction and if an automatically seeded region is employed, this algorithm will be more operative. As a result, denoising and segmentation of ultrasound images to enhance the identification rate of follicles, potentials the essential for research.

In [14], denoising of ultrasound images of ovary is done by with Homogeneous Region Growing Mean Filter then edge is found using the Kirsch's operator then area, compactness and eccentricity are the parameters used to frame a rule to detect follicles. The inner walls and outer walls of follicles in ovary is detected from ultrasound images using watershed segmentation technique and knowledge based graph search approach [15] and it is reported that over segmentation is performed by watershed method.

Viher *et al.,* [16] used Cellular Automata for follicle identification in ultrasound ovary image. Cellular Automata is separated into 2 stages to solve the detection issue. Each object in the image was able to establish an „immune system" that characterized object features at its boundary cells in the first phase. In the second phase, there was a massive attack on the established "immune systems". The attack was able to destroy all the phantom follicles and the real follicles were left untouched. The drawback was that the approach had large computational complexity.

Cellular Neural Network (CNN) is used in [17] in which the dominant follicle are detected first by successive connected CNN; the first CNN estimated the rough position of the follicle then expanded the detected follicles to the border then the positions of the recessive follicles are identified by using CNN, the results are combined to differentiate the real and phantom follicles.

A novel approach for differentiating the normal and polycystic ovary is reported by Lawrence et al., in [18]. The authors adopted region growing algorithm for segmentation operation then from the segmented follicles they computed volume density, surface density, number of follicle regions per image, maximum follicle diameter and mean follicle diameter and these features are combined to form a feature vector. The k nearest neighbor, linear discriminant and SVM are used in the classification stage. The authors reported that linear discriminant approach attaints best classification rate.

A system for complete automatic follicle quantification in 3D ultrasound data is proposed in [19]. They suggested framework based on size and location of each separate ovarian follicle by fusing data from global as well local level. The ovarian follicles are segmented using a database guided segmentation approach. A clustered marginal space learning technique is adopted to proficiently explore the hypothesis in high dimensional space for multiple object detection. The authors [19] reported that the suggested approach is proficient to recognize and segment ovarian follicles with high robustness and accuracy, and also much faster than the existing ultrasound manual workflow.

Hiremath and Tegnoor [20] employed Gaussian low pass filter and contourlet transforms for removing the speckle noise from the ultrasound ovary images. In order to segment the image canny edge detector is used. In addition to that major axis and minor axis length are computed and these two features are used to frame a set of rules to classify the identified regions as either follicles or non-follicles. The authors reported that 75.2% of follicle detection rate is attained with contourlet transform whereas the Gaussian low pass filter method produces 62.3% of follicles detection rate.

In [21], in the preprocessing phase, to decrease speckle noise Wiener filter is adopted then they perform negative transformation, histogram equalization and morphological operations to obtain the denoised image. Then, active contour without edge approach is used to obtain the segmented output. Finally from the segmented output the texture features like contrast, correlation, energy and homogeneity are computed by utilizing the grey-level co-occurrence matrix. The computed texture features are classified into follicles and non-follicles using the multi-layer perceptron neural network.

Yinhui Deng *et al.,* [22] suggested an automated system for PCOS diagnosis on ultrasound images in which adaptive morphological filter is adopted to eliminate the speckle noise, improved labeled watershed algorithm is employed to compute contours of objects then object growing approach is used to identify the follicles based on the cost map and it is compared boundary vector field, level set method and fuzzy SVM for 31 ultrasound images of PCOS.

Bian *et al.,* [23] computed texture features using gray level co-occurrence matrix from the manually selected follicles to discriminate the dominant follicles.ian et al., is differentiating the follicles of women using oral contraceptive and follicles during natural cycle, and deciding when these two follicles show difference during their growth. In [23], to choose the regions of follicle walls both automatic and manual contouring methods are used and the pixel values of contour are used as threshold for segmentation operation. From the segmented follicle, totally 14 features including the homogeneity, contrast, correlation, energy, etc. are computed from the gray-level occurrence matrix. Then the authors computed edge contrast and edge density based the measure of edge frequency. The authors also computed Law's texture feature for improving the discrimination ability of the proposed feature descriptor. For classification the authors used MATLAB 7's classify() function and the authors reported that the combination of edge contrast, edge density, homogeneity and energy features of gray level co-occurrence matrix attains 100% accuracy.

In [24], a review on detection of PCOS has been carried out by Saranya and Maheswari. They also performed a comparative study and deep analysis on PCOS detection using the various combinations of techniques proposed in the literature.

Fully computerized segmentation technique based on active contours without edge technique for effective classification of PCOS is explored by Chen et al., in [25] for 3D ultrasound images. In [25], the location and size of the follicle is computed automatically by combining information from both local and global circumstances using a new probabilistic framework then the identified follicles are segmented using database guided graph cut segmentation. Afterwards, clustered marginal space learning method is used to effectively identify the multiple object detection. In [25], the proposed system is evaluated using 501 ovarian volumes consisting either right or left ovary of women and totally 8108 follicles are there and reported that their approach is first to fully automatic identification and segmentation of ovarian follicles in 3D ultrasound volumes.

Acharya *et al.,* [26] suggested an automatic approach for accurately classifying ultrasound images of ovarian tumors into benign and malignant in which they used local binary pattern, laws texture energy, entropy and Hu invariant moments for computing 16 texture features and for classification they employed support vector machine with radial basis function as kernel, and reported that they attained high accuracy using 1000 benign and 1000 malignant images.

Acharya *et al.,* [27] used standard deviation, fractal dimension, gray-level co-occurrence matrix, run length matrix and higher order statistics texture features which results in 729 features and they adopted Students *t* test to choose the unique features and employed decision tree as classifier to effectively classify the lesions into benign and malignant.

Hiremath and Tegnoor [28] proposed a method for detecting the ovarian follicles they employed Gaussian low pass filter to remove speckle noise and edge based segmentation approach is employed to identify the ovarian follicle and the classification is done using the 4σ intervals around mean feature values and the authors reported that the fusion of various aforesaid methods achieves better accuracy for the detection of follicles.

The authors in the paper [29], highlighted an pioneering method for automated computerized approach for pre-processing, active contours without edge for segmenting region of interest and fuzzy logic for classification. The method proposed in [29] identifies the follicles and also count number of follicles and they classified the ovary as PCOS and not PCOS more effectively then the state-of-art techniques.

Sandy Rihana *et al.,* [30] suggested an automated system for classification of cysts in ovary and reported that their approach attains an accuracy of 90% for ultrasound images.
In [30], top and bottom hat morphological operations are carried out for contrast enhancement. The top hat results in original image minus morphological opening of image and the second one is the original image minus morphological closing of image. Since conventional edge detection techniques failed in producing better results owing to noise included in the medical images captured and pixel values in the follicle are more are less equal and it seems to be homogeneous region, horizontal and vertical scanline thresholding approach is used in [30] and the results of both of those approaches are combined to obtain better quality in results and it results in binary image in which unnecessary component are removed. Since, detection of cyst is based on number of follicle, size of follicle and location follicle in an ovary, the authors combined both geometrical and texture features for analyzing the images. The features like area, minor axis length, major axis length, ratio of minor axis length and major axis length, centroid and compactness extent are used in [30]. In order to predict the disease, the computed feature vectors are classified using the linear separate vector machine and the results are verified using receiver operating characteristics analysis in which sensitivity and specificity is used.

In [31], to measure the visual difference, images are transformed into L*a*b* colour space then discrete wavelet transform is used for removing speckle noise and is followed by k-means clustering method for segmentation, and to detect the edges they used Laplacian of Gaussian edge operator to identify the edges of follicles more effectively.

In [32], in the preprocessing phase, to decrease speckle noise Wiener filter is adopted then they perform negative transformation, histogram equalization and morphological operations to obtain the denoised image. Then, active contour without edge approach is used to obtain the segmented output. Finally from the segmented output the texture features like contrast, correlation, energy and homogeneity are computed by utilizing the grey-level co-occurrence matrix. The computed texture features are classified into follicles and non-follicles using the multi-layer perceptron neural network.

In [33], it is reported that 2D endovaginal imaging is significantly better image in ovary follicles than the 2D transabdominal ultrasound and 3D/4D volumetric study is less used in non-obstetrical trans-abdominal exploration and can provide data comparable to 2D endovaginal imaging providing a good quality image which leads to an accurate evaluation of micro-polycystic and multi-follicular stages in adolescents.

Bedy Purnama *et al.*, [34] presented an approach based on follicle detection for classification of PCOS in which low pass filter, histogram equalization, binarization and morphological operations are performed in preprocessing phase then the follicles are extracted using the segmentation based on contours, and Gabor wavelet is applied to compute mean, variance, entropy, skewness and kurtosis features and are classified using the k-nearest neighborhood, learning vector quantization method and support vector machine with radial basis function as kernel, and reported that support vector machine with radial basis function attains better results for classification of PCO and non-PCO follicles.

Saranya *et al.*, [35] introduced variance of the standard particle swarm optimization named adaptive particle swarm optimization for identifying the follicle. By using the adaptive particle swarm optimization, optimal threshold value computed and is used for follicle segmentation. In order to compute the optimal threshold value, they modified the Ostu method.

Untari *et al.*, [36] suggested Gabor Wavelet based feature estimation method and used a modified backpropagation method for follicle classification. They introduced Levenberg - Marquardt optimization and Conjugate Gradient - Fletcher Reeves to increase the convergence rate in the backpropagation algorithm and they found that the though the proposed modified approach consume more time than the existing approach, it achieve better accurate results than the Conjugate Gradient.

Rajendran *et al.*, [37] described a new approach called Pigeon Inspired Optimization (PIO) to compute optimal threshold value and which will be used for segmenting the follicles from the ovary and they reported that the proposed approach is suggestively good than the invasive weed optimization method. To find out the optimized threshold value, they maximized the between class variance of modified Otsu technique.

Setiawati *et al.*, [38] suggested an automatic system for detecting the follicles from the ovary based on a novel non-parametric fitness function based Particle Swarm Optimization and supervised learning approach. In the experiments they found that the proposed fitness function obtains better convergence and they used Logistic Regression, Support Vector Machine and Backpropagation Neural Networks for classification. They conclude that the proposed combination of novel Particle Swarm Optimization and back propagation attain better results for follicle detection.

Neetha and Kavitha reviewed the various causes of PCOS and various data mining approches incorporated for identifying the PCOS and non PCOS in [39].

Dewi *et al.*, [40] proposed a automatic system for follicle identification based on Gabor wavelet based feature estimation method and Competitive Neural Network which is the combination of Hemming Net and Max Net and such a combination leads to better classification rate.

Kumar *et al.*, [41] suggested median filter and histogram equalization for image preprocessing of Ultrasound imaging of ovaries and they performed a comparative analysis of particle swarm optimization, chaotic particle swarm optimization, pigeon, inspired optimization and Gaussian pigeon inspired optimization algorithms, and they adopted Dice and Jaccard coefficients for measuring the similarity. The authors conclude that Gaussian pigeon optimization approach performs better for PCOS detection than other approaches considered in their study. Though so many researches has been taken in the past by many of the researches in the past, still they have reported around 90-95% of accuracy and it is because of the lack of appropriate techniques in image preprocessing and failure in accurate segmentation of follicles in ovary.

Thufailah *et al.*, [42] Proposed an approach for identification of PCOS based on Gabor based features and Elman Neural Network which encompasses context layer to recall the previous state and is reported that it acquires better results than the existing methods.

Narayan *et al.*, [43] described a novel approach for identifying and segmenting follicles in 3D ultrasound images. The method proposed in [43] is fully automated and it adopted noise-robust phase symmetry feature map for the detection of follicles and for segmentation it employs Max-flow approach, and for post processing the results it used weighted distance transform. The authors reported that they achieved 90% true positive detection rate.

III. CONCLUSION

Polycystic Ovary Syndrome is the common endocrine disorders for women in their reproductive age and it is characterized by the follicles in ovary. Ovarian follicles can be detected using ultrasound images of ovaries, which is more challenging task for the researchers working in this domain due to number of reasons like noise, improper segmentation, etc. In the literature number of automated systems has been reported for the detection of Polycystic Ovary Syndrome and non Polycystic Ovary Syndrome. However, still the accuracy of the automated systems needs to be improved. The present computer vision and data mining techniques adopted for the analysis of Polycystic Ovary Syndrome is not sufficient. So new methods for feature computation and representation, or various combinations of existing features need to be identified as well an effective denoising, segmentation and classification methods need to be identified in future to bring the research in correct direction which will give better results in automatic identification of Polycystic Ovary Syndrome and non Polycystic Ovary Syndrome.

REFERENCES

[1] IF Stein, ML Leventhal, "Amenorrhea associated with bilateral polycystic ovaries", *Am J Obstet Gynecol*, pp.181–191, 1935.

[2] P.S. Hiremath and J.R. Tegnoor, "Automated detection of follicle in ultrasound images of ovaries uses edge based method," *Recent trends in image processing and pattern recognition (RTIPPR'10),* pp. 120-125, 2010.

[3] M. J. Lawrence, R.A. Pierson, M.G. Eramian, E. Neufeld, "Computer assisted detection of polycystic ovary morphology in ultrasound images," *In Proc. IEEE Fourth Canadian conference on computer and robot vision (CRV'07),* pp. 105-112 , 2007.

[4] L. Farah, A. J. Lazenby, L. R. Boots, R. Azziz, "Prevalence of polycystic ovary syndrome in women seeking treatment from community electrologists", *Alabama Professional Electrology Association Study Group, J Reprod Med*, 44, pp.870–874, 1999.

[5] Chris C. J. Kelly, Helen Lyall, John R. Petrie, Gwyn W. Gould, John M. C. Connell, And Naveed Sattar, "Low Grade Chronic Inflammation in Women with Polycystic Ovarian Syndrome", *The Journal of Clinical Endocrinology & Metabolism*, pp. 2453-2455, 2001.

[6] D. Cibula, R. Cifkova, M. Fanta, R. Poledne, J. Zivny and J. Skibova, "Increased Risk of non-insulin dependent diabetes mellitus, arterial hypertension and coronary artery disease in perimenopausal women with a history of the polycystic ovary syndrome", *Human Reproduction*, Vol. 15, No. 4, pp.785-789.

[7] E.M. Velazquez, Soaira Mendoza, Tracy Hamer, Felix Sosa, C. J. Glueck, "Metformin Therapy in Polycystic Ovary Syndrome reduces hyperinsulinemia, insulin resistance, hyperandrogenism, systolic blood pressure, while facilitating normal menses and pregnancy", May 1994.

[8] G. E. Sarty, W. Liang, M. Sonka, and R. A. Pierson, "Semiautomated segmentation of ovarian follicular ultrasound images using a knowledge-based algorithm", *Ultrasound in Med and Biol,* Vol. 24:27–42, 1997.

[9] J. Singh, G. P. Adams, and R. A. Pierson. Promise of new imaging technologies for assessing ovaian function. Animal Reproduction Science, Vol. 78:371–399, 2003.

[10] Ashika Raj, "Ovarian Follicle Detection for Polycystic Ovary Syndrome using Fuzzy C Means Clustering", *International Journal of Computer Trends and Technology*, pp. 2146-2149, July 2013.

[11] Robert J Norman, Didier Dewailly, Richard S Legro, Theresa E Hickey, 2007. Polycystic ovary syndrome.

[12] Adiwijaya *et al., J. Phys.: Conf. Ser.* 622 012027, 2015.

[13] Amma Kyei-Mensah, Jamal Zaidi, Stuart Campbell, "Ultrasound diagnosis of polycystic ovary syndrome", *Baillière's Clinical Endocrinology and Metabolism,* Vol. 10, No. 2, pp. 249-262, 1996

[14] B. Potocnik, D. Zazula, and D. Korze, "Automated Computer-Assisted Detection of Follicles in Ultrasound Images of Ovary", *Journal of Medical Systems,* Vol. 21, No. 6, pp. 445- 457, 1997.

[15] Krivanek, A. and Sonka, M, "Ovarian Ultrasound Image Analysis: Follicle Segmentation", *Medical Imaging, IEEE Transactions on,* Vol. 17, No. 6, pp. 935-955, 1998.

[16] B. Viher, A. Dobnikar, and A. Zazula, "Cellular Automata and Follicle Recognition Problem and Possibilities of Using Cellular Automata for Image Recognition Purposes*", International Journal of Medical Informatics,* Vol. 49, pp. 231–241, 1998.

[17] B. Potocnik, B. Cigale, and D. Zazula, "The XUltra Project – Automated Analysis Ovarian Ultrasound Images", *In Computer-Based Medical Systems, (CBMS), Proceedings of the 15th IEEE Symposium,* pp. 262-267, 2002.

[18] Lawrence, M. J., Eramian, M. G., Pierson, R. A. and Neufeld, E, "Computer Assisted Detection of Polycystic Ovary Morphology in Ultrasound Images", *Fourth IEEE Canadian Conference on Computer and Robot Vision (CRV),* Vol. 7, pp. 105- 112, 2007.

[19] T. Chen, W. Zhang, S. Good, K. S. Zhou, and D. Comaniciu, "Automatic Follicle Quantification from 3D Ultrasound Data Using Global/Local Context with Database Guided Segmentation", *In Computer Vision, IEEE 12th International Conference,* pp. 795-802, 2009.

[20] P. S. Hiremath and Jyothi R. Tegnoor, "Automatic Detection of Follicles in Ultrasound Images of Ovaries using Edge based Method", *IJCA Special Issue on Recent Trends in Image Processing and Pattern Recognition*, pp. 120-125, 2010.

[21] P. S. Hiremath and Jyothi R. Tegnoor, 2010. "Automatic Detection of Follicles in Ultrasound Images of Ovaries using Active Contours Method", *IEEE International Conference on Computational Intelligence*

[22] Yinhui Deng, Yuanyuan Wang , Yuzhong Shen, "An automated diagnostic system of polycystic ovary syndrome based on object growing", *Artificial Intelligence in Medicine,* Vol. 51, No. 3, pp. 199-209, 2011.

[23] N. Bian, M. G. Eramian, and R. A. Pierson, "Evaluation of Texture Features for Analysis of Ovarian Follicular development", *Med Image Comput Comput Assist Interv,* pp. 1- 11, 2011.

[24] R. Saranya, and S. Uma Maheswari, 2012, "A Literature Review on Computer Assisted Detection of Follicles in Ultrasound Images of Ovary", *International Journal of Computer Applications,* pp. 38-41.

[25] Terrence Chen, Wei Zhang, Sara Good, Kevin S. Zhou and Dorin Comaniciu, "Automatic Ovarian Follicle Quantification from 3D Ultrasound data using Global/Local with database Guided Segmentation", pp. 1-8, 2012.

[26] U. Rajendra Acharya, Vinitha Sree Subbhuraam, Muthu Rama Krishnan Mookiah, "Luca Saba, ovarian Tumor Characterization Using 3D Ultrasound", *Technology in cancer research & treatmen*t, Vol. 11, No. 6, 2012.

[27] U. Rajendra Acharya, S. Vinitha Sree,Luca Saba, Filippo Molinari, Stefano Guerriero, and Jasjit S. Suri, "Ovarian Tumor Characterization and Classification Using Ultrasound- A New Online Paradigm", *J Digit Imaging,* Vol. 26, No. 3, pp. 544–553, 2013.

[28] P. S. Hiremath and Jyothi R. Tegnoor, "Automated Ovarian Classification in Digital Ultrasound Images", *International Journal of Biomedical Engineering and Technology*, pp. 46-65, 2013.

[29] S. Hiremath and Jyothi R. Tegnoor, "Automated Ovarian Classification in Digital Ultrasound Images", *International Journal of Biomedical Engineering and Technology*, pp. 46-65, 2013.

[30] Sandy Rihana, Hares Moussallem, Charles Yaacoub, "Automated algorithm for ovarian cysts detection in ultrasonogram", *2nd International Conference on Advances in Biomedical Engineering,* DOI: 10.1109/ICABME.2013.6648887, 2013.

[31] V. Kiruthika, and M. M. Ramya, "Automatic Segmentation of Ovarian Follicle Using K-Means Clustering", *Fifth International Conference on Signals and Image Processing,* pp. 137-141, 2014.

[32] A. D. Usman, O. R. Isah and A. M. S. Tekanyi, "Application of Artificial Neural Network and Texture Features for Follicle Detection", *African Journal of computing and ICT,* pp. 111-118, December 2015.

[33] Bedy Purnama, Untari Novia Wiseti, Adiwijaya, Fhira Nhita, Andini Gayatri and Titik Mutiah, "A Classification of Polycystic ovarian Syndrome Based on Follicle Detection of Ultrasound Images", *3rd International Conference on Information and Communication Technology*, pp. 399-403, 2015.

[34] Bedy Purnama, Untari Novia Wisesti, Adiwijaya, Fhira Nhita, Andini Gayatri, Titik Mutiah, "A classification of polycystic Ovary Syndrome based on follicle detection of ultrasound images", *3rd International Conference on Information and Communication Technology (ICoICT),* Nusa Dua, Bali, 2015.

[35] R. Saranya, Maheswari, S. Uma, "Follicle Detection in Ovary Image Using Adaptive Particle Swarm Optimization", *Journal of Medical Imaging and Health Informatics,* Vol. 6, No. 1 pp. 125-132, February, 2016.

[36] Untari N. Wisesty, Jondri Nasri, Adiwijaya, "Modified Back propagation Algorithm for Polycystic Ovary Syndrome Detection Based on Ultrasound Images", *International Conference on Soft Computing and Data Mining (SCDM 2016: Recent Advances on Soft Computing and Data Mining,* pp. 141-151.

[37] Rajendran, Saranya; M. Sankareswaran, Uma, "A Novel Pigeon Inspired Optimization in Ovarian Cyst Detection", *Current Medical Imaging Reviews,* Vol. 12, No. 1, pp. 43-49, February 2016.

[38] Setiawati, Eni; Adiwijaya, Wirayuda, A. B. Tjokorda, Astuti, Widi, "Classification of Polycystic Ovary Syndrome Based on Ultrasound Images Using Supervised Learning and Particle Swarm Optimization", *Advanced Science Letters,* Vol. 22, No. 8, August 2016, pp. 1997-2001.

[39] Neetha Thomas and A. Kavitha, "A literature inspection on Polycystic ovarian morphology in women using data mining

methodologies", *International Journal of Advanced Research in Computer Science,* Vol.9, No.1, Jan-Feb 2018.

[40] Dewi, Adiwijaya, Wisesty and Jondri, "Classification of polycystic ovary based on ultrasound images using competitive neural network", *Journal of Physics: Conference Series,* Vol. 971, conference 1, 2018.

[41] Kumar, Senthil, Nirmala and Venkatalakshmi Karthikeyan, "Analysis of Optimization Algorithms on Follicles Segmentation to Support Polycystic Ovarian Syndrome Detection", *Journal of Computational and Theoretical Nanoscience,* Vol. 15, No. 1, pp. 380-391, January 2018.

[42] Thufailah, Adiwijaya, Wisesty and Jondri, "An implementation of Elman neural network for polycystic ovary classification based on ultrasound images", *Journal of Physics: Conference Series,* Vol. 971, conference 1, 2018.

[43] Nikhil S. Narayan, Srinivasan Sivanandan, Srinivas Kudavelly, Kedar A. Patwardhan and G. A. Ramaraju, "Automated detection and segmentation of follicles in 3D ultrasound for assisted reproduction", *Proceesings, Medical Imaging 2018 Computer-aided diagnosis,* Vol. 10575, 105751W, https://doi.org/10.1117/12.2293121, February 2018.