ISSN (ELECTRONIC): 2815-0562

Dileep A. (2024). *New Methods for the Automated Detection of Abnormalities in Ultrasound Images of the Ovary. International Journal of Medical Science. 4(2), 2024, 1-14.*

INTERNATIONAL JOURNAL OF MEDICAL SCIENCE

journal homepage: https://www.ijmsci.org/

NEW METHODS FOR THE AUTOMATED DETECTION OF ABNORMALITIES IN ULTRASOUND IMAGES OF THE OVARY

Dileep A

Scientist, Ailena Technologies, Bengaluru-560094, Karnataka, India.

How to Cite the Article: ***Dileep A. (2024).*** *New Methods for the Automated Detection of Abnormalities in Ultrasound Images of the Ovary. International Journal of Medical Science. 4(2), 2024, 1-14.*

DOI: https://doi.org/10.56815/IJMSCI.V4I2.2024/1-14

Article History: Submission: 19-08-2024; Revision: 05-09-2024; Acceptance: 24-09-2024;

Keywords

Polycystic ovary syndrome (PCOS), Particle Swarm Optimization (PSO), Pigeon Inspired Optimization (PIO), Invasive Weed Optimization (IWO)

Abstract

Polycystic ovary syndrome (PCOS), a hormonal disorder with diverse diagnostic criteria, is currently diagnosed through manual analysis of ultrasound images, requiring time-consuming and subjective tracking and measurement of follicles. This paper presents a novel automated approach to PCO detection. Our method employs a modified Otsu approach, where several optimization algorithms including Particle Swarm Optimization (PSO) and its variations, Pigeon Inspired Optimization (PIO), and Invasive Weed Optimization (IWO) maximize class variance to achieve optimal follicle segmentation. Following follicle extraction from ultrasound images, their features are automatically quantified using stereology, and these attributes are stored as feature vectors. These vectors are then used for binary classification based on PCO presence or absence. Correct segmentation performance is evaluated using standard quality metrics. This automated approach has the potential to significantly improve the accuracy, objectivity, and efficiency of PCO diagnosis, reducing reliance on manual assessment.

ISSN (ELECTRONIC): 2815-0562
Dileep A. (2024). *New Methods for the Automated Detection of Abnormalities in Ultrasound Images of the Ovary. International Journal of Medical Science. 4(2), 2024, 1-14.*

[1] INTRODUCTION

Advancements in high-resolution medical imaging have revolutionized diagnostic practices, with computer-aided solutions playing a crucial role in automated image analysis and interpretation. These tools offer valuable support to medical professionals in the diagnostic process. While significant progress has been made in automating the detection of anomalies in various human organs [1], the analysis of ovarian ultrasound images often still relies on manual methods, which are susceptible to human error [2]. Ovarian abnormalities, including cysts and Polycystic Ovary Syndrome (PCOS), are often linked to disrupted follicular development and represent significant concerns for women's health. This disruption can affect the delicate balance of follicle-stimulating hormone (FSH) and luteinizing hormone (LH) [3], potentially contributing to infertility and, in some cases, increasing the risk of certain cancers. The prevalence of ovarian cysts and PCOS has been reportedly increasing [4], making effective screening methods crucial. Ultrasound imaging has become a widely adopted technique for assessing the female reproductive system by radiologists and gynecologists [4]. However, the current practice of manually inspecting ovarian ultrasound data for anomalies, primarily involving follicle counting and measurement [5], is labor-intensive and prone to inter-observer variability. Therefore, this study focuses on developing a Computer-Aided System (CAS) for the automated and precise diagnosis of ovarian anomalies, specifically cysts and PCOS, in ultrasound images. Such a system has the potential to provide clinicians with more objective and reliable data for improved patient diagnosis and management [6]. A key challenge in analyzing ovarian ultrasound images is the presence of speckle noise. To mitigate this, various preprocessing filters, including Lee-Kuan-Frost, Gaussian-Wiener, Median, Hybrid Median, Modified Hybrid Median, and Fuzzy filters, were investigated [7]. Performance evaluation revealed that the Modified Hybrid Median and Fuzzy filters offered superior denoising capabilities. Consequently, a combined Modified Hybrid Median and Fuzzy filtering approach is employed in this study to enhance the quality of ovarian ultrasound images [8].

1.1. Ovary and Its Components

The ovaries are essential organs of the female reproductive system, typically described as smooth, ductless glands roughly the size and shape of an almond. This section details the structure of a normal ovary and its key components [9].

1.1.2 Normal Ovary

A healthy ovary contains numerous follicles, fluid-filled sacs housing immature eggs (oocytes). During each menstrual cycle, typically one follicle becomes dominant, growing at approximately 2 mm per day [10], and matures in preparation for ovulation, the release of the egg. This event generally occurs around the midpoint of the menstrual cycle (approximately day 14 of a 28-day cycle), triggered by a surge in luteinizing hormone (LH) [10]. At this stage, the mature follicle reaches a size of roughly 20-28 mm. Following ovulation, the ruptured follicle transforms into the corpus luteum, a temporary endocrine structure within the ovary that degenerates within approximately 10-14 days if fertilization does not occur.

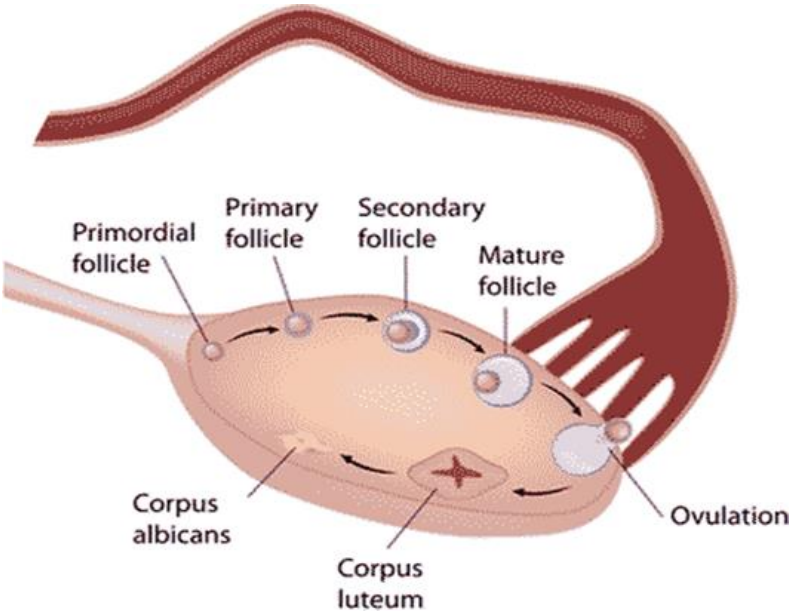


Fig 1: Normal Ovary

Figure 1 depicts a normal ovarian image showcasing the various follicles present, which are not limited to a fixed number between 1 and 10. These follicles can be categorized into two main types [11]: smaller antral follicles, typically measuring between 2 and 9 mm, and the dominant (Graafian) follicle, which is selected for maturation and ovulation, growing significantly larger to 20-28 mm as it prepares for release. This dominant follicle can develop in either ovary. Women with regular menstrual cycles typically experience ovulation at predictable intervals [12].

1.1.3 Ovarian Abnormalities

Ovarian dysfunction, encompassing conditions like ovarian cysts and Polycystic Ovary Syndrome (PCOS), represents a significant and growing health concern among women globally [17, 18]. These conditions are frequently diagnosed based on the size and number of follicles observed during imaging.

1.1.4 Ovarian Cysts

During ovulation, a small amount of fluid naturally accumulates around the developing egg within the follicle—a structure composed of the egg, fluid-producing cells, and surrounding fluid. Occasionally, these cells produce excess fluid, causing the follicle and, consequently, the ovary to swell [13]. A follicular cyst is defined as a fluid accumulation that exceeds the typical size of a mature follicle. Figure 2 illustrates a follicular cyst, depicting this fluid-filled sac within the ovary [14].

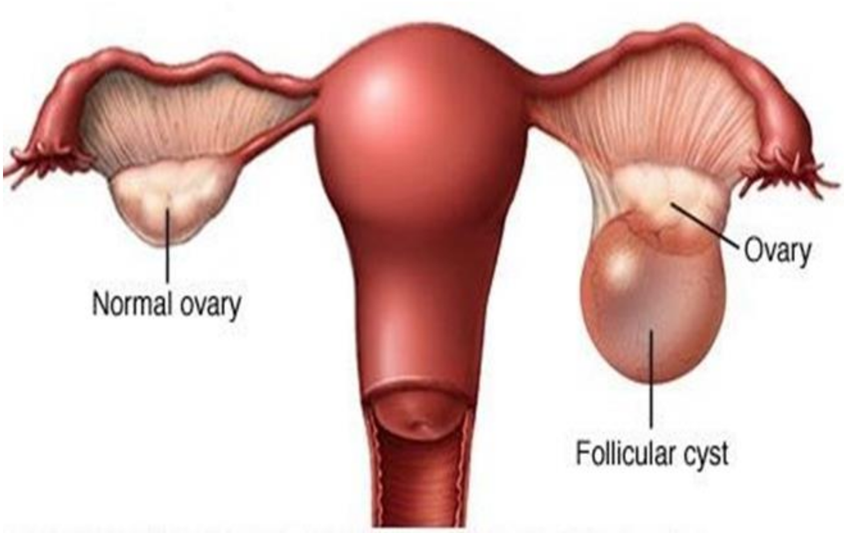


Figure 2: Cystic Ovary [Source: Mayo Foundation for Medical Education and Research. http://www.drugs.com/mcd/ovarian-cysts)]

Typically, a cystic ovary contains one or two follicles exceeding 28 mm in diameter. Women with follicular cysts may experience a range of symptoms, including

- Painful intercourse (dyspareunia)
- Breast tenderness
- Abdominal bloating
- Painful bowel movements
- Vomiting
- Abdominal pain during menstruation

It's important to note that while many women worry about a link between ovarian cysts and cancer [15], the vast majority of ovarian cysts are benign. However, although rare, some cysts can be malignant. Even benign-appearing cysts detected through imaging require ongoing monitoring to ensure accurate diagnosis and appropriate management. Regular ovarian check-ups are therefore crucial for women's health [16].

[2] FOLLICLE DETECTION BY THRESHOLDING WITH NATURE-INSPIRED OPTIMIZATION ALGORITHMS

Segmenting follicles from ovarian ultrasound images using thresholding methods, particularly Otsu's method, presents a significant challenge: determining the optimal threshold value. This is crucial for accurate segmentation but is often prone to error. Consequently, optimal threshold selection is framed as an optimization problem. Optimization, in this context, refers to finding the parameter values that minimize or maximize a specific function (the fitness function), subject to certain constraints [7]. Optimization methods aim to select the best solution from a set of possible candidates. While finding the optimal threshold for image segmentation is considered an NP-hard problem, nature-inspired algorithms offer effective and computationally feasible solutions [8]. This study explores several such techniques—including Particle Swarm Optimization (PSO) and its variants, Pigeon Inspired Optimization (PIO), and Invasive Weed Optimization (IWO) and its modified version (MIWO)—to determine the optimal threshold for follicle segmentation in ovarian ultrasound images. A crucial step in any nature-inspired algorithm is the proper formulation of the problem and the definition of a suitable fitness function [4, 5, 9].

2.1 Problem Formulation and Fitness Function

For grayscale images with 256 gray levels (0-255), the optimal threshold value lies within this range. Nature-inspired optimization algorithms are employed to select the best threshold from these 256 possibilities. A key aspect of designing an effective optimization method is the representation stage, which involves establishing a suitable mapping between the problem's solution space and the algorithm's search space (e.g., the particle swarm in PSO) [7].

[3] PARTICLE SWARM OPTIMIZATION (PSO) AND VARIANTS

Threshold determination using Otsu's method can be viewed as a continuous optimization problem. This study aims to find the optimal threshold for follicle detection in ovarian ultrasound images using various PSO variants, including Constant Inertia Weight (CIW) PSO, Dynamically Varying Inertia Weight (DVIW) PSO, and Adaptive Particle Swarm Optimization (APSO). These methods optimize the between-class variance, as defined by the modified Otsu method, as the fitness function. The convergence speed of PSO and its variants is analyzed to identify the most effective method for follicular segmentation.

3.1 Particle Swarm Optimization (PSO) Explained

PSO is a population-based optimization algorithm inspired by the social behavior of bird flocks or fish schools. Each potential solution in the search space is represented as a "particle," akin to a bird in the flock. These particles move through the search space, searching for the optimal solution (analogous to finding food). Each particle is assigned a fitness value based on the objective function. PSO iteratively updates each particle's position and velocity based on its own best-found position (personal best) and the best position found by any particle in the swarm (global best).

3.2 Adaptive Particle Swarm Optimization (APSO)

APSO dynamically adjusts the particles' step size and a stochastic acceleration component to enhance convergence towards the global optimum. This allows for more efficient exploration of the search space. Initially, a larger cognitive component (emphasis on personal best) and a smaller social component (emphasis on global best) facilitate exploration. As the search progresses, the cognitive component decreases, and the social component increases, promoting convergence towards the global optimum.

3.3 Modified Invasive Weed Optimization (MIWO)

MIWO is a modification of the standard Invasive Weed Optimization (IWO) algorithm where the standard deviation in the spatial dispersion step is modified by incorporating a cyclic function. This modification constrains the standard deviation within a specific range, resulting in smaller SD values earlier in the optimization process.

3.4 Implementation of PSO and Variants for Thresholding

The application of PSO and its variants to the ovarian image thresholding problem involves representing the range of possible threshold values (0-255) as the search space. The population of particles within this range represents the potential solutions. Initially, particles are randomly positioned within this search space with an initial velocity of zero.

Dataset and Data Transparency:

The dataset used in this study is the publicly available "Polycystic Ovary Syndrome (PCOS)" dataset hosted on Kaggle. Ethical considerations, patient consent, and data privacy policies have been adhered to as per the dataset provider's guidelines. The dataset supports transparency, reproducibility, and open access, which are essential for further research and development in this field.

[4] METHODOLOGY

4.1 Data Pre-processing: Speckle noise in ultrasound images is a significant challenge for accurate segmentation. This study employs a hybrid approach using Modified Hybrid Median filtering and Fuzzy filtering to reduce noise while preserving anatomical structures. This approach enhances image quality, enabling more accurate follicle segmentation.

4.2 Follicle Segmentation: Segmentation is achieved using thresholding methods enhanced with optimization algorithms. The process involves:

Thresholding: Otsu’s method establishes an initial threshold for image segmentation.

Optimization: PSO, PIO, and IWO algorithms optimize the threshold values to enhance segmentation accuracy. The fitness function maximizes the between-class variance of Otsu's method, ensuring precise follicle separation.

4.3 Feature Extraction

Feature extraction plays a crucial role in areas like pattern recognition, medical imaging, and biometrics by transforming input data into meaningful feature sets. In image processing, feature extraction condenses large volumes of information into concise and relevant descriptors. Color, texture, and geometric properties are the primary categories of image features. While color and texture play a role in other domains, geometrical features are vital for ovarian image analysis. Geometrical features include area, perimeter, major axis, minor axis, eccentricity, extent, circularity, and tortuosity, all of which provide essential information for identifying genuine follicles.

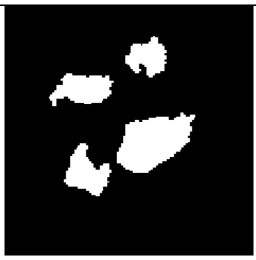
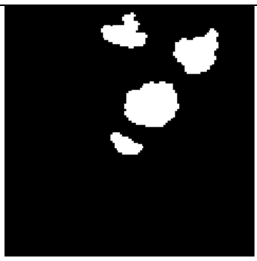
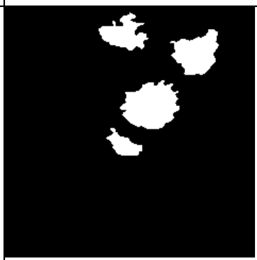
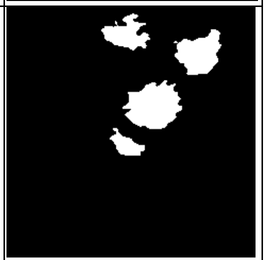
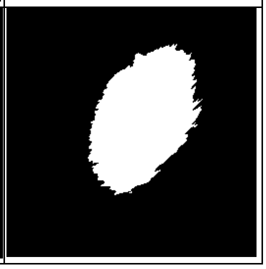
The process of feature extraction significantly influences the performance of classification models. In this study, follicle segmentation is achieved through four key methods: region-based active contour, Particle Swarm Optimization (PSO), Pigeon Inspired Optimization (PIO), and

ISSN (ELECTRONIC): 2815-0562

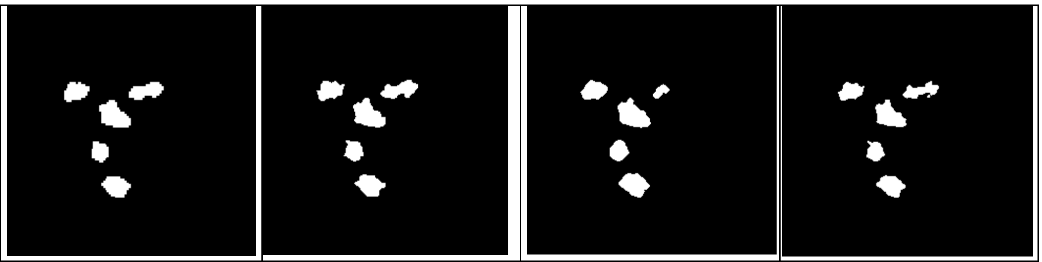
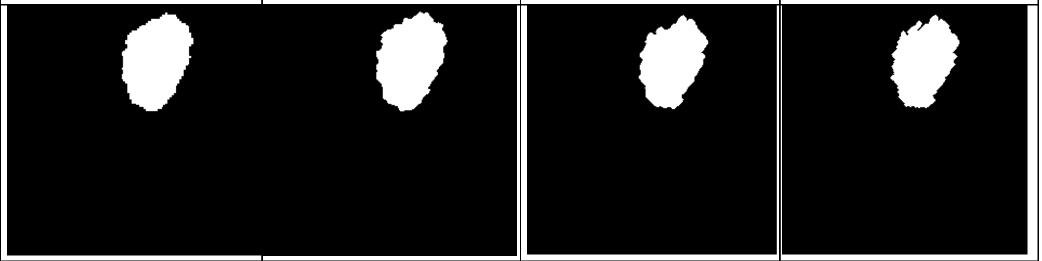
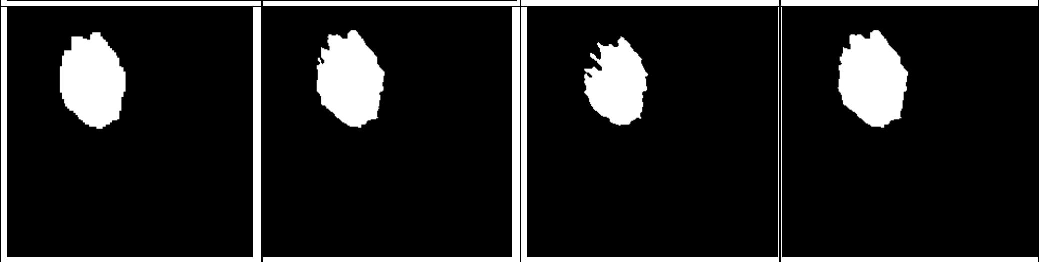
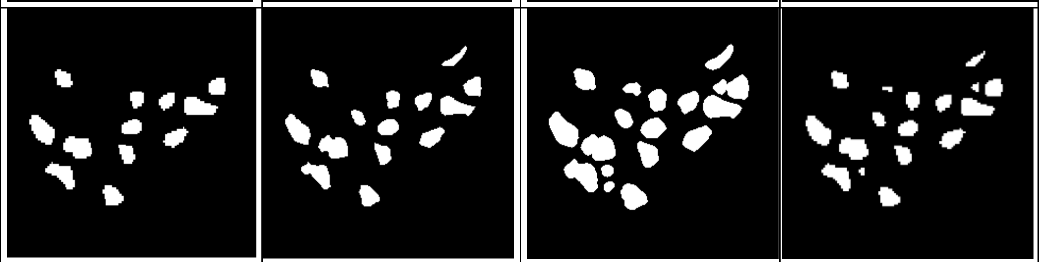
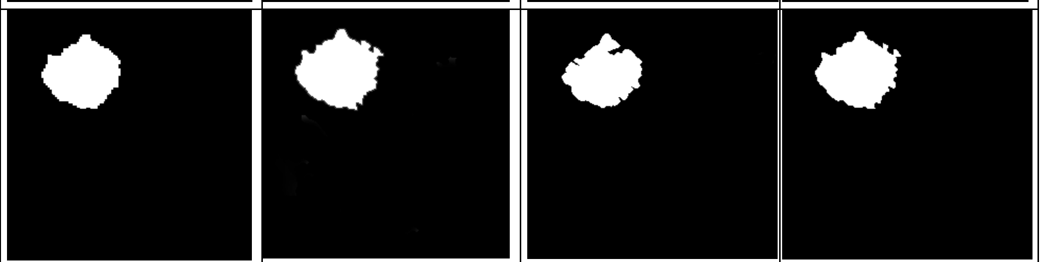
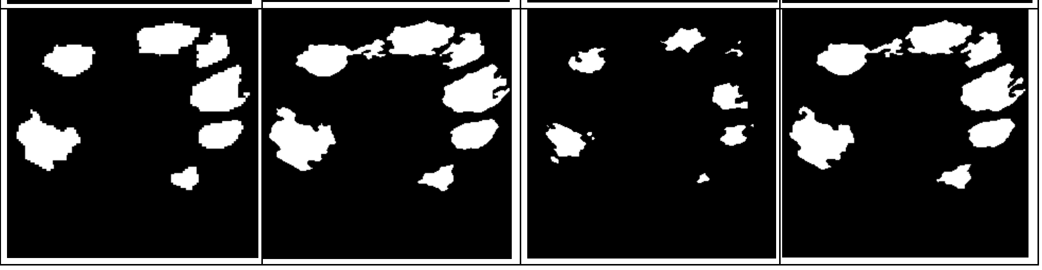
Dileep A. (2024). *New Methods for the Automated Detection of Abnormalities in Ultrasound Images of the Ovary. International Journal of Medical Science. 4(2), 2024, 1-14.*

Invasive Weed Optimization (IWO). Following a comparative performance evaluation of these methods, the best-performing techniques—the hybrid region-based active contour, APSO, PIO, and MIWO—are selected for feature extraction. The fitness function used in nature-inspired algorithms is the between-class variance, and the modified Otsu output serves as a mask for the region-based active contour. The characteristics of follicles segmented using the four methods are summarized in Table 1.

Table.1 Follicles segmented by Hybrid region based active contour, APSO, PIO and MIWO methods

Database Image	Hybrid Region Based Active Contour	APSO	PIO	MIWO
oi001				
oi002				
oi013				
oi022				

ISSN (ELECTRONIC): 2815-0562
Dileep A. (2024). *New Methods for the Automated Detection of Abnormalities in Ultrasound Images of the Ovary. International Journal of Medical Science. 4(2), 2024, 1-14.*

oi024	
oi032	
oi049	
oi056	
oi063	
oi099	
oi110	

ISSN (ELECTRONIC): 2815-0562

Dileep A. (2024). *New Methods for the Automated Detection of Abnormalities in Ultrasound Images of the Ovary. International Journal of Medical Science. 4(2), 2024, 1-14.*

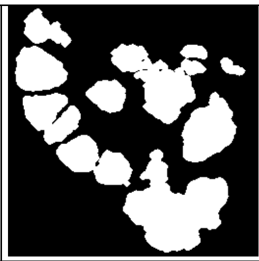
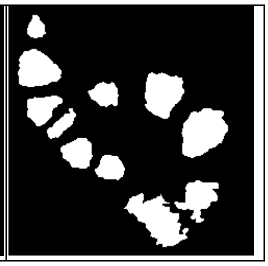
oi135				

Table 2: Geometrical Features extracted from segmented results of Hybrid region based active contour method

Image	Follicle	Area	Perimeter	Major Axis	Minor Axis	Eccen-tricity	Extent 0.2-0.7	Circularity 0.2-0.8	Tortousity 0.1-0.4
oi001	1	1487	233.9655	64.7456	31.7789	0.8712	0.5817	0.3413	0.2767
oi001	2	1435	213.0366	52.5214	41.2368	0.6193	0.5214	0.3970	0.2465
oi001	3	3164	291.5635	84.5538	49.8785	0.8074	0.6048	0.4675	0.2900
oi001	4	1088	221.6224	44.4669	37.3635	0.5421	0.5745	0.2781	0.2006
oi002	1	984	169.3553	45.5267	31.9389	0.7126	0.5694	0.4311	0.2688
oi002	2	456	98.6274	35.2099	17.3692	0.8698	0.6096	0.5890	0.3570
oi002	3	2013	192.1838	57.0497	45.3890	0.6058	0.6810	0.6845	0.2968
oi002	4	1397	175.598	48.8434	39.3137	0.5934	0.6597	0.5689	0.2781
oi013	1	864	157.9411	45.4346	27.2893	0.7995	0.5684	0.4352	0.2876
oi013	2	568	96.9705	28.1372	26.0341	0.3793	0.6802	0.7590	0.2901
oi013	3	488	97.5563	31.3651	20.7250	0.7505	0.6931	0.6443	0.3215
oi013	4	1913	200.7696	57.4718	44.1744	0.6396	0.6166	0.5960	0.2862
oi022	1	1261	518.1076	163.1315	98.9770	0.7949	0.6515	0.5900	0.3148
oi024	1	388	84.9705	27.4279	18.6401	0.7335	0.6461	0.6753	0.3227
oi024	2	300	70.7279	21.337	18.4725	0.5005	0.6575	0.7536	0.3016
oi024	3	604	107.799	35.575	23.0613	0.7614	0.6741	0.6531	0.3300
oi024	4	460	90.6274	28.4949	21.0829	0.6727	0.6969	0.7037	0.3144
oi024	5	436	100.3848	39.0420	15.1509	0.9216	0.6728	0.5437	0.3889
oi032	1	5038	322.6102	100.0387	64.9226	0.7608	0.6994	0.6080	0.3100
oi049	1	5010	310.2254	95.6718	67.1078	0.7127	0.6515	0.6539	0.3083
oi056	1	526	94.3259	36.3597	18.9801	0.8529	0.5903	0.7429	0.3854
oi056	2	507	101.7401	37.4562	19.6206	0.8518	0.5451	0.6155	0.3681
oi056	3	256	64.6274	21.8529	15.5748	0.7014	0.6485	0.7702	0.3381
oi056	4	528	97.8406	32.7006	21.3394	0.7577	0.6173	0.6931	0.3342
oi056	5	62	34.4852	9.4884	8.8533	0.3597	0.6901	0.6548	0.2751
oi056	6	167	52.2132	18.7232	11.5428	0.7873	0.6958	0.7693	0.3585
oi056	7	370	75.9411	25.0690	19.6243	0.6222	0.6702	0.8062	0.3301
oi056	8	91	40.9705	15.9477	8.6988	0.8381	0.6066	0.6812	0.3892
oi056	9	279	67.4558	24.4527	15.5603	0.7714	0.6739	0.7705	0.3624

Classification of Ovarian Images

A Support Vector Machine (SVM) classifier was employed to categorize ovarian ultrasound images as normal, cystic, or PCOS based on extracted follicle features. SVMs were chosen for their efficacy even with limited training data, as they maximize the margin between classes by mapping data into a higher-dimensional space separated by a hyperplane (Sathish et al., 2009). A one-versus-one strategy was used for multi-class classification, training separate SVMs for each class pairing. The training process utilized features extracted from segmented follicles obtained through four distinct methods: hybrid region-based active contour, APSO, PIO, and MIWO. Eight geometrical features—area, perimeter, major axis, minor axis, eccentricity, extent, circularity, and tortuosity—were extracted, providing information about follicle number and size. The SVM learned relationships between these features and image categories (normal, cyst, or PCOS). The radial basis function (rbf) kernel was used, with parameters C and gamma controlling the influence of training data and the balance between margin maximization and misclassification minimization, respectively, initially set to 1. The training phase evaluated image features, categorizing data with matching labels, creating a knowledge base of shape characteristics. These characteristics aided in determining follicle count and average size, ultimately classifying the ovarian image as normal, cystic, or PCOS based on these follicle properties.

Table 3.- Classification results on ultrasound ovarian images by SVM

Ovarian Images	Hybrid Region Based Active Contour	APSO	PIO	MIWO	Medical Expert
oi001	Normal	Normal	Normal	Normal	Normal
oi002	Normal	Normal	Normal	Normal	Normal
oi013	Normal	Normal	Normal	Normal	Normal
oi022	Cyst	Cyst	Cyst	Cyst	Cyst
oi024	Normal	Normal	Normal	Normal	Normal
oi032	Cyst	Cyst	Cyst	Cyst	Cyst
oi049	Cyst	Cyst	Cyst	Cyst	Cyst
oi056	PCOS	PCOS	PCOS	PCOS	PCOS
oi063	**Normal**	PCOS	PCOS	PCOS	PCOS
oi099	Cyst	Cyst	Cyst	Cyst	Cyst
oi110	Normal	Normal	Normal	Normal	Normal
oi135	PCOS	**Normal**	**Normal**	PCOS	PCOS

Analysis of the classification results presented in Table 2 reveals inconsistencies in the performance of the various feature extraction methodologies. The hybrid region-based active contour method erroneously classified ovarian image oi063, a confirmed case of PCOS, as Normal. Similarly, both the APSO and PIO algorithms misclassified ovarian image oi135, also a PCOS case, as Normal. In contrast, the MIWO algorithm demonstrated superior performance, achieving complete agreement with the medical expert's diagnoses across all ovarian image

ISSN (ELECTRONIC): 2815-0562
Dileep A. (2024). *New Methods for the Automated Detection of Abnormalities in Ultrasound Images of the Ovary. International Journal of Medical Science. 4(2), 2024, 1-14.*

types.

Table 4. Accuracy of the SVM classifier

Methods	Accuracy (%)
Hybrid Region Based Active Contour	97.3
Adaptive Particle Swarm Optimization	92.6
Pigeon Inspired Optimization	95.6
Modified Invasive Weed Optimization	98.3

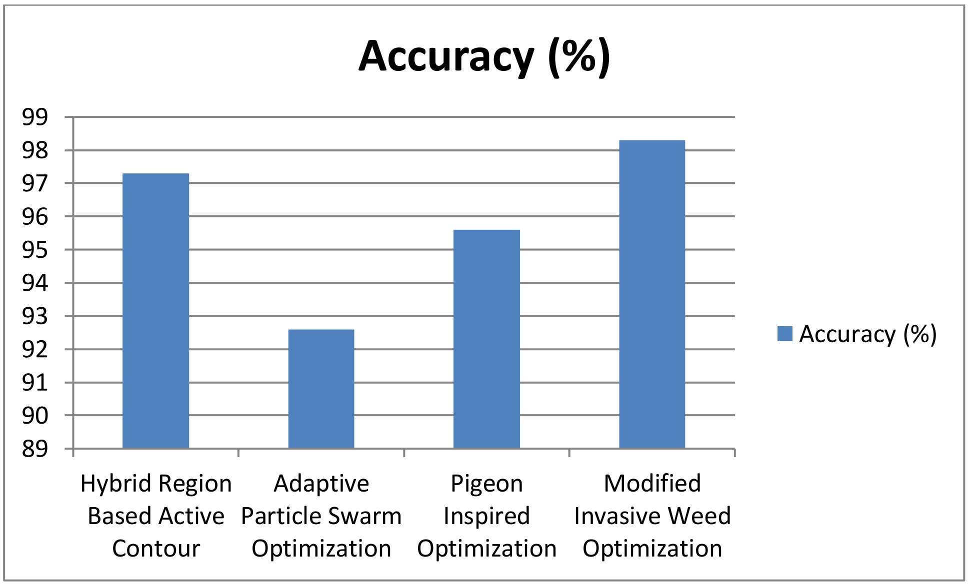


Figure 3: Accuracy of the different segmentation methods

Figure 3 graphically represents the SVM classifier's accuracy for each segmentation method. As depicted, the SVM classifier achieved the highest accuracy when applied to images segmented using the MIWO algorithm, surpassing the performance of all other segmentation techniques evaluated in this study.

[5] CONCLUSION

This study presented an automated system for ovarian abnormality detection using ultrasound images, combining nature-inspired optimization for follicle segmentation with SVM classification. The MIWO algorithm demonstrated superior segmentation performance, leading to the highest classification accuracy (98.3%). This automated approach offers improved objectivity and efficiency compared to manual assessment. The results highlight the potential of MIWO-SVM for assisting clinicians in diagnosing ovarian abnormalities. Future work will focus on expanding datasets and exploring further enhancements.

[6] DISCUSSION

This study's findings demonstrate the potential of automated systems to improve ovarian abnormality diagnosis. MIWO's superior segmentation performance highlights the effectiveness of its modified spatial dispersion in handling ultrasound image challenges. The high accuracy of the MIWO-SVM combination underscores the importance of effective feature extraction combined with robust classification. Automation reduces subjectivity and analysis time compared to manual methods. While the study's dataset size is a limitation, the results suggest strong clinical potential. Future research should focus on larger, diverse datasets, varying image quality, and exploring additional features and algorithms. Clinical trials are crucial for real-world validation. This research contributes significantly to developing more efficient and accurate diagnostic tools for ovarian health.

[7] AUTHOR(S) CONTRIBUTION

The authors agreed to have no connections or engagements with any group or body that provides financial and non-financial assistance for the topics and resources covered in the article.

[8] ACKNOWLEDGEMENT

Individuals / resources participated in the work are acknowledged properly.

[9] SOURCES OF FUNDING

The authors received no financial aid to support the study.

[10] PLAGIARISM POLICY

The authors declare that any kind of violation of plagiarism, copyright, and ethical matters will be handled by all authors. Journalists and editors are not liable for the aforesaid matters.

[11] CONFLICT OF INTEREST

The authors declared that no potential conflicts of interest concerning the research, authorship, and/or publication of this article.

[12] PROTECTION OF RESEARCH PARTICIPANTS

This study does not involve any such criteria or condition.

REFERENCES

[1] B. Poorani and R. Khilar, "Identification of Polycystic Ovary Syndrome in ultrasound images of Ovaries using Distinct Threshold based Image Segmentation," 2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT), Gharuan, India, 2023, pp. 570-575, doi: 10.1109/InCACCT57535.2023.10141800.

[2] P. B and R. Khilar, "Classification of PCOS Using Machine Learning Algorithms Based on Ultrasound Images of Ovaries," 2023 Eighth International Conference on Science

Technology Engineering and Mathematics (ICONSTEM), Chennai, India, 2023, pp. 1-7, doi: 10.1109/ICONSTEM56934.2023.10142359.

[3] S. Tiwari and P. Maheshwari, "PCOS-WaveConvNet: A Wavelet Convolutional Neural Network for Polycystic Ovary Syndrome Detection using Ultrasound images," 2023 9th International Conference on Information Technology Trends (ITT), Dubai, United Arab Emirates, 2023, pp. 117-122, doi: 10.1109/ITT59889.2023.10184271.

[4] P. H. Panicker, K. Shah and S. Karamchandani, "CNN Based Image Descriptor for Polycystic Ovarian Morphology from Transvaginal Ultrasound," 2023 International Conference on Communication System, Computing and IT Applications (CSCITA), Mumbai, India, 2023, pp. 148-152, doi: 10.1109/CSCITA55725.2023.10104931.

[5] A. K. M. Salman Hosain, M. H. K. Mehedi and I. E. Kabir, "PCONet: A Convolutional Neural Network Architecture to Detect Polycystic Ovary Syndrome (PCOS) from Ovarian Ultrasound Images," 2022 International Conference on Engineering and Emerging Technologies (ICEET), Kuala Lumpur, Malaysia, 2022, pp. 1-6, doi: 10.1109/ICEET56468.2022.10007353.

[6] N. Jan, A. Makhdoomi, P. Handa and N. Goel, "Machine learning approaches in medical image analysis of PCOS," 2022 International Conference on Machine Learning, Computer Systems and Security (MLCSS), Bhubaneswar, India, 2022, pp. 48-52, doi: 10.1109/MLCSS57186.2022.00017.

[7] M. Sarkar and A. Mandal, "Follicle Segmentation from Ultrasound images of Ovary by using sub-band Entropy-based Wavelet thresholding and object contours," 2021 IEEE 18th India Council International Conference (INDICON), Guwahati, India, 2021, pp. 1-6, doi: 10.1109/INDICON52576.2021.9691677.

[8] K. Srilatha and V. Ulagamuthalvi, "Performance Analysis of Ultrasound Ovarian Tumour Segmentation Using GrabCut and FL-SNNM," 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), Bhilai, India, 2021, pp. 1-7, doi: 10.1109/ICAECT49130.2021.9392630.

[9] Eliyani, S. Hartati, A. Musdholifah and D. Dasuki, "Active Contour Without Edge and Watershed for Follicle Detection in Ultrasound Image of Ovary," 2020 International Conference on Advanced Computer Science and Information Systems (ICACSIS), Depok, Indonesia, 2020, pp. 295-300, doi: 10.1109/ICACSIS51025.2020.9263115.

[10] S. Marques et al., "Segmentation of gynaecological ultrasound images using different U-Net based approaches," 2019 IEEE International Ultrasonics Symposium (IUS), Glasgow, UK, 2019, pp. 1485-1488, doi: 10.1109/ULTSYM.2019.8925948.

[11] P. Singh, R. Mukundan and R. d. Ryke, "Feature Enhancement in Medical Ultrasound Videos Using Multifractal and Contrast Adaptive Histogram Equalization Techniques," 2019 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), San Jose, CA, USA, 2019, pp. 240-245, doi: 10.1109/MIPR.2019.00050.

[12] Acharya, UR, Mookiah, MRK, Sree, SV, Yanti, R, Martis, R, Saba, L, Molinari, F, Guerriero, S & Suri, JS 2013, Ovarian Neoplasm Imaging, Springer, US.

[13] Agrawal, S, Panda, R, Bhuyan, S & Panigrahi, BK 2013, „Tsallis entropy based optimal multilevel thresholding using cuckoo search algorithm‟, Swarm and Evolutionary Computation, vol. 11, pp. 16-30.

[14] Cai, H, Yang, Z, Cao, X, Xia, W & Xu, X 2014, „A new iterative triclass thresholding technique in image segmentation‟, IEEE Transactions on Image Processing, vol. 23, no. 3, pp. 1038-1046.

[15] Chinnu, A 2015, „MRI brain tumor classification using SVM and histogram Based image segmentation‟, International Journal of Computer Science and Information Technologies, vol. 6, no. 2, pp. 1505-1508

[16] Gopinathan, S & Deepa, P 2015, „Enhancement of image segmentation using automatic histogram thresholding‟, International Journal on Recent and Innovation Trends in Computing and Communication, vol. 3, issue. 4, pp. 1863-1872.

[17] Bozdag, G., Mumusoglu, S., Zengin, D., Karabulut, E., & Yildiz, B. O. (2016). The prevalence and risk factors for polycystic ovary syndrome: a systematic review and meta-analysis. Human reproduction update, 22(6), 736–752.

[18] Practice Committee of the American Society for Reproductive Medicine. (2015). Diagnostic evaluation of the infertile female: a committee opinion. Fertility and sterility, 103(6), 1 e43–e50.