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Research Article

Enhanced Endometriosis Detection Using the Deep Feature Enquiring Based on Hyper Capsule Resnet50-CNN Algorithm

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ABSTRACT
Endometriosis is a chronic condition in which the lining of the uterus grows outside the uterus, causing pain, swelling, and fertility problems. It usually affects the ovaries, fallopian tubes, and pelvic lining, leading to severe menstrual cramps and other complications. Traditional methods for diagnosing endometriosis, such as laparoscopy and ultrasound, are often invasive, time-consuming, and can lead to delayed diagnosis. Relying on symptom-based assessment lacks accuracy, making early and affective treatment challenging. To solve the problem a novel Hyper capsule Resnet50-CNN algorithm is introduced for classifying the ovarian cysts by utilizing the ultrasound images processed datasets and applied to the image processing technique. Initially, Butterworth Filter preprocessing enhanced the details of the input data set and gave a clear view of the input dataset. Modified Watershed Segmentation algorithm (MWSA) separates follicles or cysts that specifically differentiate for selection features. An improved Recursive Bee Colony (RBC) Feature Selection algorithm is trained to identify biologically significant markers, ensuring accurate feature extraction without errors. ResNet50 with CNN architecture is a deep learning approach to extract complex features methodically hyper capsule ResNet50 contains 50 layers of network operation, which is a disappearing gradient issue that is frequently observed. RESNET 50 classification identifies ovarian cysts into three stages based on the condition: regular nodule, ovarian growth, and polycystic ovary. The accuracy is 94.15%, sensitivity 95.82%, Specificity 94.54%, FI– Score 94.89% and RMSE 84.25% measure parameters are analyzed, and the performance Matrix obtains results.

Keywords: Endometriosis, Recursive Bee Colony (RBC), hyper capsule Resnet50-CNN algorithm, RESNET 50 classification

Introduction

In cases of endometrial cancer, sentinel lymph node biopsy provides a less invasive option to complete lymphadenectomy, minimizing side effects such as lymphedema while preserving a high level of diagnostic precision for the identification of lymph node metastases.1. It is a common condition linked to reproductive hormones. Unusual hair growth, acne, unpredictable menstrual periods, and decreased fertility are some of its typical disruptive symptoms. Women produce more male hormones than usual 2. This capacity to identify such minute quantities of biomolecules is advantageous for identifying illnesses early on, allowing doctors to communicate and assist patients 3.

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Given that AMH (anti-Müllerian hormone) levels are frequently used as a fertility indicator, it is important to comprehend any potential correlation between them and body mass. While some studies have identified an inverse link, others have found no relationship at all in groups without diagnosis 4. Accurate diagnosis is made more difficult in underdeveloped nations by a lack of access to sophisticated tools and knowledge. Effective therapy may be delayed as a result of these difficulties, highlighting the necessity of more standardized diagnostic procedures. To overcome these obstacles, standardized, effective diagnostic techniques possibly including AI and machine learning are desperately needed 5.

Contribution of Work

- Proposed an enhanced ResNet50-based Capsule CNN architecture, termed Hyper Capsule ResNet50-CNN, for precise endometriosis detection. Introduced a deep feature enquiring mechanism that refines feature extraction, improving classification accuracy.
- Utilized Capsule Networks to enhance spatial hierarchies and reduce loss of critical feature details. Improved the robustness of feature representation, enabling better differentiation between normal and endometriosis-affected tissue.
- Implemented an automated feature selection method to focus on relevant deep features, reducing redundancy. Leveraged attention mechanisms to prioritize key features, leading to enhanced diagnostic precision.

The remaining portion of the document is divided into significant sections, which are described as follows: Section II examines the current research efforts in Enhanced Endometriosis detection using the deep feature enquiring based on hyper capsule Resnet50-CNN algorithm used by different authors. The workflow of the suggested approach is explained in Section III and consists of feature selection, data collection, pre-processing, and classification models. Section IV presents the findings analysis and performance data. Section V presents the conclusion.

1) Related Work

Adenomyosis and endometriosis are crippling gynecological disorders that significantly impair women's quality of life. Laparoscopic surgery and hormone therapy are two examples of traditional diagnostic and therapeutic approaches that have serious drawbacks, including poor lesion identification, high recurrence rates, and unfavorable side effects. Promising approaches to the accurate detection and treatment of various illnesses are provided by emerging bioengineering technology [6]. One of the major malignant processes of endometrial cancer is epithelial-mesenchymal transition (EMT), and identifying EMT targets is a crucial task in order to investigate the mechanism of endometrial carcinoma malignancy and identify new treatment targets [7]. In this work, we examined the critical function of ITGB3 in ESCs and its impact on EM development, with a special emphasis on the regulatory function of macrophages [8]. The importance of training datasets in improving diagnostic accuracy through the use of recent advancements in machine learning algorithms to endometriosis diagnosis is the main emphasis of this work. We examine the contributions made by different research and talk about the difficulties and potential paths forward in this area [9]. To confirm that endometriosis can be evaluated using probe-based Confocal Laser Endomicroscopy during both traditional and robot-assisted laparoscopy [10].

To do this, the study classifies ultrasound pictures of the ovaries using VGG19 Net combined with several ML techniques. To distinguish between benign and possibly malignant cysts, the study analyzes ultrasound imaging [11]. The time spent manually tracking follicles and measuring each one's geometric characteristics would be reduced with the use of an automated diagnosis tool [12]. The LeNet model, which featured convolution and max-pooling layers, serves as the foundation for much contemporary deep-learning architecture [13]. Once more; some researchers used Convolution Neural

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Networks and deep learning techniques to identify ultrasound pictures. When it comes to picture classification, sophisticated deep-learning algorithms usually achieve a high degree of accuracy [14]. Using a KNN classifier, the suggested approach was able to classify data with an accuracy of above 97%. The classifier will increase the accuracy and speed of diagnosis, lowering the possibility of deadly consequences from a delayed diagnosis [15].

Table 1. Various parameter Analyses of disorder Endometriosis

References	Types of disorder	Dataset	Algorithm Used	Output
Luo, et al., (2024)	Endometriosis	Image dataset	ResNet50, DenseNet169, DenseNet201	Accuracy of 0.809%,0.911%
Zaidi, et al., (2025)	Endometriosis	Gynecologic Laparoscopy Endometriosis Dataset	VGG19, ResNet50, and Inception V3	Accuracy of 0.89 %, 0.91%, and 0.93%.
Nouri,et al., (2024)	Endometriosis	Data augmentation	Machine learning techniques	Accuracy of 0.76.
Guare, et al., (2024)	Endometrial cancer	complex fluorescent metabolomic datasets	Random Forest, Logistic Regression,	Accuracy of 0.94%
Leibetsedel, et al., (2022)	Endometriosis	Data augmentation	deep neural networks	precision of 32.4% at 50-95%
Zhao, et al., (2023)	endometrial polyps	training and test datasets	Deep Learning	Accuracy 95.83% and 77.33%
Gopalakrishnan, C., et al., (2019)	PCOS	image acquisition	Support Vector Machine	Accuracy 94.40
Mridul et al., (2024)	PCOS	Data Augmentation	Convolution Neural Network and Long Short-Term Memory	accuracy rate of 99.32%
Zou, et al., (2022)	PCOS	PCOS dataset	Protein-protein interaction network construction, survival analysis.	The AUC 0.617, 0.682, and 0.651, respectively
Ahmed et al., (2023)	PCOS	PCOS dataset	machine learning algorithms	Accuracy of 98.89%

Table 1 provides an analysis of various parameters associated with Endometriosis, highlighting the major physiological, hormonal, and metabolic factors that contribute to the disorder. The table provides a comparative analysis of affected and non-affected individuals, helping researches and healthcare professionals identify patterns and risk factors associated with the condition.

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2) Proposed Methodology

Figure 1 illustrates the in detail procedure of the proposed Endometriosis classification framework. It begins with the input of ultrasound images, which are first preprocessed using the Butterworth filter to enhance image clarity. Next, the Modified Watershed Segmentation algorithm is applied to accurately separate follicles or cysts, enabling effective feature extraction. The Improved Recursive Bee Colony (RBC) algorithm then identifies biologically significant features while minimizing errors. These extracted features are then fed into the Hyper Capsule ResNet50-CNN model. Finally, the system evaluates classification performance using accuracy, sensitivity, and F-measure metrics, ensuring reliable identification of Endometriosis conditions.

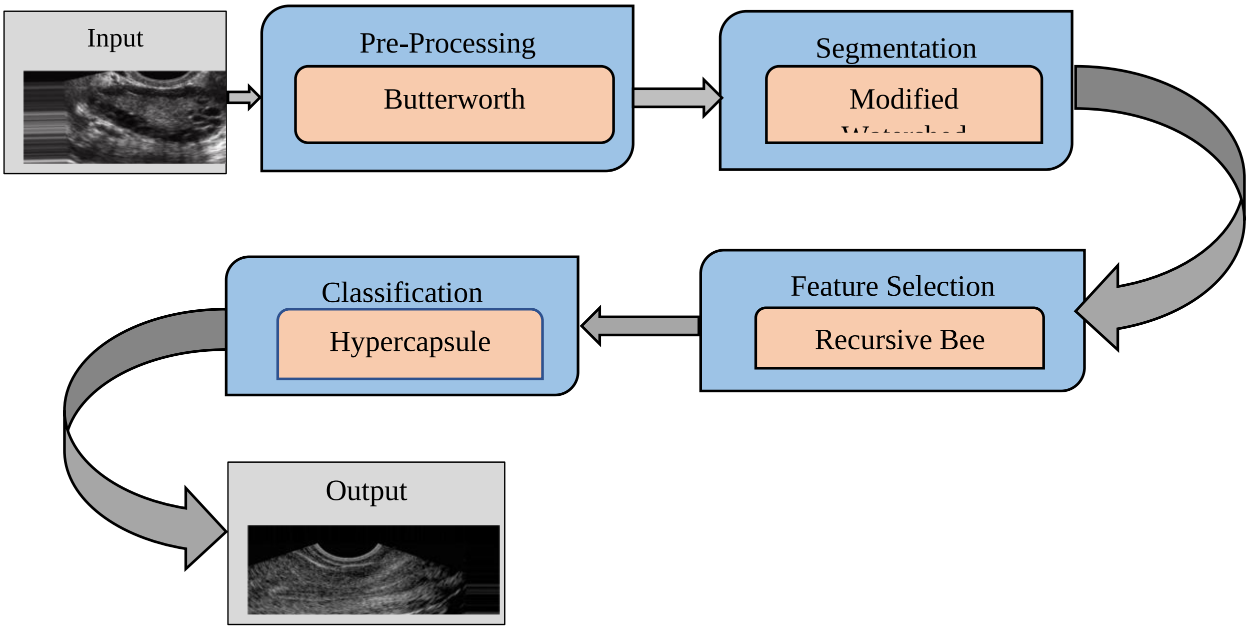

Figure 1. Proposed Architecture Diagram

3.1 Pre-Processing Using Butterworth Adaptive 2D Wavelet

This method effectively filters and enhances ultrasound images by preserving crucial anatomical structures while reducing noise and irrelevant details. The Butterworth filter, known for its smooth frequency response, is combined with an adaptive 2D wavelet transform to dynamically adjust to varying image characteristics, ensuring optimal feature preservation. This approach improves contrast and sharpness, allowing for better visualization of ovarian follicles and cystic formations, which are key indicators of Endometriosis. By refining image quality and highlighting essential diagnostic features, the Butterworth Adaptive 2D Wavelet Transform significantly contributes to the improved detection and classification of Endometriosis, aiding medical professionals in making more precise and reliable diagnoses.In this instance, the gathered Endometriosis dataset is pre-processed to enhance image quality and contrast. This enhances contrast and captures the image's clarity and the deep pit pixel's texture.

$$Mean\ (\mu) = \sum_T X_{m,n} \quad (1)$$

The image's mean value, μ, is determined using the equation above. Here, we assume that X is the input image pixel of coordinates (m, n) and that T is the total quantity of pixels in the Endometriosis image.

$$\sigma = \sqrt{\frac{1}{T}\sum_T (X_{m,n} - \mu)^2} \tag{2}$$

The standard deviation σ is computed using the equation above. The noise-free image is found using the following equation, which is based on μ and σ calculated as.

$$N_f(m,n) = m\left(\mu_{y1} - \mu\right)^2 + n\left(\mu_{y2} - \mu\right)^2 \tag{3}$$

In this case, N_f μ is the mean intensity value of y1 and y2 with two adjacent regions, and is the noise-free image that corresponds to pixel (m, n).

$$E_e = \sum_T (\mu_{mn} - \mu) \tag{4}$$

Analyze the edge enhancement E_e picture from equation 4. Assume that μ represents the average intensity of two locations with a total of T pixels in the Endometriosis dataset image.

$$N_q(i,j) = \frac{N_f(m,n) - \mu_y}{\sigma_y} \tag{5}$$

The noise-free image, mean intensity values, and standard deviation intensity values in the equation above are used to calculate the normalized quality image.

$$C_v = \sum_{m,n=0}^{T-1} N_{q(m,n)} (i-j)^2 \tag{6}$$

Equation 6 is used to escalate image contrast C_v based on the normalized quality image.

The Butterworth Adaptive 2D Wavelet method improves ultrasound images by filtering and preserving important anatomical structures by reducing noise. It combines the smooth frequency response of the Butterworth filter with the dynamic adjustments of the 2D wavelet transform, improving image contrast and sharpness.

3.2 Segmentation Using Modified Watershed Algorithm

After the pre-processing stage, the filter images segmented using the Modified Watershed Algorithm technique.

The region contour will shift positionally due to the loss of contour edge information, even though the typical pre-smoothing filter is simple to use and produces excellent results when eliminating noise and irregular features. Moreover, it doesn't since the contour of the area that is still visible in the reconstructed image has changed. The definition of morphological reconstruction is:

$$c_v + 1 = (h_k + se) \cap f \tag{7}$$

Where: $h_k^{se} ere\ (g, f)$ shows how to use the marker image f to morphologically recreate the mask image g, where f is the original image as a mask and se is the structural element that makes the marker image swell; h_k is the final iteration's outcome image, while h is the marker image g's first iteration. The final iteration of equation (7) occurs when $c_{v+1} = h_k$ Morphological closed reconstruction, like morphological open reconstruction, restores the target edge completely while excluding bright noise and texture features smaller than structural elements. However, as closed reconstruction or morphological reconstruction might only eliminate a single feature or bit of noise from the image, the target contour's position may easily change. To minimize pseudo-minimum values and maximize boundary information, image morphology reconstruction is utilized and the hybrid opening and closing reconstruction technique can be used to concurrently remove shading noise and texture features.

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Morphological Restoration Filter: The shape of the region changes because the conventional pre-smoothing filter loses information about the contour borders, even if it is good at reducing noise and irregular features. Filtering and denoising the Endometriosis MRI image can greatly retain the objective's edge shape data. Additionally, it maintains the reconstructed image's outlines the definition of morphological restoration is:

$$M_{n+1} = (M_n \oplus StEl) \cap x, \quad (8)$$

Where: M_(n^asters) (y,x) demonstrates a morphological restoration image of the mask y that has been reformed by the x (marker image), where the structural element is StEl, the real image is x, the final iteration's resultant image is Mn, and the first iteration of equation (8) is M0, which is iterated as far as feasible when Mn+1 = Mn. Morphological reconstruction can restore the objective edge because it may more subtly remove bright turbulence and surface characteristics than underlying elements. Only morphological or closed reclamation on the other hand, can remove a single detail or disruption from the image, shifting the objective form's location. The crossbreed introduction and final rebuilding operations can be used to concurrently remove the surface subtleties and concealing noise. Image morphology rebuilding is used to improve the restricted data and decrease the amount of pseudo-least features when the half, half commencing, and final reclamation procedures are used.

Based on the initial and final acts, the morphological initial and final restorative action is defined as follows:

$$H_{StEl}^{rs} = I_{StEl}^{rs}\lfloor F_{StEl}^{rs}(x), x\rfloor \quad (9)$$

Where I_{StEl}^{rs}(x) is the initial action restoration and $F_{StEl}^{rs}(x)$ is the final action restoration.

3.3 Feature Selection Using Recursive Bee Colony

A swarm intelligence algorithm called Recursive Bee Colony mimics how a colony of honey bees forages. It has been widely utilized to solve optimization problems in a variety of fields. Three different bee species are employed, and observers and scout are tasked with foraging in the hive. Using the information from the previous source, employed bees locate better food sources and educate other bees about them. By using the knowledge that hired bees communicate, bees waiting outside the hive can take advantage of a source.

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Pseudocode1: Recursive Bee Colony

(1) Capacity training samples
(2) Create the early population z_i, i=1,…..,SN
(3) Estimate the fitness (f_i) of the population
(4) Set cycle to 1
(5) Repeat
(6) FOR each employed bee {
    Produce new solution v_i
    Calculate the value f_i
    Apply greedy collection procedure}
(7) Estimate the value f_i
(8) FOR each onlooker bee {

Select a solution z_i depending on p_i

Produce new solution v_i

Estimate the value f_i

Relate greedy selection process}

(9) If there is an abandoned solution for he scout
    Then substitute it with a new solution which will
    Be casually produced by (7)
(10) Memorize the greatest solution so far
(11) Cycle = cycle +1
(12) Until cycle = MCN

The connection between two probability distribution functions is referred to as cross-entropy.

$A = \{a_1, a_2, \ldots . a_N\}$ And $B = \{b_1, b_2, \ldots . b_N\}$ and is expressed as.

$$H(R,S) = \sum_{i=1}^{N} A_i^c \log \frac{A_i^c}{B_i^c}; \{1,2,3\ for\ image \tag{10}$$

$$I_{tb=\left\{\frac{u^{c(1,tb)I(x,y)<tb}}{u^{c(tb,L+1)I(x,y)>tb}}\right.} \tag{11}$$

To retain the colour information, the three colour components of the cropped image were combined to determine the original image, histogram, and threshold value, which are represented by equation (11). I(x, y), b^c(i), and tb, respectively, and $(UCR, s) \sum_{i=r}^{s-1} ib^c\ (i)$ respectively.

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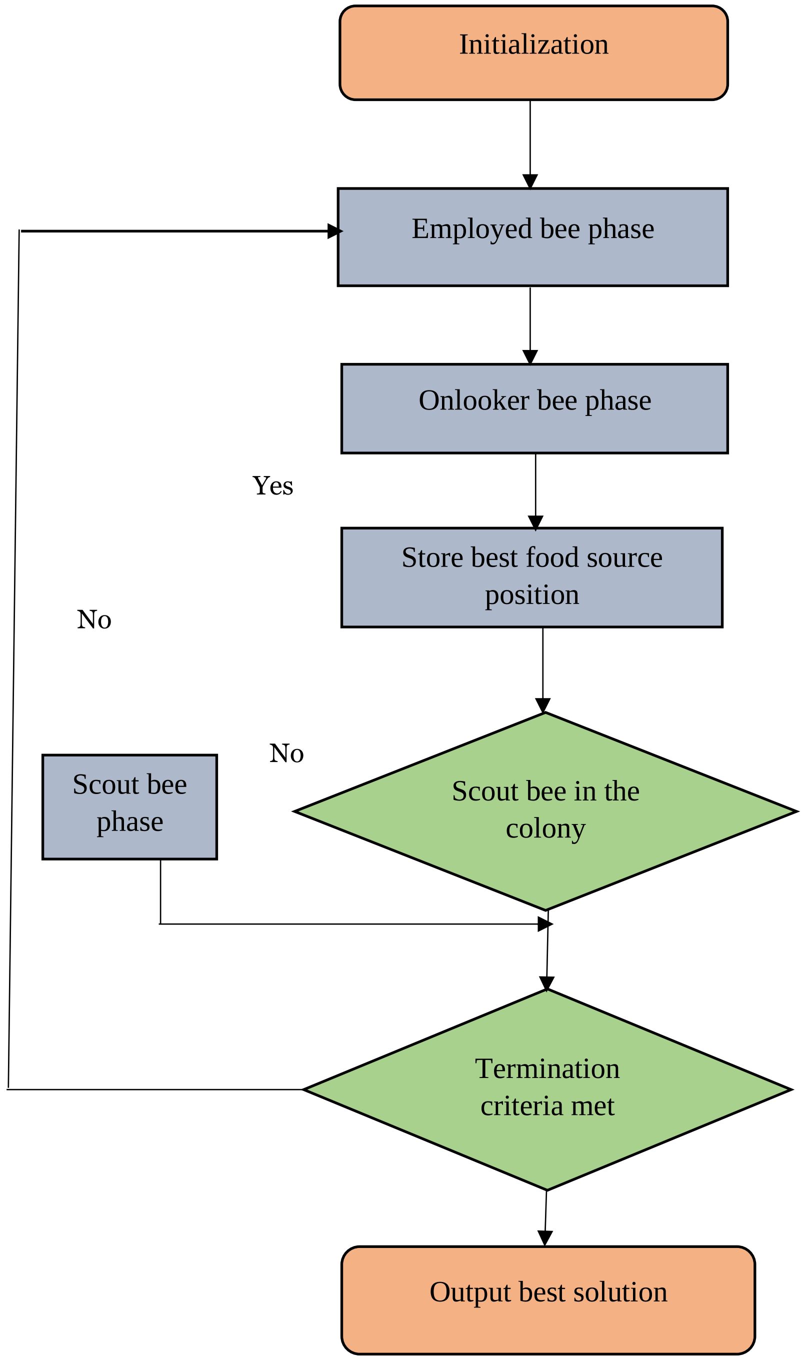

Figure 2. Flow chart of Recursive Bee Colony optimization algorithm

As seen in Figure 2, the Recursive Bee Colony Optimization algorithm employs a methodical approach that draws inspiration from honeybee foraging behavior. Initial food source positions (possible solutions) are established during the Initialization step. The algorithm then advances to the Employed Bee Phase, when newly recruited bees utilize established sites to look for fresh food sources and adjust their positions in response to a fitness assessment. The Onlooker Bee Phase follows, during which onlooker bees evaluate the quality of the food sources that hired bees share and choose the best ones to investigate further. The optimal food source level will thereafter be preserved. When a food

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supply runs out, the algorithm moves on to the Scout Bee Phase, where scout bees haphazardly look for fresh food sources to keep the solution space diverse. In order to ascertain if an ideal solution has been discovered or whether the algorithm should keep iterating, the procedure proceeds by looking for Termination Criteria. The algorithm produces the Best Solution if the requirements are satisfied. Because RBCO is recursive, it guarantees that the search process strikes a balance between exploitation and exploration.

Improved Endometriosis detection using the recursive bee colony method improves diagnostic accuracy by optimizing feature selection through recursive learning. It refines medical data analysis by iteratively enhancing relevant features and eliminating redundant ones. The recursive mechanism enables adaptive search, leading to higher classification accuracy and reduced false positives. Compared to traditional methods, RBC efficiently handles complex datasets, ensuring better generalization in Endometriosis detection.

3.5 Hyper capsule Resnet50-CNN

The Hyper Capsule ResNet50-CNN is an advanced deep-learning architecture designed for Endometriosis recognition using ultrasound images. It integrates the ResNet50 architecture with capsule networks, enhancing feature extraction and spatial hierarchy understanding. ResNet50, with its 50-layer deep residual network, efficiently extracts hierarchical features while avoiding the vanishing gradient problem through skip connections. However, traditional CNNs, including ResNet50, lose spatial relationships due to max-pooling operations. To address this, Capsule Networks (CapsNet) use dynamic routing and vector-based neurons (capsules) to preserve spatial hierarchies and orientation invariance.

The Heavy-duty design if the ResNet 50 makes it well-suited for applications such as image recognition, object detection, with state-of-the-art performance and high accuracy.

$$(X * Y)_{X,Y} = \sum_t \sum_b X\,[x+q, y+n].\,p[q,n] \tag{12}$$

In this case, P is the filter, x, y are the locations, and X is the known input image. The process moves a filter across the input image to determine a weighted sum of pixel values. It recognizes feature spatial hierarchies in images.

$$f(j) = \max\,(0, j) \tag{13}$$

This formula ensures that the network learns nonlinear decision boundaries by setting all negative pixel values to zero. To reduce the spatial dimension of the feature maps, we use the pooling layer in equation 14.

$$G_{y,z} = \max(X|k, l|) \tag{14}$$

In this case, k, l are the feature maps, and $G_{y,z}$ is the spatial dimension of the input images. By down sampling the input and preserving only the greatest value within a region, this lowers over fitting and computational complexity. The residual link, which incorporates information from a layer into it the output is a crucial ResNet element. Equation 15 calculates a residual block for an input.

$$l = F(k) + i \tag{15}$$

Here, F (k) represents the outcome of a sequence of operations, adding I to the block improves the gradient flow during back propagation. Using the following equation 16, we normalize the set.

This hybrid model enhances the representation of complex ovarian structures, reducing false positives and negatives. It achieves faster convergence and better generalization across diverse datasets, ensuring reliable performance. The method significantly improves sensitivity and specificity, making it more effective than traditional CNN-based approaches. Overall, it provides a robust, efficient, and scalable solution for Endometriosis detection.

ResNet 50 – CNN Architecture

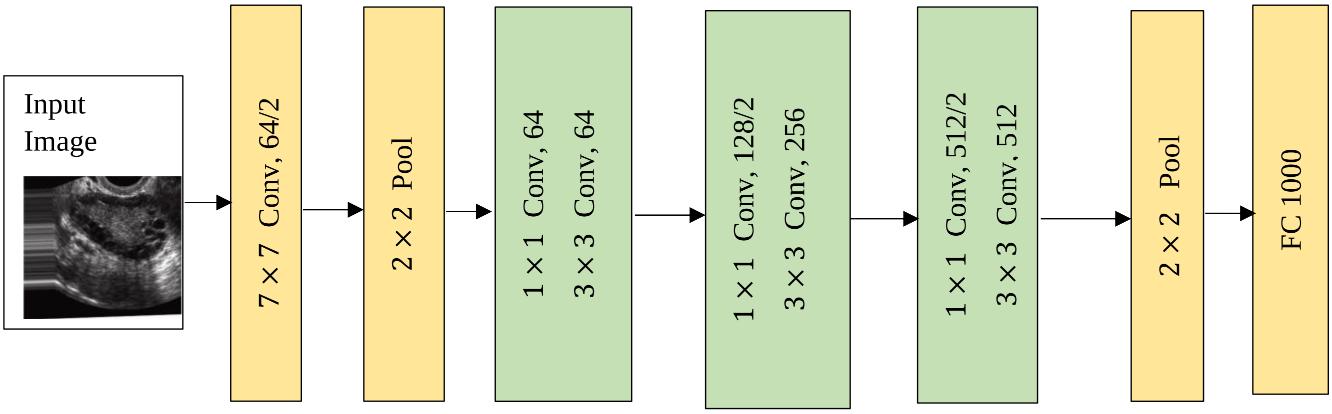

Figure 3. ResNet 50- CNN Architecture

Convolutional neural network design for feature extraction or image categorization is depicted in Figure 3. A 2 x 2 pooling layer is used to minimize spatial dimensions after an input picture is fed into the first convolutional layer, which uses a 7 × 7 convolution with 64 filters and a stride of 2. To extract deeper information, a sequence of convolutional layers is then deployed.

The first set consists of a 1 × 1 convolution with 64 filters followed by a 3 × 3 convolution with 64 filters, enabling dimensionality reduction and feature extraction. The second set follows a similar structure but increases the number of filters, starting with a 1 × 1 convolution with 128 filters, followed by a 3 × 3 convolution with 256 filters. This pattern continues with another block consisting of a 1 × 1 convolution with 512 filters, followed by a 3 × 3 convolution with 512 filters. As the network progresses, another 2 × 2 pooling operation is performed to further reduce the feature map size. Finally, a fully connected layer with 1000 output neurons is applied, which is typically used for classification tasks, mapping extracted features to the final output categories. The use of 1 × 1 convolutions helps reduce computation and maintain important spatial information, while 3 × 3 convolutions capture detailed patterns in the image.

3) Result & Discussion

The novel Hyper Capsule ResNet50-CNN algorithm effectively addresses the challenges in Endometriosis detection by classifying ovarian cysts from ultrasound images. Through Butterworth Filter preprocessing, the image details are enhanced, and the Modified Watershed Segmentation isolates cysts for feature selection. The Recursive Bee Colony (RBC) Feature Selection ensures the use of biologically relevant markers. ResNet50 with CNN extracts complex features while overcoming the vanishing gradient issue. Performance metrics (accuracy, sensitivity, specificity, RMSE, F1-score) demonstrate its effectiveness in accurate, robust Endometriosis diagnosis.

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4.1) Performance Metrics

Accuracy

Accuracy is realized when the mathematical standards are intended using the selected population's genuine positive outcome %. Accuracy was achieved in this investigation when the algorithm's percentage of follicles matched the number of follicles detected by medical experts.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{16}$$

Sensitivity

Sensitivity, also known as Recall or True Positive Rate, measures how well the model detects positive instances in this case, Endometriosis. It's particularly important when false negatives misclassifying Endometriosis as non- Endometriosis are costly in medical diagnoses.

$$Sensitivity = \frac{TP}{TP+FN} \tag{17}$$

Specificity

The model's ability to identify negative, non- Endometriosis occurrences is measured by its specificity, sometimes referred to as its true negative rate. Preventing false positives and the misclassification of non- Endometriosis as Endometriosis is especially crucial.

$$Specificity = \frac{TN}{TN+FP} \tag{18}$$

Root Mean Squared Error

In regression tasks, RMSE is frequently used to calculate the average size of errors between predicted and actual values. For a classification task like Endometriosis detection, RMSE can be used to assess the error in continuous predictions.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \tag{19}$$

F1-score

Precision and Recall's harmonic mean is the F1-score. When there is an imbalance in the distribution of classes, it is extremely helpful. They strike a balance between recall, or the capacity to identify all positives, and precision, or the accuracy of positive predictions.

$$FI - Score = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{ Recall}} \tag{20}$$

4.2 Dataset description

For continuous multi-section scanning of the uterus, cervix, and ovary utilizing an ACUSON Sequoia system (Siemens Healthineers, Germany) or LOGIQ (GE Healthcare, United States) ultrasonic diagnostic system, all individuals were placed in the lithotomy position with the vulva exposed. With 7.5–12 MHz intracavitary (transvaginal) probes and 3.5–6.0 MHz convex array probes, all equipment has the default gynecological examination mode. Three ultrasonographers with at least five years of clinical experience conducted these exams. The source available in "https://figshare.com/articles/dataset/A_histopathological_image_dataset_for_endometrial_disease_diagnosis/7306361". The picture archiving and communication system (PACS) workstation stored the US photos in the Joint Photographic Experts Group (JPEG) format. The study's sample dataset image is displayed in Figure 4 and 5.

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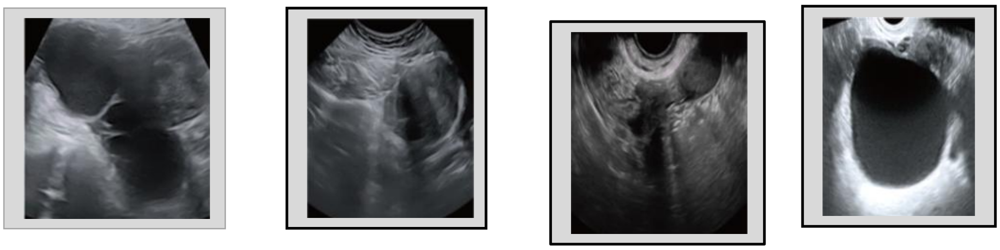
Figure 4. Ovarian endometriosis cyst



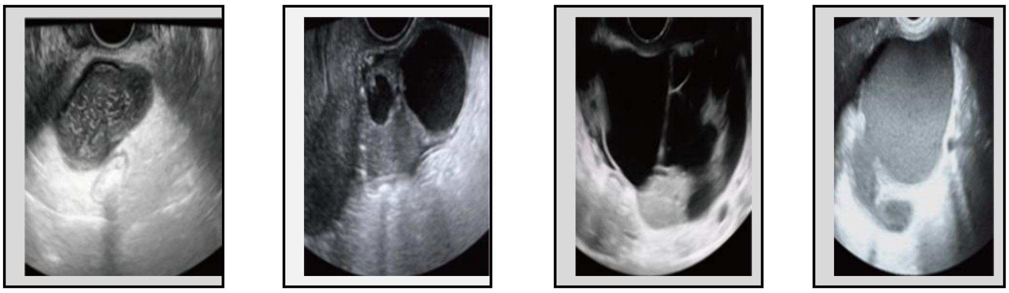


Figure 5. Tubal-ovarian abscess

4.3 Comparison Results

The proposed Hyper Capsule ResNet50-CNN model was evaluated using ultrasound image datasets classification. The performance was measured using standard evaluation metrics, including accuracy, sensitivity, specificity, Root Mean Squared Error, and F1-score.

Table 2. Evaluation of Performance Metrics

Performance Metrics	**CNN**	**SVM**	**ResNet50**	**Capsule Network**	**Hyper capsule ResNet50-CNN**
Accuracy	85.20 %	88.45%	91.75%	93.60%	94.15%
Sensitivity	82.50 %	86.10%	89.32%	91.90%	95.82%
Specificity	86.40%	89.70%	92.10%	93.25%	94.54%
FI-Score	83.12%	86.74%	89.88%	92.37%	94.89%
RMSE	87.80%	90.25%	93.20%	92.15%	84.25%

Table 2.Validates proposed Hyper Capsule ResNet50-CNN model outperforms traditional models (CNN, SVM, ResNet50, and Capsule Network) in Endometriosis classification using ultrasound images. It achieves the highest accuracy (94.15%), with improved sensitivity (95.82%), specificity (94.54%), and FI-Score (94.89%), ensuring fewer misclassifications and RMSE (92.78%) confirming its superior diagnostic reliability.

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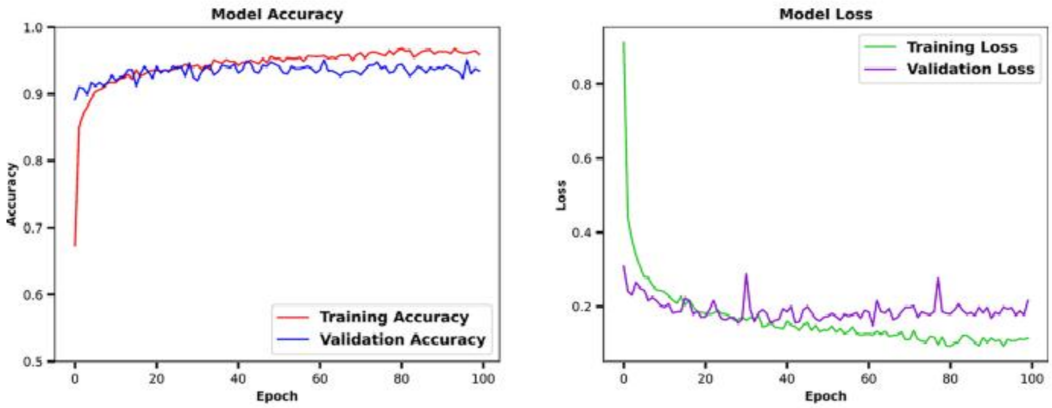

Figure 6. Evaluation of accuracy for CNN, SVM, ResNet50, Capsule Network and Hyper capsule ResNet50-CNN

Figure 6. The performance the accuracy evaluation of different models for Endometriosis recognition using ultrasound images highlights the superiority of the Hyper Capsule ResNet50-CNN model over traditional approaches. The CNN model achieves 85.20% accuracy, indicating its effectiveness but limitations in feature extraction. The SVM model improves slightly to 88.45%, leveraging statistical learning but struggling with complex patterns. ResNet50, a Convolutional neural network, reaches 91.75%, benefiting from residual learning. The Capsule Network further enhances accuracy to 93.60% by capturing spatial hierarchies. Finally, the proposed Hyper Capsule ResNet50-CNN attains the highest accuracy of 94.15%.

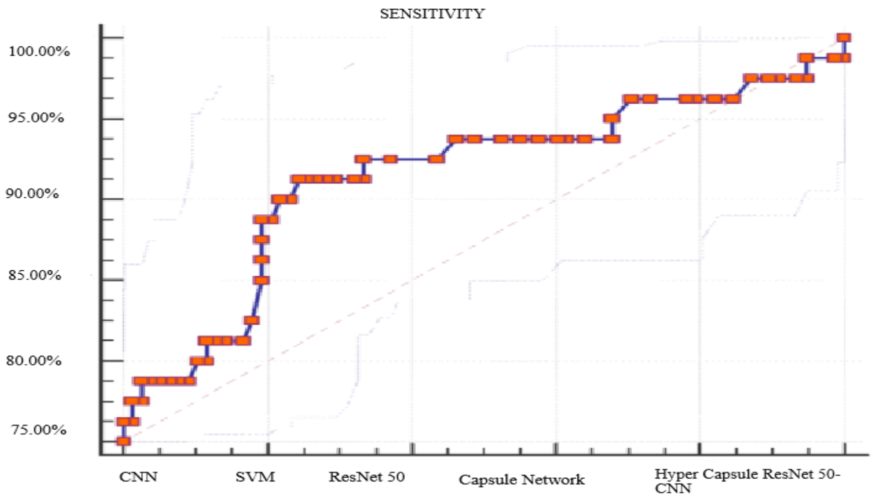

Figure7. Evaluation of Sensitivity for CNN, SVM, ResNet50, Capsule Network and Hyper capsule ResNet50-CNN

Figure 7 illustrates the sensitivity evaluation of different models for Endometriosis findings using ultrasound images, showcasing the ability of each model to correctly identify affected cases. The CNN model achieves a sensitivity of 82.50%. The SVM model improves to 86.10%, benefiting from its classification boundaries. ResNet50 enhances sensitivity to 89.32%, leveraging deep learning features. The Capsule Network reaches 91.90%, effectively capturing spatial relationships. The proposed Hyper Capsule ResNet50-CNN model achieves the highest sensitivity of 95.82%.

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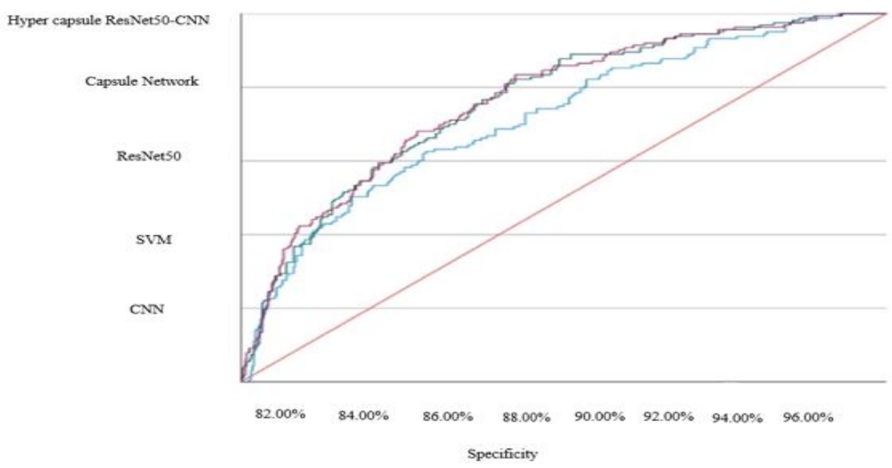

Figure 8. Evaluation of Specificity for CNN, SVM, ResNet50, Capsule Network and Hyper capsule ResNet50-CNN

Figure 8 presents the specificity evaluation of various models for Endometriosis detection using ultrasound images. The CNN model achieves 86.40% specificity, indicating a reasonable capacity to avoid false positives. The SVM model improves to 89.70%, benefiting from its strong decision boundaries. ResNet50 further enhances specificity to 92.10%, leveraging deep residual learning. The Capsule Network reaches 93.25%, effectively preserving spatial relationships. The proposed Hyper Capsule ResNet50-CNN model achieves the highest specificity of 94.54%.

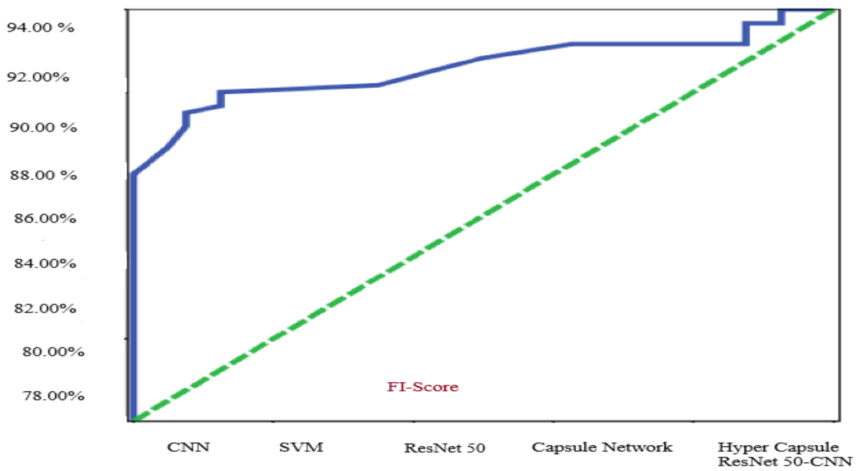

Figure 9. Evaluation of Sensitivity forCNN, SVM, ResNet50, Capsule Network and Hyper capsule ResNet50-CNN

Figure 9 presents the evaluation of sensitivity for five different machine learning and deep learning models: CNN, SVM, ResNet50, Capsule Network, and Hyper Capsule ResNet50-CNN. The sensitivity values, represented by the FI-Score, indicate the models' ability to correctly identify positive cases. Among the five models, CNN demonstrates the lowest sensitivity at 83.12%, followed by SVM at 86.74%. ResNet50 shows an improvement, achieving 89.88%, while the Capsule Network further enhances sensitivity with a score of 92.37%. The highest sensitivity is observed in the Hyper Capsule ResNet50-CNN model, which reaches 94.89%.

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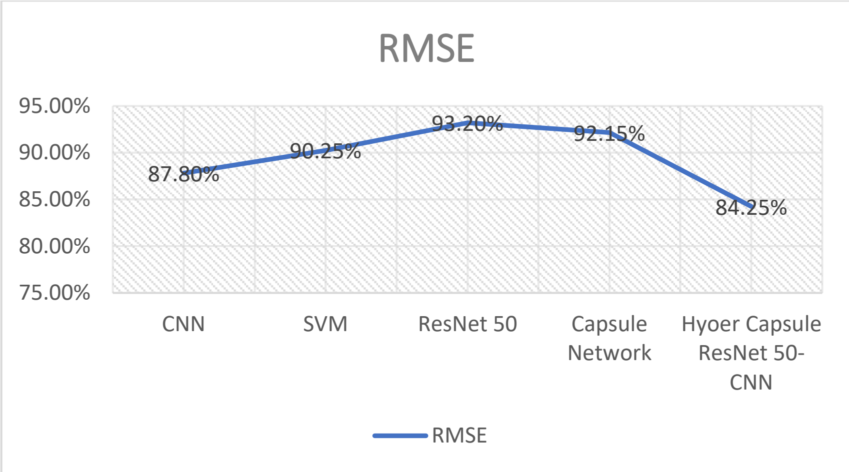

Figure 10. Evaluation of RMSE for CNN, SVM, ResNet50, Capsule Network and Hyper capsule ResNet50-CNN

Figure 10 presents the evaluation of the Root Mean Square Error (RMSE) for five different models: CNN, SVM, ResNet50, Capsule Network, and Hyper Capsule ResNet50-CNN. RMSE is a key metric used to measure the prediction error, where lower values indicate better model performance. The CNN model exhibits the highest RMSE at 87.80%, followed by SVM at 90.25%, indicating relatively higher error rates. ResNet50 achieves an improved RMSE of 93.20%, showing enhanced accuracy in predictions. However, the Capsule Network slightly reduces its performance with an RMSE of 92.15%, suggesting a minor increase in error. Notably, the Hyper Capsule ResNet50-CNN model records the lowest RMSE at 84.25%.

5) Conclusion

In conclusion, the proposed Hyper Capsule ResNet50-CNN algorithm offers a robust solution for accurately classifying endometriosis in ultrasound images, overcoming challenges faced by traditional methods. The use of a Butterworth Filter preprocessing technique enhances the input dataset, providing clearer and more detailed images for further analysis. The modified Watershed Segmentation algorithm effectively separates follicles or cysts, improving feature differentiation for classification. Additionally, the improved Recursive Bee Colony Feature Selection algorithm ensures biologically significant markers are correctly identified, minimizing feature extraction errors. By leveraging ResNet50's deep learning architecture, the system efficiently extracts complex features and resolves the issue of vanishing gradients. The model's classification accuracy, sensitivity, specificity, FI-Score, and RMSE metrics indicate strong performance, with an accuracy of 94.15%, sensitivity of 95.82%, specificity of 94.54%, FI-Score of 94.89%, and RMSE of 84.25%. These results demonstrate the potential of this algorithm for precise and reliable ovarian cyst detection, this will significantly contribute to early diagnosis and better management of Endometriosis.

References

[1] Asma' Amirah Nazarudin, Noraishikin Zulkarnain, Siti Salasiah Mokri, Wan Mimi Diyana Wan Zaki, Aini Hussain, Mohd Faizal Ahmad and Ili Najaa Aimi Mohd Nordin "Performance Analysis of a Novel Hybrid Segmentation Method for Polycystic Ovarian Syndrome Monitoring", Diagnostics 2023, 13, 750.

[2] Jaganathan, Gowthami, and Shanthi Natesan. "Blockchain and explainable-AI integrated system for Polycystic Ovary Syndrome (PCOS) detection." PeerJ Computer Science 11 (2025): e2702.

[3] Imran, Ruaa E., and Rawaa A. Faris. "Diagnosis of Polycystic Ovary Syndrome using Free Testosterone Levels via Surface Enhanced Raman Spectroscopy Induced by Gold Nanostar." Iraqi Journal of Laser 23, no. 2 (2024): 1-8.
[4] Kloos, Jacqueline, Jaime Perez, and Rachel Weinerman. "Increased body mass index is negatively associated with ovarian reserve as measured by anti-Müllerian hormone in patients with polycystic ovarian syndrome." Clinical Obesity 14, no. 3 (2024): e12638.
[5] Bedi, Pradeep, S. B. Goyal, Anand Singh Rajawat, and Manoj Kumar. "An integrated adaptive bilateral filter-based framework and attention residual U-net for detecting polycystic ovary syndrome." Decision Analytics Journal 10 (2024): 100366.
[6] Peng, Yujie, Meng Zhang, Jingjing Yan, Rong Wang, Yu Xin, Xiaoling Zheng, Libo Zhu, Weidong Fei, and Mengdan Zhao. "Emerging bioengineering breakthroughs in precision diagnosis and therapy for endometriosis and adenomyosis." Journal of Materials Chemistry B 13, no. 3 (2025): 742-762.
[7] Ma, Ying, Ruiyao Ma, Zhe Zhang, Heng Jiang, Yuting Li, Shen Jiang, and Yang Li. "Surface-enhanced Raman spectroscopy-based detection of EMT-related targets in endometrial cancer: potential for diagnosis and prognostic prediction." Analytical Chemistry 96, no. 22 (2024): 8973-8980.
[8] Gao, Xiaoxiao, Wei Shao, Jiaqi Wang, Han Gao, Xiaolu Zhang, Chen Xia, Mingqing Li, and Songping Liu. "Integrin β3 enhances glycolysis and increases lactate production in endometriosis." Journal of Reproductive Immunology 165 (2024): 104312.
[9] Scutelnicu, Liviu-Andrei, Radu Maftei, and Mihaela Luca. "An overview on diagnosis of endometriosis disease based on machine learning methods." In International Congress on Information and Communication Technology, pp. 237-250. Singapore: Springer Nature Singapore, 2024.
[10] Okita, Fernanda, Marina Paula Andres, Renata de Almeida Coudry, Luiza Gama Coelho Riccio, Edmund Chada Baracat, and Maurício Simões Abrão. "Confocal Laser Endomicroscopy as a method for assessing endometriosis: A pilot study." European Journal of Obstetrics & Gynecology and Reproductive Biology 302 (2024): 225-231.
[11] Jha, Manika, Richa Gupta, and Rajiv Saxena. "Noise cancellation of polycystic ovarian syndrome ultrasound images using robust two-dimensional fractional Fourier transform filter and VGG-16 model." International Journal of Information Technology 16, no. 4 (2024): 2497-2504.
[12] Rachana, B., T. Priyanka, K. N. Sahana, T. R. Supritha, B. D. Parameshachari, and R. Sunitha. "Detection of polycystic ovarian syndrome using follicle recognition technique." Global Transitions Proceedings 2, no. 2 (2021): 304-308.
[13] Lv, Wenqi, Ying Song, Rongxin Fu, Xue Lin, Ya Su, Xiangyu Jin, Han Yang et al. "Deep learning algorithm for automated detection of polycystic ovary syndrome using scleral images." Frontiers in Endocrinology 12 (2022): 789878.
[14] Suha, Sayma Alam, and Muhammad Nazrul Islam. "An extended machine learning technique for polycystic ovary syndrome detection using ovary ultrasound image," Scientific Reports 12, no. 1 (2022): 17123.
[15] Rachana, B., T. Priyanka, K. N. Sahana, T. R. Supritha, B. D. Parameshachari, and R. Sunitha. "Detection of polycystic ovarian syndrome using follicle recognition technique." Global Transitions Proceedings 2, no. 2 (2021): 304-308.
[16] Luo, Yi, Meiyi Yang, Xiaoying Liu, Liufeng Qin, Zhengjun Yu, Yunxia Gao, Xia Xu et al. "Achieving enhanced diagnostic precision in endometrial lesion analysis through a data enhancement framework." Frontiers in Oncology 14 (2024): 1440881.
[17] Zaidi, Shujaat Ali, Varin Chouvatut, Chailert Phongnarisorn, and Dussadee Praserttitipong. "Deep learning based detection of endometriosis lesions in laparoscopic images with 5-fold cross-validation." Intelligence-Based Medicine (2025): 100230.

[18] Nouri, Behnaz, Seyed Hesan Hashemi, Delaram J. Ghadimi, Siavash Roshandel, and Meisam Akhlaghdoust. "Machine learning-based detection of endometriosis: a retrospective study in a population of iranian female patients." International Journal of Fertility & Sterility 18, no. 4 (2024): 362.

[19] Guare, Lindsay A., Leigh Ann Humphrey, Margaret Rush, Meredith Pollie, James Jaworski, Alexis T. Akerele, Yuan Luo et al. "Enhancing genetic association power in endometriosis through unsupervised clustering of clinical subtypes identified from electronic health records." Research Square (2024): rs-3.

[20] Leibetseder, Andreas, Klaus Schoeffmann, Jörg Keckstein, and Simon Keckstein. "Endometriosis detection and localization in laparoscopic gynecology." Multimedia Tools and Applications 81, no. 5 (2022): 6191-6215.

[21] Zhao, Aihua, Xin Du, Suzhen Yuan, Wenfeng Shen, Xin Zhu, and Wenwen Wang. "Automated detection of endometrial polyps from hysteroscopic videos using deep learning." Diagnostics 13, no. 8 (2023): 1409.

[22] Gopalakrishnan, C., and M. Iyapparaja. "Detection of polycystic ovary syndrome from ultrasound images using SIFT descriptors." Bonfring International Journal of Software Engineering and Soft Computing 9, no. 2 (2019): 26-30.

[23] Mridul, Aunik Hasan, Nowreen Ahsan, Syeda Sadia Alam, Sonia Afrose, and Zakia Sultana. "Polycystic Ovary Syndrome (PCOS) Disease Prediction Using Traditional Machine Learning and Deep Learning Algorithms." International Journal of Computer Information Systems and Industrial Management Applications 16, no. 3 (2024): 25-25.

[24] Zou, Juan, Yukun Li, Nianchun Liao, Jue Liu, Qunfeng Zhang, Min Luo, Jiao Xiao et al. "Identification of key genes associated with polycystic ovary syndrome (PCOS) and ovarian cancer using an integrated bioinformatics analysis." Journal of Ovarian Research 15, no. 1 (2022): 30.

[25] Ahmed, Samia, Md Sazzadur Rahman, Ismate Jahan, M. Shamim Kaiser, ASM Sanwar Hosen, Deepak Ghimire, and Seong-Heum Kim. "A review on the detection techniques of polycystic ovary syndrome using machine learning." IEEE Access 11 (2023): 86522-86543.

[26] Ping Hu, Yanjuan Gao, Yiqian Zhang et al., " Ultrasound image –based deep learning to differentiate tubal-ovarian abscess from ovarian endometriosis cyst", Frontiers in Physiology.