Endometriosis Labelling using Machine learning

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***Abstract*— Endometriosis is a disease affecting the women's reproductive system. The lesion-like structure that exists in the women's reproductive organ creates an impact on their fertility. The diagnostic approach of endometriosis was performed by a radiologist using scanning procedures. Those procedures predict the occurrence of endometriosis but not the severity of endometriosis. Amidst the radiologist, machine learning techniques play a predominant role to identify the severity of endometriosis. Among all machine learning techniques, the proposed approach uses a support vector machine. Support vector machine is a contemporary technique for predicting clinical-based data. Support vector machine analyzes the influencing factor that incorporates Adnexal mass, Tube blockage, Lesion size, and lesion color for predicting the severity of endometriosis as well as classifying the endometriosis as Ovarian and Deep Infiltrating endometriosis. The execution was performed and trained accuracy obtained was 85%, test accuracy was 84.5% for radius basis function (rbf) kernel and the cross-validation score was 82.5%. Also, the available data was trained using Random Forest and Linear Regression. Among all three models, the Support vector machine outperforms well with hyper parameter as rbf for the given data to classify the endometriosis and identify the severity of endometriosis.**

Keywords—Adnexal mass, Cross-validation score, Deep Infiltrating endometriosis, Radius basis function, Support vector machine

I. INTRODUCTION

Endometriosis is a progressive condition that influences women of fertile age groups. Endometriosis was diagnosed by sonographers through traditional scanning procedures and advanced stages of endometriosis were identified through laparoscopic procedures. The symptoms of endometriosis include severe pelvic pain, dysmenorrhea, Irregular period cycle, etc. The region of occurrence of endometriosis was different for everyone. Based on the region of occurrence and lesion type, endometriosis is classified as ovarian endometriosis, Peritoneum Endometriosis and Deep infiltrating endometriosis.

Ovarian endometriosis is the type of endometriosis that occurs in the ovary which occurs brown, and the size of the lesion was found to be small. Peritoneum endometriosis is the type that occurs along the outer wall of the uterus and along with the layers of peritoneum. Generally, the lesion size of ovarian and peritoneum endometriosis is lesser than 5mm, whereas the lesion size of Deep Infiltrating Endometriosis was found to be greater than 5mm. Deep Infiltrating endometriosis largely penetrates the various regions.

The traditional procedure of identifying endometriosis was a) Magnetic Resonance Imaging, b) Ultrasound scanning, c) Pelvic Scan. These methods help in the identification of ovarian endometriosis. Laparoscopic surgery acts as the golden standard for gynecologists in predicting peritoneum and Deep Infiltrating endometriosis. Along with sonographers, machine learning techniques help in predicting the exact location of Deep Infiltrating endometriosis.

There exist several learning techniques for the prediction and classification of data. Support vector machine (SVM) is one of the most popular algorithms mainly used for analyzing the medical dataset [1]. The support vector machine is a supervised learning technique used for predicting data. The SVM uses several hyper parameters for fine-tuning the features to predict the data more precisely. The SVM algorithm creates a hyperplane that separates multiple classes more accurately.

In the support vector machine, hyper parameters [2] are important for assessing the model's performance. An empirical analysis needs to be performed for evaluating the model. The hyper parameters identified for support vector machine are kernel, gamma value and parameter c. The kernels used in support vector machines are linear, radius basis function (rbf), poly and sigmoid. Based on the dataset size, features availability kernel needs to be selected for implementation.

Multiple types of endometriosis are identified and a major classification was executed using a support vector machine to classify into two types namely normal endometriosis and deep infiltrating endometriosis. The factors influencing endometriosis [3] are identified as a feature for execution. The factors include Adnexal mass, size of the lesion, color of the lesion and blockages in fallopian tubes.

Severity of Covid 19 was predicted by using the hybrid algorithm as the "SVM-Enhanced slime mould algorithm". The features used were the patient's basic details and their hematological values. The proposed approach yields an accuracy of 89% [4]. A method known as "Artificial Immune System" was proposed to predict endometrial cancer. The proposed algorithm was executed along with a support vector machine where it achieves an accuracy of 92.5%. Here the histological details were used as features for execution [5]. Analyzed several machine learning models for evaluating the endometriosis bowel movements. Nearly 300 patients were used for evaluation. For the given dataset neural network model outperforms well with an accuracy of 74% [6]. "Deep Myometrial Invasion" was predicted using Magnetic resonance images. Probability-based Support vector machine and geometric feature were the proposed techniques used for predicting the severity with an accuracy of 89% [7]. Convolution neural network was used for predicting endometrial tuberculosis in women. Transvaginal scanned images are used for execution with a testing accuracy of 91% [8]. "Atomic Force Microscopy" was implemented for

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evaluating the severity of endometriosis using pathological images [9]. A deep learning approach was implemented for predicting endometrial tuberculosis. Resnet50 was implemented on 80 patient scanned images where it achieves an accuracy of 81% [10]. Implemented principal component analysis for reducing the dimensionality of endometriosis dataset, where the variance achieved was 95% with "IPCA value as 300" [11]. Identified the exact location of endometriosis using the "Mask R-CNN" segmentation process on laparoscopic images. The proposed approach performs well with IOU as 95% [12].

The study evaluates various algorithms including Support vector machine, Convolution neural network, Ensemble for predicting the severity of endometriosis. The proposed approach identifies the influencing factor as the major feature for execution. The paper is arranged as follows: Section I: Introduction II: Endometriosis categorization using Influencing factors, III: Results and Discussion, and IV: Conclusion.

II. Endometriosis Labelling Using Machine Learning

Various factors influencing Endometriosis were identified through the retrospective study. The most influencing factors identified are a) Adnexal mass, b) Tube Blockage, c) Lesion Color, d) Lesion Size [13]. These factors play a major role in identifying endometriosis as either Ovarian Endometriosis or Deep Infiltrating endometriosis. Based on the retrospective study nearly 600 records were chosen for execution. The rubric value identified for each influencing factor were as follows in table I:

TABLE I. Description of Features

Features	Detailed Description
Adnexal mass	Yes=1. No =0
Tube blockage	Yes=1 No=0
Lesion color	Brown, Black, Red, Light brown
Lesion size	DIE > 5mm, OE < 5mm

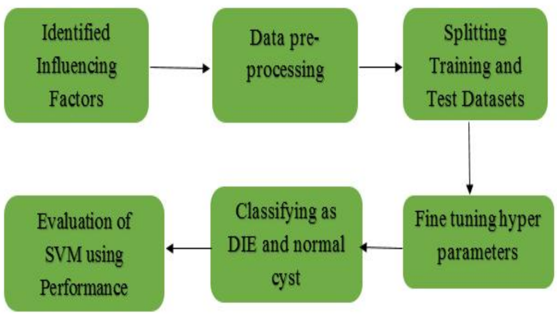


Fig. 1. Steps Involved in Classification of Endometriosis using SVM

Based on analysis various combinations of these values were identified for classification. The steps involved in classifying the endometriosis are as follows:

1. Collection of influencing factors
2. Data Pre-processing
3. Splitting of Training and Test Datasets
4. Fine-tuning of Hyper parameters.
5. Evaluation of SVM using Performance metrics

A. Pre-processing

The influencing factors for predicting endometriosis were collected based on a retrospective study. The identified factors were used as parameters for classification. To classify the parameters, the values of those parameters are pre-processed. The pre-processing includes Scaler Transformation [14]. The scaler transformation was used to normalize the dataset from the mean value obtained in Equations 1 and 2. The Min-max scalar is applied to convert the minimum value is 0 and maximum as 1.

$$F_{sd} = \frac{F - F.\text{mini}\,(axis=0)}{F.\max i(axis=0) - F.\text{mini}\,(axis=0)} \quad (1)$$

$$F_{scaled} = F_{sd} * (maxi - mini) + mini \quad (2)$$

Where maxi and mini represent the feature range. The transformed values were used for further execution.

B. Various Machine Learning Algorithms for categorization

The preprocessed dataset was implemented using various machine learning algorithms. The algorithms identified for executing medical data were a) Support Vector machine, b) Random Forest, c) Linear regression, and d) Extreme Gradient Boost.

1) Support Vector Machine

Support vector machine (SVM) belongs to the category of supervised machine learning technique. SVM can be applied for both classification as well as regression problem. Here we plot each value of feature on position. Finally, a hyperplane was created by differentiating features that leads to classification. Several hyperplanes were created for segregating multiple features. To find the most suitable hyperplane, a parameter known as kernel function was implemented. Based on the classification, the kernels were chosen for execution. SVM can be used in application [28] that includes text classification, image classification and detecting the face.

2) Random forest

Random forest is yet another supervised learning category. Random forest implements the concept of classifying multiple parameters to improve the performance of model. Random forest prevents the process of overfitting. Random forest selects n number of data points, through which decision tree was constructed. Multiple decision trees were constructed where prediction was evaluated for each tree. Random forest can be used in applications [29] including medicine, banking and marketing.

3) Linear regression:

Linear regression employs a statistical approach for prediction. This approach establishes a linear relationship between targeting and independent features. The performance of the linear regression was evaluated using mean square error and R-Squared method. The area [30] where the linear regression applied were weather forecasting and stock prediction.

C. Hyper parameters

The dataset was split as 70% and 30% as training set and validation set respectively. The hyper parameters were fine-tuned based on empirical analysis.

The hyper parameters used for analysis are as follows: The hyper parameter kernel was used to simplify complex calculation. A) Kernel: Linear, rbf, and poly. Linear kernel was used for classifying dataset that holds a greater number of features. Rbf (Radial basis function) is a non-linear function used for optimization. The polynomial kernel was similar to linear kernel function, where the polynomial kernel was applied to complex dataset.

The formula for linear, rbf and poly kernel are as follows:

Linear function:

$$res = c * a + b \tag{3}$$

Radial basis function:

$$res = \exp\left(-B\left||A - b\ |\right|^2\right) \tag{4}$$

Poly function:

$$res = (c * a + b)^\wedge 2 \tag{5}$$

The next parameter identified for execution was the c value. The value of C was also called as "penalty parameter". The higher c values avoid misclassification for the specified dataset. The value of C identified for the given dataset was [0, 1, 10, and 100]. The next parameter used for supporting vector machine model was gamma. Gamma was used to analyze the influence of training datasets. The gamma parameter identified for the given model was [1, 0.1, 0.01, and 0.001]. Endometriosis was categorized as ovarian endometriosis and deep infiltrating endometriosis by training the pre-processed data with the detected hyper parameters.

Steps in Support Vector machine:

1. Identify the features using retrospective study.
2. Apply preprocessing using scaler transformation.
3. Split the pre-processed dataset as training and test dataset.
   a. Training – 70%
   b. Test -30%
   c. Random size-200
4. Identify the suitable hyper parameters for SVM learning.
   a. Kernel as rbf
   b. 'C': [0.1, 1, 10, and 100], 'gamma': [1, 0.1, 0.01, and 0.001]
5. Analyze the metrics using Confusion matrix.
6. Compute the cross-validation score and stratified cross validation score.

D. Performance metrics

To evaluate the model trained, various performance metrics are used for evaluation. They are as follows:

1) Accuracy

Accuracy is defined as a tool used for computing the relationship between various parameters used in the execution model.

$$Accuracy = \frac{Correct\ Prediction}{Total\ no\ of\ Prediction} \tag{6}$$

2) Precision

Precision is used for identifying the positive prediction made by the parameters used in the execution model.

$$Precision = \frac{True\ positive}{Overall\ Positive} \tag{7}$$

3) Recall

Recall is used for identifying the relevant prediction made by executing the model using the available parameters.

$$Recall = \frac{True\ Positive}{Positive+Negative} \tag{8}$$

4) Support

Support is defined as positive values identified in each class of Final targeted parameters. [18]. Along with performance metrics evaluation, the Correlation matrix [19] was executed to identify how far the variables correlate with each other. Positive values indicate the closeness of parameters and negative values indicate there exists no relation between those parameters. There exists a positive correlation between Adnexal mass and Lesion size. Also, there exists another correlation between Lesion size and Tube blockage. The output was illustrated in figure 2.

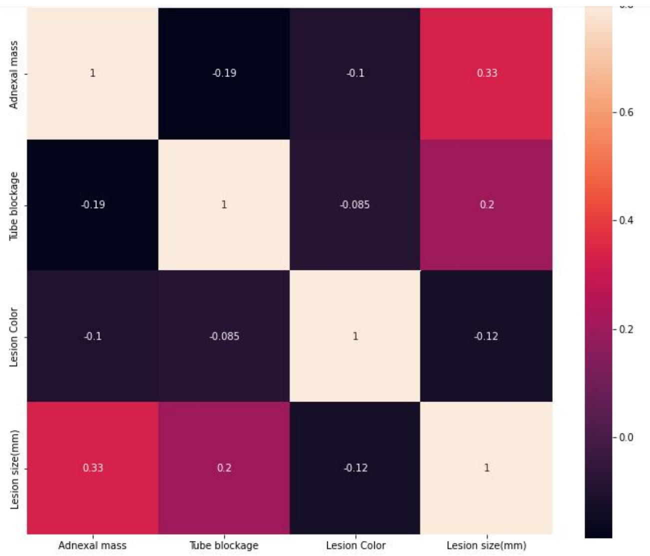


Fig. 2. Correlation matrix for various Influencing factors

III. Results And Discussion

The identified influencing factors that create a major impact on predicting the type of endometriosis were chosen as parameters for execution. Based on empirical analysis, the support vector machine model was selected for execution. The process of executing the model to classify the endometriosis was illustrated in figure 3.

The support vector machine uses multiple pre-processed parameters as input for execution. The parameters were split as training and testing set. Along with those parameters [20, 21], Kernel value, C, and gamma values were used for execution. The model was executed and classifies the endometriosis as Ovarian Endometriosis and Deep infiltrating endometriosis.

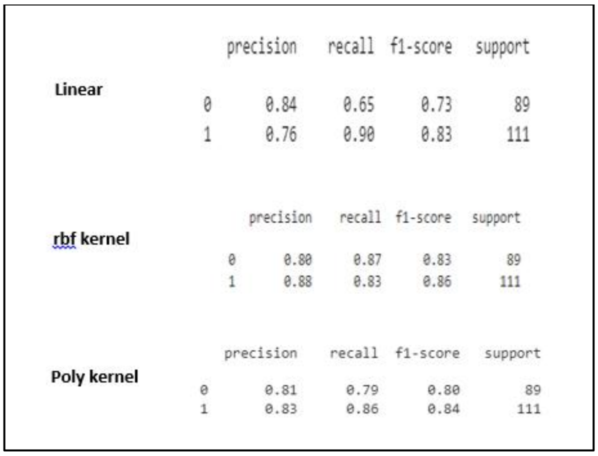
The executed testing model was evaluated using confusion matrix [22] as True Positive, True Negative, False positive, and False Negative values.

TABLE II. Confusion Matrix For Various Kernel

	LINEAR KERNEL		RBF KERNEL		POLY KERNEL	
	DIE	Ovarian	DIE	Ovarian	DIE	Ovarian
DIE	100	11	92	19	95	16
OVARIAN	31	58	12	77	19	70

From the confusion matrix obtained, linear kernel obtains true positive value as 100, true negative was 58, false positive was 11, and false negative was 31. When applying radius basis function(rbf) as the kernel for the given model, the true positive was 92, true negative was 77, false positive was 19 and false negative was 12. Finally, polynomial function was used as the kernel, where the value obtained for true positive, true negative, false positive and false negative was 95,70,16 and 19 respectively. Among all the kernels, rbf outperforms well for the given dataset. The support vector machine classifies the data as Ovarian and Deep Infiltrating Endometriosis. Around 200 data were tested, 169 were found to be Deep Infiltrating endometriosis and 31 were found to be ovarian endometriosis.

The performance metrics were evaluated for the given dataset. An empirical analysis was done by using three kernels in support vector machine model for the given dataset. The performance metrics were evaluated for the testing dataset. They were precision, recall, f1-score, support, and accuracy. The values obtained are illustrated as follows in figure 3.



		precision	recall	f1-score	support
Linear	0	0.84	0.65	0.73	89
	1	0.76	0.90	0.83	111
rbf kernel	0	0.80	0.87	0.83	89
	1	0.88	0.83	0.86	111
Poly kernel	0	0.81	0.79	0.80	89
	1	0.83	0.86	0.84	111

Fig. 3. Performance of SVM using Various Kernel

The performance metrics were performed for three kernels including linear, rbf and poly kernel. Among all it was found that rbf kernel performs well.

The most important metric evaluated was accuracy. The linear kernel obtain accuracy in training score was 77.5%, testing score was 79%. The rbf kernel yielded training accuracy of 85.2% and testing accuracy was 84.5%. The poly kernel yielded training accuracy of 85.7% and testing accuracy of 82.5%. The performance of the model was found to be more effective while implementing rbf kernel for the given dataset was illustrated in figure 4.

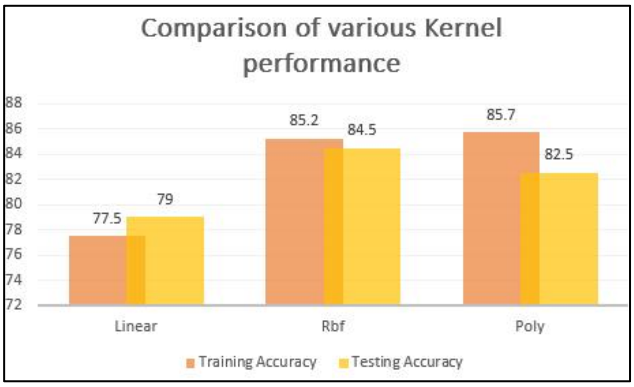


Fig. 4. Accuracy obtained for various kernel

Along with the kernel, another hyper parameter chosen was C. The training and testing score of using identified C value in three different kernel was evaluated. The average training score while using c parameter with linear kernel as c value 1000 was 77.7, testing score value was 79.5. With rbf kernel the training score with c value 1000 was 92.2, whereas the testing score was 90.5. Similarly for poly kernel, training score with c value was 87.5, testing score was 87. The comparison of c parameter with various kernels was illustrated in figure 5.

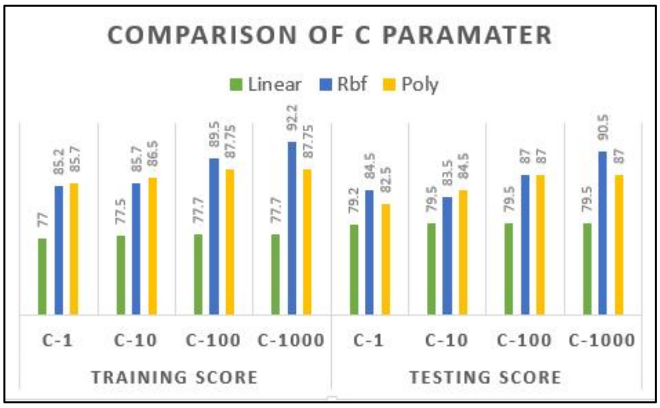


Fig. 5. Comparison of C parameter using various kernel

Along with Confusion matrix evaluation, Cross-validation score [23] and Stratified cross-validation score was evaluated. Here the cross-validation score was used to identify how the individual parameters were involved in evaluating the model. The comparison of various kernels was illustrated in Table III and Figure 6.

TABLE III. CROSS VALIDATION SCORE

KERNELS	AVERAGE CROSS-VALIDATION SCORE
LINEAR	77.5%
RBF	82%
POLY	80.5%

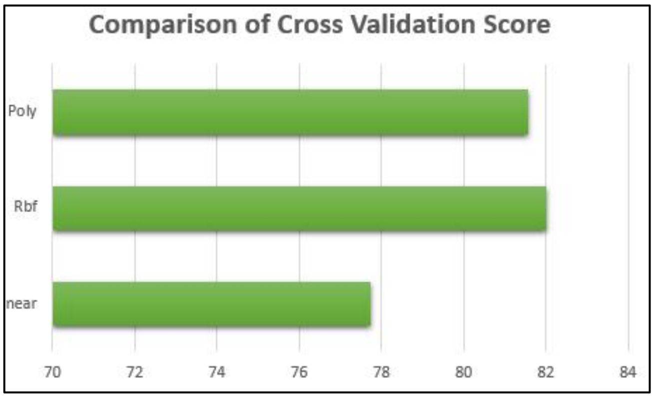


Fig. 6. Comparison of Cross validation score for various kernel

Along with the support vector machine, other model's metrics were evaluated for the given dataset. The Models evaluated were Random Forest and Linear Regression [24, 25, 26]. The support vector machine performs well with the value of precision as 86, Recall as 82, F1-Score as 83, Accuracy as 86. The random forest was executed for the given dataset to obtain a value of precision as 85, Recall as 80, F1-score as 84, Accuracy as 84.35. The Linear regression was executed for the given dataset and obtained a value of precision as 83.5, Recall as 81.35, F1-score as 84.35, Accuracy as 82.5. The comparison was performed across Support vector machines, Random Forest and Linear Regression were Support Vector machines well with an accuracy of 86% and it was illustrated in figure 7.

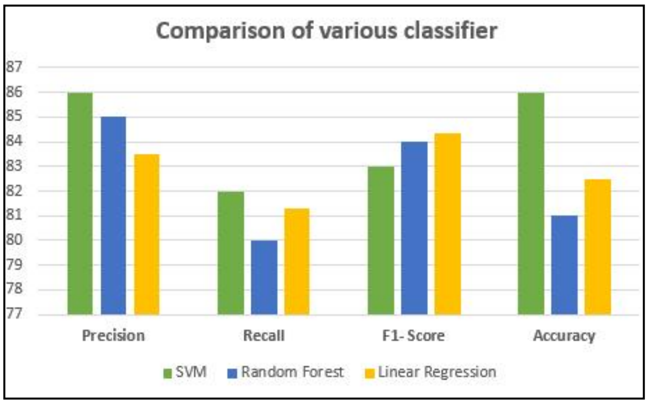


Fig. 7. Comparisons of various classifier

TABLE IV. COMPARISON OF EXISTING METHOD WITH PROPOSED METHOD

Ewa J. Kleczyk[29]	eXtreme Gradient Boosting	85%, 85%, 84%, and 0.9 as accuracy, precision, Recall, F1 Score
Proposed method	Support Vector Machine	86%, 86%, 82%, and 0.83 as accuracy, Precision, Recall, F1 Score

The proposed approach was compared with the work of [29], where Gradient Boosting algorithm was used for predicting endometriosis. In this method the features used are presence of endometriosis at various locations (peritoneum, ovary, and deep infiltrating endometriosis). This existing method obtains an Accuracy of 85%, precision of 85%, Recall of 84% and F1 score of 0.9. The proposed method using support vector machine outperforms well with an accuracy of 86%. The comparison was illustrated in figure 8.

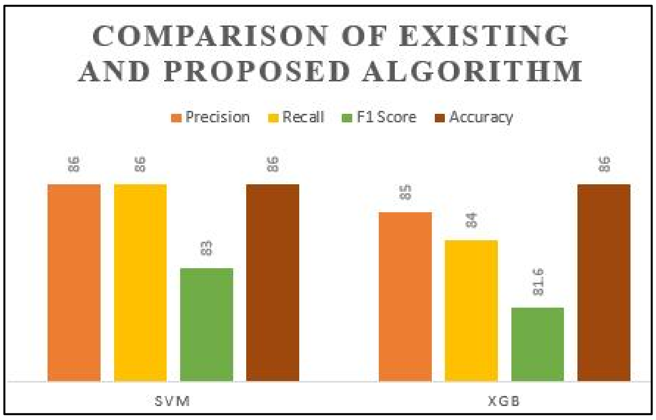


Fig. 8. Comparison of Proposed method using SVM with existing method (xGB)

IV. CONCLUSION

Medical experts find it difficult to identify the severity of endometriosis using traditional scanning procedures. Laparoscopic surgery helps the gynecologist to predict the severity of endometriosis. To overcome this problem, the proposed approach implements machine learning algorithms to assist the sonographers to find the severity of endometriosis. Support vector machine is a cutting-edge technology employed to predict the severity as well as the type of endometriosis. Influencing factors were used as features for prediction. Approximately 600 data were used for execution. Around 200 data were for validation where 152 was predicted as Deep Infiltrating endometriosis with a test accuracy of 84.5%, precision was 74%, F1 score was 83%.Along with the Support vector machine, two more models namely Random forest tree and linear regression were used for training the same dataset. SVM obtained an accuracy of 86%, Random forest tree obtained accuracy of 84.5%, and linear regression obtain the accuracy of 82.3%. SVM model obtains the cross-validation score of 77.5%. Along with the Support vector machine, a Heat map was generated to identify the closely influenced factors. Support vector machine performs well for the given dataset and classifies the type of endometriosis more precisely.

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