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A COMPREHENSIVE REVIEW OF CLASSIFICATION TECHNIQUES FOR ENDOMETRIOSIS DISEASE IDENTIFICATION

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ABSTRACT

Medical disorders in women can often be the underlying cause of various symptoms and are frequently associated with anovulatory conditions, such as Endometriosis. The limitation of finding the specific diseases in image processing approach is complex structure tissue, early detection and treatment of these conditions are essential. To address these challenges, this review research with Multiple Machine Learning (ML) approaches such as Gradient Boosted Decision Tree, SE-ResNet-34 network, and CNN-based deep learning, for classification purpose for diseases identification. The datasets taken an ultrasound image related to Endometriosis, obtained from open-source platforms provided by women's healthcare facilities. Prior to analysis, these input images undergo data preprocessing techniques to enhance their quality and relevance, facilitating accurate evaluation of Endometriosis cases. The CNN network architecture is applied to extract intricate features from the input datasets. SE-ResNet-34 networks are particularly effective for image classification tasks due to their ability to address the advanced gradient problem, allowing for the construction of deeper network architectures with enhanced performance. Similarly, CNN, a powerful ensemble learning method, improves predictive accuracy by iteratively reducing classification errors. Performance metrics such as accuracy, sensitivity, and F1-score are used to evaluate the efficacy of these algorithms in the early diagnosis of Endometriosis and improving healthcare outcomes for women.

Key words: *endometriosis, residual network (resnet), convolutional neural network, se-resnet-34, machine learning (ml),*

INTRODUCTION

In endometriosis, tissue resembling the endometrium (i.e., facing of the uterus) raises external on uterus, often causing pelvic pain. Women with endometriosis may also experience infertility, fatigue, multisite pain, and other comorbidities. Therefore, it is essential to recognize endometriosis as a condition that can manifest differently and have varying implications at different stages of life. Endometriosis can also present as severe menstrual cramps (dysmenorrhea), ongoing pelvic pain, and pain associated with bladder or bowel issues. Endometriosis can affect a woman's quality of life because of pain, fatigue, and possible complications related to fertility [1].

Endometriosis is characterized by a histological review of an endometrial-like specimen (consisting of glands and endometrial stroma) growing out of the uterine cavity, usually implanted in the peritoneal cavity. Given the clinical circumstances and patient preferences for intervention, there are opportunities for both medical and surgical management of deep endometriosis. Medical treatments, such as progestins, gonadotropin-releasing hormone agonists, and gonadotropin-releasing hormone antagonists, can help minimize the development of lesions. Surgical management may adversely affect the bladder, ureter, and intestines, leading to difficult-to-manage short-term consequences such as bleeding and ureteral damage, as well as long-term sequelae that include rectal or ureteral stricture [41].

Variations in the pathway may include cellular adhesion and proliferation, somatic mutation, inflammation, localized steroidogenesis, neurogenesis, and immunological dysregulation. Changes in this pathway, collectively, likely contribute to the development of endometriosis. Risk factors associated with endometriosis include low birth weight, Mullerian abnormalities, early menarche, short menstrual cycles, heavy menstrual bleeding, low body mass index, and nulliparity. The identification of an endometrioma by ultrasonography should prompt further evaluation, particularly in a patient who complains of significant pain, as endometriomas necessarily co-exist with deep endometriosis [3].

Chronic pelvic pain (CPP) is a common condition experienced by women that can have detrimental effects on their wellness and quality of life. In order to assess pelvic pain, and specifically diagnose endometriosis with concomitant surgical excision, laparoscopy and histology have been deemed suitable options. However, 30-50% of women with pain also have endometriosis, making it challenging to link endometriosis to pelvic pain definitively. Women complained of pain and were then referred to a public gynecology clinic (as per standards of care) and then randomly assigned to one of two gynecology units, where they received standard care as patients. Women were followed for 36 months, with 6-monthly survey assessments of their demographics, medical history, quality of life, and Likert scale pain perceptions. Staging for endometriosis was carried out, and operational notes were reviewed [42].

Key factors in PCOS include age, Body Mass Index (BMI), hormone levels, irregular menstruation, and lifestyle patterns. These variables can inform predictive models that assist healthcare providers in early PCOS risk detection. Hyperparameter tuning, which considers factors such as age, weight, blood group, and Respiratory Rate (RR), is critical to enhancing model accuracy and preventing overfitting. The decision tree algorithm is utilized for model training and initialization, providing a robust and clinically valuable tool for PCOS risk assessment [5].

In young girls, acne is a common and typically normal condition. In such cases, acne often proves resistant to treatment. Another concerning symptom of PCOD is hair thinning, particularly on the scalp, including areas like the temples, forehead, or crown. Hair may also appear thinner across the body. Diagnosing PCOD requires a comprehensive blood test panel commonly referred to as the PCOD panel to measure levels of prolactin, and additionally, pelvic examinations are performed to detect masses, abnormal growths, or other irregularities [43].

Feature selection involves using statistical techniques or algorithms, such as Recursive Feature Elimination, to identify the most significant predictors, including BMI, hormone levels, and menstrual cycle patterns. To optimize model performance and prevent feature overload, three distinct feature selection techniques were applied to extract multiple reduced feature sets. After that, the dataset was separated into subsets for testing, validation, and training to guarantee a thorough assessment. Neural Networks, particularly suited for capturing complex feature relationships in large datasets, were utilized to achieve the most accurate and descriptive representation of the data [7].

Contribution of the Work

This study focuses on the study analysis of Endometriosis, providing a comprehensive analysis of Endometriosis disease classification methods and emphasizing the limitations of current approaches. It consolidates diverse datasets for disease detection and evaluates three key machine learning algorithms Gradient Boosted Decision Tree, Residual Network (ResNet), and CNN based deep learning technique with feature selection predictive capabilities and limitations [2] [4]. By synthesizing prior research, the study underscores underexplored challenges and variability in the field, offering detailed descriptions of relevant datasets and classification strategies. Additionally, it examines performance metrics, such as accuracy, commonly used in Endometriosis research [12].

The analysis explores various Endometriosis detection methods, focusing on classification techniques employed across studies. The three key algorithms Gradient boosted decision tree, Residual Network (ResNet), and CNN based deep learning technique, are critically examined for their effectiveness in machine learning applications. A detailed explanation of the different dataset types used in these studies is also provided, emphasizing their role in influencing algorithmic performance [8]. The study identifies the performance of datasets when applied to different machine learning algorithms, enabling a comparison of their efficacy.

A significant emphasis is placed on comparing the performance of current methods for Endometriosis detection. Moreover, the review presents research ideas for future work, identifying critical challenges associated with using machine learning for Endometriosis detection. These include issues related to data variability, feature selection, and model optimization, which must be addressed to improve the reliability and applicability of machine learning approaches in this domain.

LITERATURE REVIEW

This section explores the methodologies and algorithms discussed in various studies, providing a concise summary and comparative review for a brief analysis. The identified research gaps highlight key algorithms, their parameters, workflows, and outcomes, followed by a performance evaluation

Sumana et al. [44] proposed the Gynaecological Disease Diagnosis Expert System (GDDES), which leverages Natural Language Processing (NLP) to compute cosine similarities and retrieve the most relevant voice recordings of disease diagnoses [10]. The system initiates the process by prompting users to report their symptoms in their native language. Subsequently, a Support Vector Classifier (SVC) model predicts the disease, storing diagnostic results in a knowledge base that also serves as the dataset repository. The SVC model demonstrated robust performance, achieving an accuracy and precision of 93% and F1 scores of 92%.

Junfang Fan et al. [9] introduced a lightweight classification and diagnostic network incorporating a reverse bottleneck design to enhance feature extraction. Shuffle Net, a lightweight mobile terminal, employs pointwise and depth wise convolutions. Initially, it uses a conventional convolution with a stride of 4 and a kernel size of 4 × 4 for feature extraction, followed by a down sampling procedure based on optimal pooling, The classification accuracy of the network is reported at 95.93%.

Ren et al. [45] reviewed the in clinical practice, determining the lymph node metastatic status of Endometrial Cancer (EC) is a significant difficulty. Machine learning has been used by some researchers to detect lymph node metastases in EC patients early. However, because of the variety of models and modelling variables, the predictive usefulness of machine learning is debatable. However, when there is a significant disparity in the number of lymph node metastatic and non-metastasis samples, the c-index is unable to accurately represent the model's predictive accuracy for lymph node metastasis. The kind of machine learning models built using clinical features, radiomic features, and radiomic characteristics mixed with clinical features were used to conduct subgroup analyses.

Fazakis et al. [11] detailed a diabetes risk prediction framework using a Knowledge Discovery in Database (KDD) process. The dataset construction, feature selection, and classification tasks are addressed using several supervised machine learning techniques. Decision Trees create classification models by segmenting datasets into smaller subsets, while Random Forests build multiple decision trees to perform regression and prediction simultaneously. The proposed ensemble Weighted Voting LRRFs ML model demonstrates enhanced diabetes prediction performance with an Area Under the ROC Curve (AUC) of 0.884.

Yan Xiao et al. [46] explored the viability of treating female infertility with Low-Intensity Focused Ultrasound (LIFU), especially when PCOS and Premature Ovarian Insufficiency (POI) are present. It is commonly acknowledged that POI and PCOS are the main causes of infertility in women. Because of its mechanical effects, Low-intensity ultrasound focus with pulses (LIFU) has the potential to minimize ovarian tissue damage while promoting follicle formation. Potential treatments have been investigated through experimental studies carried out in controlled facilities with conditions of 22 ± 2 °C, 45–55 % humidity, and a 12-hour light/dark cycle.

Fouzia Akhter et al. [13] discussed a detection of clinical and biochemical evidence of hyperandrogenism (after ruling out other possible diseases) in conjunction with chronic menstrual abnormalities allowed for the diagnosis of PCOS in teenage females age of 10 and 19 were included in the inclusion criteria, however certain medical problems and active therapies were excluded. According to BMI study, overweight (29.70%) and obesity (39.40%) were quite prevalent. 76.60% of people had normal levels of abdominal fat, whereas 20.00% had pre-hypertensive conditions and 3.40% had hypertension. There was variation in the glycaemic state, with 21.10% prediabetic, 2.90% diabetic, and 76.00% normoglycemic.

Krishna et al. [14] developed a diagnose PCOS, the tunica albuginea oculi region is separated from full eye images using a visual segmentation technique. Using pre-trained deep learning, the tunica albuginea oculi images were segmented and then classified as either PCOS or healthy. To guarantee that each category had an equal number of women, women who were selected at random from the university campus were questioned about whether they showed any symptoms of PCOS. The "no" class has a 92 % precise predictability, while the "yes" class has an 85 % precision, with recall rates of 85 and 92 %, respectively.

Pushkarini et al. [15] utilized a PCOS dataset is used for model testing and training. Divide the previously processed dataset into train and test sets; for instance, designate 20% of the dataset as a test and 80% as a training set. The models are trained and adjusted using training sets, With the highest $R2$ = 0.985, R2 = 0.985, the lowest Mean Absolute Error (MAE = 1.556), and the lowest Root Mean Square Error (RMSE = 3.079), the Random Forest model performs the best and makes reliable predictions. With $R2$ = 0.978, R2 = 0.978, greater MAE (3.282), and RMSE (3.930), Linear Regression performs marginally worse.

Zhang et al. [16] In this retrospective study, 122 patients with pre-operative MRI were included (78 AEH and 44 CEC). Radiomics features were extracted from apparent diffusion coefficient (ADC), diffusion-weighted imaging (DWI), and T2-weighted imaging (T2WI) maps. The best area under the curve (AUC) was 0.932 (95% confidential interval [CI]: 0.880-0.984), with a bootstrap corrected AUC of 0.922 in the training set, and an AUC of 0.942 (95% CI: 0.852-1.000) in the validation set for the radiomics-clinical model. The radiomics-clinical model included multimodal radiomics features and clinical variables-endometrial thickness >11mm, and nulliparous status. Our output data (F1 score = 0.900 for inconsistent group; F1 score = 0.865 for consistent group).

Agrawal et al. [17] conducted a single centre cross-sectional study enrolled 80 women diagnosed with PCOD to examine the impact of body image perception on depression severity and quality of life. The WHOQOL-BREF scale was employed to assess quality of life, revealing that women with PCOD and depression had significantly lower physical ($p < 0.001$), psychological ($p < 0.001$), and overall quality of life ($p = 0.025$) scores. Additionally, 73.8% of the participants were found to have depression, a notably high prevalence. The study also highlighted the compounded effects of other mental health conditions and substance use disorders (excluding caffeine and nicotine addiction) on these outcomes.

Kumar et al. [18] Depending on the population and diagnostic criteria employed, the prevalence rate of PCOS, the most prevalent endocrine disorder affecting women of reproductive age, can range from 8 to 13%. two train-test ratios (70:30 and 80:20), a thorough examination of nine machine learning techniques for PCOS classification was carried out. Particle Swarm Optimization (PSO) was used in conjunction with these models to improve performance, and the results showed 94.44% sensitivity, 97.22% specificity, and 94.44% precision. The accuracy of the models' positive case detection was greatly enhanced by this integration.

Elsayed et al. [19] investigated the impact of female infertility, imposing both financial and psychological burdens on patients. A clinical study comparing two groups revealed significant differences in pregnancy outcomes. Group 1, with 35 out of 50 cases confirmed via ultrasound to have gestational sacs (score > 6), showed a significantly higher clinical pregnancy rate compared to Group 2, with 18 out of 50 cases ($p = 0.0007$). Furthermore, the miscarriage rate was markedly lower in Group 1 (1 out of 35) compared to Group 2 (5 out of 18; $p = 0.006$), emphasizing the importance of effective treatment approaches.

Paramasivam et al. [20] proposed the particle swarm optimization (PSO) The Hybrid Attention-Enhanced MobileNetV2 using Particle Swarm Optimization (PSO) is a deep learning model that accurately classifies endometrial cancer using CT image data. MobileNetV2 acts as a lightweight backbone, and is substituted with a hybrid attention mechanism that concentrates on critical tumour regions, while reducing extraneous background noise from medical imaging features. The specificity 91.45 %, sensitivity 86.02 %, precision 86.75 %parameters and feature selection are enhanced using PSO to optimize speed and accuracy. Diabetic diagnoses and treatment recommendations can now take place significantly quicker using our hybrid model, as our documentation demonstrates the documentation described considerably less computational expense; while still retaining diagnostics. The model design is ideally suited for early detection of cancer in clinical settings where computational resources may be scarce and limited.

PREVIOUS ENDOMETRIOSIS DETECTION TECHNIQUE

In table 1 below presents a review and analysis of various classification methods, outcomes, from Endometriosis approaches. This comparison highlights the differences between conventional approaches and Machine Learning (ML)-based techniques, focusing on key performance metrics such as F1-score, recall, precision, and accuracy.

Many research studies have utilized ultrasound images as input datasets, often incorporating data augmentation techniques to analyse large datasets, identify patterns, and improve analytical accuracy. Advanced algorithms, including DenseNet-121, Logistic Regression, Random Forests, and ResNet-50, have been employed to detect conditions such as PCOD and PCOS.

Table 1. Various review and parameter analysis of disorder endometriosis

References	**Types of disorder**	**Dataset**	**Algorithm Used**	**Output**	**Limitation**
Visalaxia et al	traumatic disorder	Endometriosis Dataset	CNN	1. Accuracy 90% 2. Precision 83%. 3. Recall 82%	Limited to specific types of endometritis data; does not generalize well to other forms of gynaecological disorders.
Kotaro Kitaya et al 2021	Chronic endometritis (CE)	Endometriosis Dataset	1. VGG-19 2. Dense Net-121	1. sensitivity 93.6 % 2. specificity 92.3 % 3. accuracy 92.8 % 4. precision 88.0 % 5. F1-score 90.7 %	Moderate accuracy; limited model optimization and dataset diversity.
Ping Hu et al 2021	Ovarian Endometriosis disorder	Endometriosis Dataset	1. ResNet-152. 2. DenseNet-161	AUROC 0.986	Dependence on structured EHRs; accuracy varies with reporting completeness.
Zhao et al 2022	Endometriosis disorder	Hysteroscopic images	YOLOX	ACC 95.83%	Relies heavily on image preprocessing; not robust to variations in imaging conditions.
James et al 2023.	microsatellite status	H&E-stained whole slide images (WSIs)	MSI classification	Sensitivity 0.857 F1-Score 0.826 AUROC 0.799	Limited to detecting hyperandrogenism; does not encompass other PCOS markers.

Hassan et al 2020	PCOS	In Kaggle site patient PCOS health report data set	1. Logistic Regression, 2. CART, 3. Naïve Bayes	1. Acc-92%, 2. Acc-90% 3. Acc-81%.	Limited feature engineering; performance varies significantly across algorithms.
Akanbi et al 2024	PCOS	Patient PCOS health report data set on the Kaggle website	1. AdaBoost 2. Logistic Regression 3. Gradient Boost	1. Acc-91%, 2. Acc-90% 3. Acc-95%.	High accuracy but limited generalizability to non-Kaggle datasets.
Mukta Agarwal et al 2024	gynecological issues	Women Health care Data	1. Diseases diagnosis algorithm	1. Abdominal discomfort 15.6% 2. Vaginal discharge 7.2%.	Limited to symptomatic classification; lacks validation on diverse data sources.
Al-Ghazali et al 2022	PCOS	Specific women Health care Data	classification technique	1. Sensitivity 90.9%, 2. Specificity 90.9%, 3. Accuracy 90%	Classification depends on structured and high-quality data; results may degrade with noisy inputs.
Nandipati et al 2020	PCOS	significance health care report data set	KNN	In RapidMiner 1. Accuracy 90.38 % 2. Precision 90.83 % 3. Recall 90.83 %	KNN is computationally intensive for large datasets; prone to overfitting with noisy data.

METHODS

This review explores feature selection techniques, three key classification methods, and performance metrics in the context of machine learning applications for detecting Endometriosis disorders. The input dataset primarily consists of ultrasound images, including both affected and unaffected cases, complemented by healthcare data specific to women's medical analyses. The study evaluates key performance metrics and assesses the effectiveness of various approaches. By iteratively training algorithms on these images and refining their parameters based on prediction errors, the models learn to identify patterns distinguishing healthy ovaries from those affected by different types of Endometrioses. The integration of machine learning techniques holds great promise for significantly improving the early detection and treatment of Endometriosis.

Data Set

The ovarian ultrasound dataset analyzed in this study was obtained from the open-source website and consists of medical data, which we analyzed in collaboration with four radiologists in the Department of Radiology. The radiologists assessed 1,250 patients, which consisted of 1,000 patients with the normal ovaries or other pathologies and 250 patients with endometriosis, a chronic gynecological disease characterized by the growth of endometrial-like tissue outside the uterus. While some patients had multiple ultrasound studies, only the most recent study for each patient was included in the review. In the interest of consistency and clarity, we selected only images showing the ovary with surrounding structures. The radiologists categorized the images into two groups for classification: images showing sonographic features consistent with endometriosis (such as ovarian endometriomas or deep infiltrating lesions) and ones with normal ovarian morphology (Figure 1).

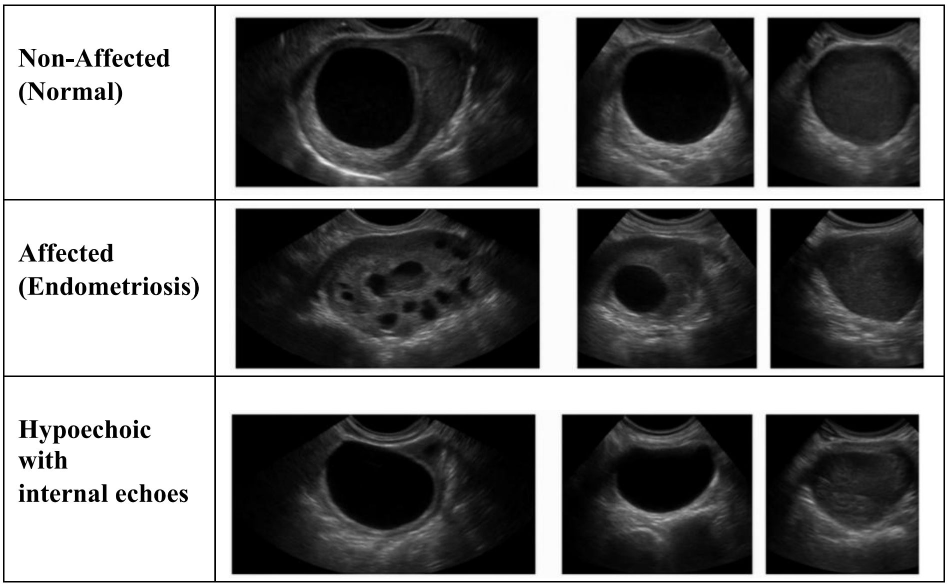

Figure 1. Ultrasound image dataset of endometriosis

Endometriosis

Endometriosis has a complex and multifaceted etiology influenced by environmental, genetic, and intergenerational factors. These factors contribute to ovarian and adrenal hyperandrogenism, which, in turn, disrupts the signaling of the hypothalamic pituitary ovarian axis. The syndrome is further characterized by metabolic dysfunctions, including lipid toxicity, oxidative stress, and insulin resistance, all of which are exacerbated by adipose tissue accumulation associated with hyperandrogenism. Consequently, Endometriosis manifests as a broad clinical spectrum, affecting metabolic, reproductive, and psychological health. While genetic predisposition plays a pivotal role in Endometriosis, environmental factors likely interact with these genetic elements to worsen the condition. However, more recent examinations have revealed a polygenic basis for the syndrome. The genetic complexity of the syndrome is underscored by the identification of 19 risk loci associated with neuroendocrine, metabolic, and reproductive pathways through genome-wide association studies.

Although Endometriosis lacks a well-established physiopathology, it is an inflammatory condition, and endocrine-immunological interactions likely influence its etiology. Endometrial cells that are lost during menstruation and exit the uterus are typically cleared by the immune system. These cells may not be removed efficiently in Endometriosis, possibly due to decreased NK cell activity or other immunological dysfunctions. Instead of removing endometrial cells, macrophages may release cytokines and growth factors [31].

Endometriosis frequently manifests as infertility, pelvic discomfort, and dysmenorrhea, which can lead to a worse quality of life and a high rate of morbidity in chronic situations. Although the precise pathophysiology and natural history of Endometriosis are not entirely known, the most widely accepted explanation states that endometrial cells are implanted and develop in the pelvic cavity during retrograde menstruation due to the intricate interactions of growth, angiogenic, and immunological factors. Although little is known about the mediating processes behind the inverse association between obesity and endometriosis risk, several theories and pathways have been proposed in published research domains.

PCOD

PCOD is Stein-Leventhal Syndrome, is characterized by clusters of small, pearl-like cysts in the ovaries. These fluid-filled cysts contain immature eggs and often outcome from a combination of genetic and environmental factors. PCOD leads to a variety of symptoms, including physical changes, irregular menstruation, and, if left untreated, serious health complications such as diabetes, heart disease, obesity, mood disorders, endometrial cancer, and sleep apnea. The condition primarily affects women between the ages of 14 and 44. A hallmark feature of PCOD is the overproduction of androgens, which are essential for follicular development. While luteinizing hormone levels are noticeably elevated, the absence of hormonal balance impairs optimal progesterone and estrogen production.

Compensatory hyperinsulinemia, a common characteristic of the disorder, exacerbates ovarian dysfunction. In women health care data analysis hyperinsulinemia increases ovarian androgen production, inhibits ovulation, and contributes to hyperandrogenism. This occurs as insulin stimulates theca cells ovarian cells responsible for testosterone production through androgen biosynthesis. As an outcome of this cascade, the excess androgens generated by insulin resistance and abnormal ovarian function lead to hyperandrogenism. Hyperandrogenism disrupts normal ovulation and inhibits follicular growth, impairing the development of eggs within the ovarian sacs [32].

Feature Selection

In ovarian and ovary disease prediction, feature selection also helps to address challenges like overfitting, which occurs when the model learns noise instead of underlying patterns in the data. By removing irrelevant features, feature selection reduces the risk of overfitting and enhances the generalizability of the model to new patient data. For example, in detecting ovarian cancer, feature selection might isolate a small set of biomarkers strongly associated with malignancy, enabling early diagnosis and personalized treatment planning. Additionally, this process supports the identification of novel disease mechanisms, paving the way for improved diagnostic tools and therapeutic targets**.**

Grey Wolf Optimizer (GWO) Algorithm

The Grey Wolf pack or group, which typically consists of five to twelve wolves, is the model for this optimizer algorithm. Every wolf can be classified as an alpha, beta, delta, or omega wolf, and it has a special connection to teamwork.

$$\text{Deviation}: \ \sigma \sum_{i=1}^{n} (1-\mu)^2 \, h(i) \qquad \ldots \qquad (1)$$

In equation (1) Let f(i), where Ax is the vision's surface and (i = 1, 2, n) is the number of points in the image with strength i.

$$wcobx = \frac{\sum_e i\, B(i,j)}{\sum_e i\, B(i,j)} \qquad \ldots \qquad (2)$$

In equation (2) Between 0 and 180°, recovered H1 and two weighted centres of spectrum features for each 1° Radon transform. Consequently, 724 (181 × 3) characteristics would be extracted in total. In summary, the steps to determine the HOS traits from an ultrasound image are as follows:

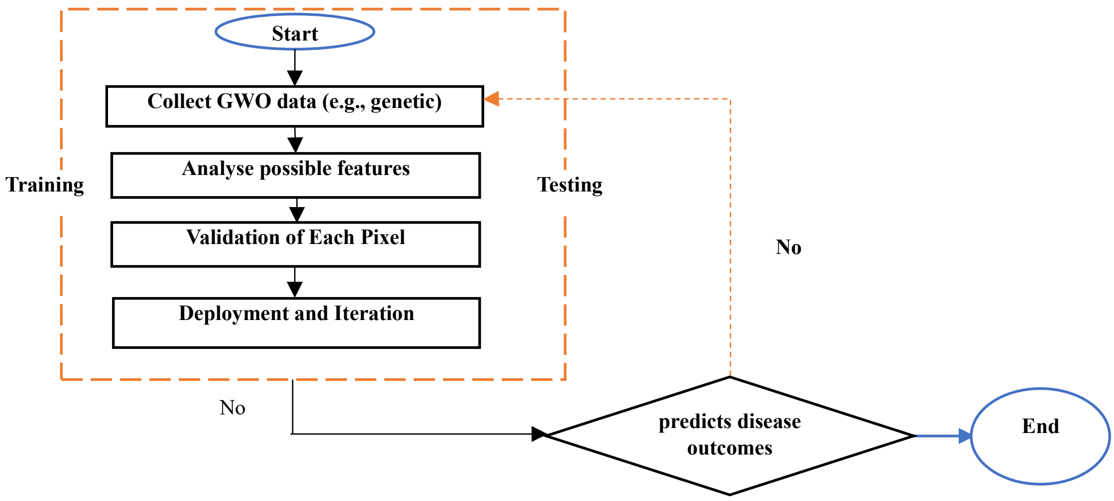

Figure 2. Flow chart of GWO Feature selection

In training and testing for ovarian and ovary disease prediction, feature selection works by identifying and retaining only the most relevant variables from the image dataset to build predictive models shown in Figure 2. During the training phase, feature selection methods analyze the dataset to determine which features (e.g., biomarkers, genetic mutations, or clinical parameters) have the strongest correlation with the target outcome, such as the presence of a disease. GWO reduces the dimensionality of the data, allowing the model to learn patterns more efficiently and minimizing the risk of overfitting. During testing, the selected features are used to evaluate the model's performance on unseen data, ensuring that the model generalizes well and accurately predicts disease outcomes. This streamlined approach improves model interpretability, computational efficiency, and diagnostic [33].

Classification Technique

Classification plays an essential role in classifying patient disorder related to Endometriosis In the review approaches such as Gradient Boosted Decision Tree, SE-ResNet-34 network, and CNN based deep learning technique have demonstrated exceptional structural efficiency and predictive accuracy. These models excel in predicting group identifiers or class labels for previously hidden data, enabling precise categorization and deeper insights into complex diagnostic challenges.

Gradient Boosted Decision Tree

In order to create a strong predictive model, gradient boosted decision tree classifiers for Endometriosis disorder employ an ensemble learning technique that sequentially combines multiple weak models, typically decision trees. An initial model that generates predictions, typically a basic one, is used to start the process. Using the residual errors differences between the actual and predicted values from the earlier models, Gradient Boosted Decision Tree iteratively improves this model by training more decision trees. By focused on areas where the earlier models underperformed, each new tree progressively raises the overall accuracy. Combining these trees creates a strong classifier that can handle intricate, non-linear relationships in the data, which makes it ideal for identifying ovaries related patterns [34].

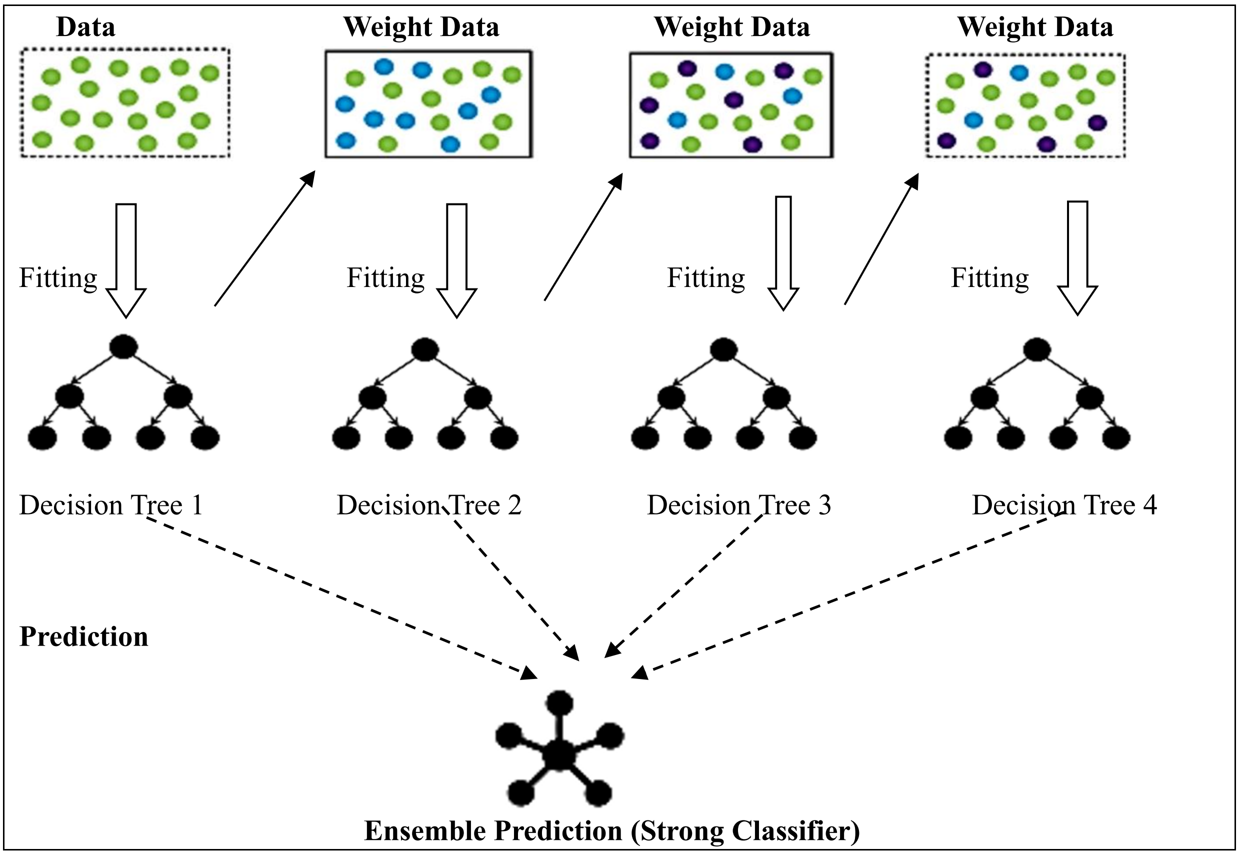

Figure 3. Architecture of gradient boosted decision tree classifiers [36]

Figure 3 show the prediction models in order to improve medical decision-making, an event rate of R percent among patients with a predicted risk of R percent is commonly used to define calibration. Plotting calibration curves and calculating brier scores were used to confirm the reliability of the models. By averaging the squared difference between expected and observed risk, the Brier score an estimated calibration index that builds upon a flexible calibration analysis is converted into a number between 0 and 1

$$f_1(x) \approx y \quad \ldots \quad (1)$$

$$f_1\,(X)\; \approx y - \; f_1\,(X)\,, f_2\,(X), \;\text{---}\;\; f_3\,(n) \quad \ldots \quad (2)$$

In equation (1) classifier evaluates a f_1 number of characteristics, including body measurements, lifestyle factors, hormonal levels, and ultrasound results, in order to determine a person's probability of having Endometriosis. Gradient Boosted Decision Tree maintains its accuracy even when there are more healthy samples than diseased ones because of its capacity to manage imbalanced datasets, which are typical in medical diagnosis scenarios. $f_n(n)$ such as Tree's feature importance analysis assist in determining which clinical factors have the greatest influence on predictions, which helps to better understand and enhance diagnostic procedures and personalized medicine, this approach works especially well [35].

SE-ResNet-34 network

The vanishing gradient issue, which can arise in very deep networks, is addressed with SE-ResNet-34 network classifiers, a kind of neural network. ResNet introduces the concept of residual learning through skip connections or shortcuts, which bypass one or more layers in the network. These connections allow the network to learn identity mappings, ensuring that the deeper layers can focus on learning the residual (or incremental changes) instead of the full transformation. This architecture facilitates the training of much deeper networks by enabling gradients to flow directly through the skip connections, improving convergence and avoiding overfitting. ResNet classifiers are especially effective for extracting high-level features in complex data, such as patterns in medical imaging or multidimensional datasets.

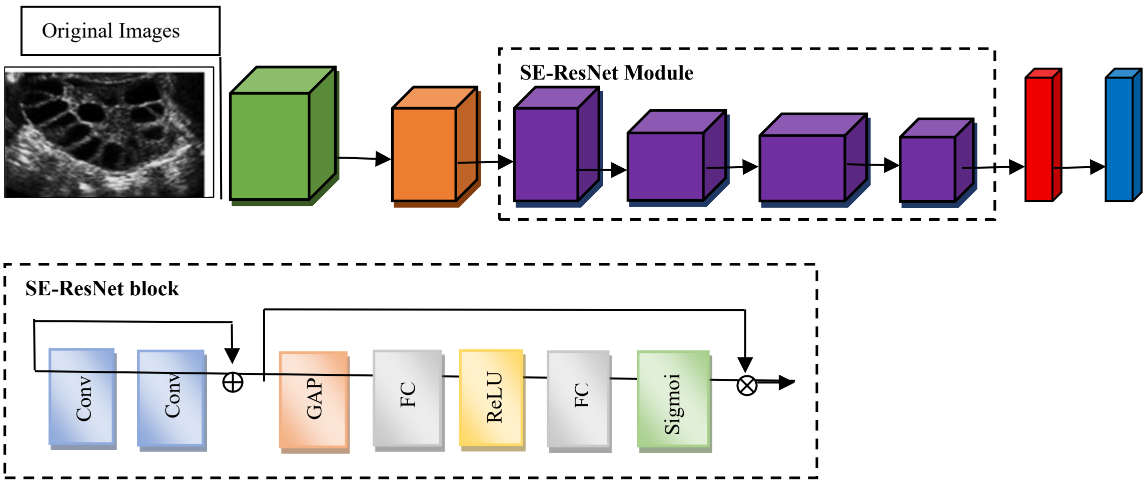

Figure 4. Architecture of SE-ResNet-34 network [37]

Figure 4 shows working architecture of a SE-ResNet-34 network detailed features from ultrasound images, hormonal patterns, or other diagnostic data to detect subtle markers of the condition. The skip connections in ResNet allow the model to capture both low-level features (e.g., pixel intensities in an ultrasound) and high-level features (e.g., ovarian cyst patterns or hormonal trends). This hierarchical feature extraction is particularly advantageous in medical diagnostics, where small yet critical differences in the data can indicate the presence of endometriosis. Additionally, ResNet's robustness to overfitting makes it suitable for medical datasets, which are often limited in size. By leveraging its deep architecture and residual learning, ResNet provides accurate and reliable classification, assisting in early detection and personalized treatment planning [38].

CNN Based Deep Learning Technique

CNNs are distinguished by their convolutional layers, which are made to automatically and adaptively construct spatial hierarchies of information from input images. The foundation of a CNN is its convolutional layer. which filters the input image in a variety of ways. The subsequent layer of the network receives the resultant collection of feature-rich maps. Identifying and learning features from images is the responsibility of CNNs' convolutional layers, which use filters that extract local patterns and hierarchies. In addition, pooling layers provide a better representation of the features, reduce the spatial dimensions of the feature maps, increase computational efficiency, and prevent overfitting. When combined, these layers allow in Figure 5 CNNs architecture to effectively and efficiently carry out tasks like object detection, image classification, and medical image analysis [6] [39].

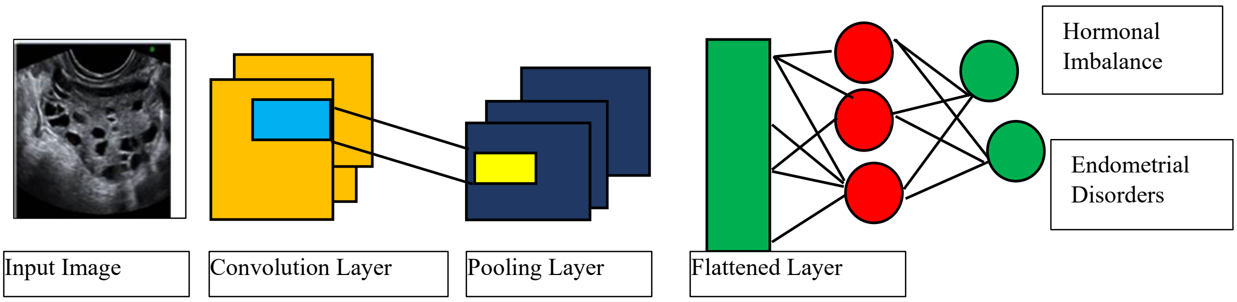

Figure 5. CNN Architecture [40]

CNNs can now recognize intricate patterns linked to endometriosis, like ovarian morphology or follicle distribution, without the need for manually created features. characterized by a combination of symptoms related to hormonal imbalance, Endometrial Disorders, and reproductive health. Image classification, particularly through medical imaging techniques enhanced by machine learning approach for understanding endometriosis as well as identifying associated diseases and disorders.

PERFOAMCNE EVALUATION

The performance comparison between the suggested endometriosis classification approach and previous research approach is calculated below. By contribution better classification techniques that enable the data to be arranged as women's medical health care data with a specified age, this review work has helped to gain recognition. The suggested networks are able to more effectively classify the available data.

Table 2. Dataset comparison of feature selection response for endometriosis

Different Parameters	**Different classification**	**Value**
Gradient Boosted Decision Tree	Affected Ultrasound Image	Matthews Corr. Coeff.: 0.87
	Non-Affected Ultrasound Image	Log Loss: 0.12
SE-ResNet-34 network	Affected Ultrasound Image	Matthews Corr. Coeff.: 0.89
	Non-Affected Ultrasound Image	Log Loss: 0.09
CNN-based Deep Learning Technique	Affected Ultrasound Image	Matthews Corr. Coeff.: 0.92
	Non-Affected Ultrasound Image	Log Loss: 0.07

In Table 2 performance of different classification models on ultrasound image data can be compared through various parameters. For the Gradient Boosted Decision Tree, the Matthews Correlation Coefficient (MCC) for affected ultrasound images is 0.87, and for non-affected images, the Log Loss is 0.12. The SE-ResNet-34 network achieves a slightly higher MCC of 0.89 for affected images and a Log Loss of 0.09 for non-affected images. The CNN-based deep learning technique shows the highest performance with an MCC of 0.92 for affected ultrasound images and a Log Loss of 0.07 for non-affected images, indicating better accuracy and lower error compared to the other models.

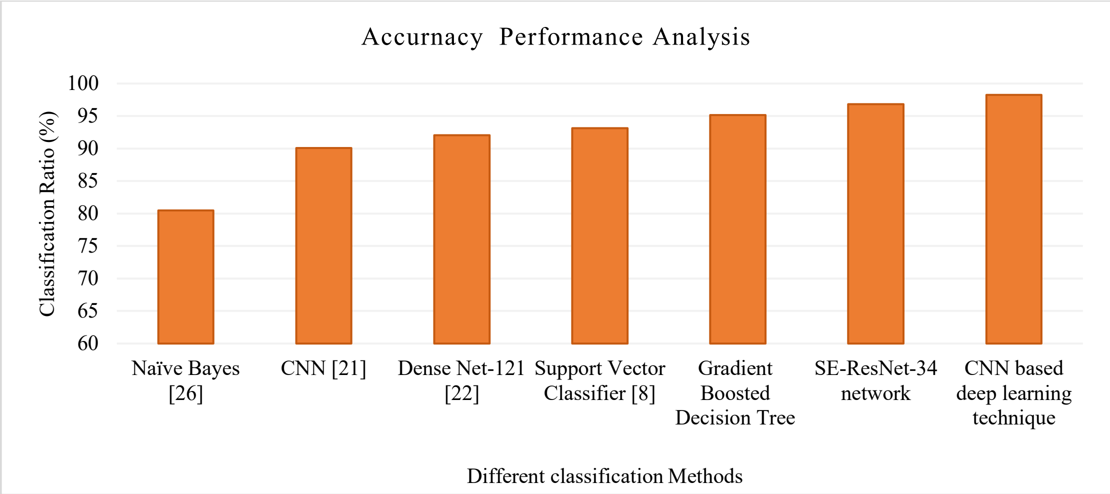

Figure 6. Comparing different performance metrics of accuracy

Figure 6 show the classification accuracy of various machine learning and deep learning models. Previous machine learning models such as Naïve Bayes achieve a lower accuracy of 80.46%, while CNN show a 90.06%. Dense Net-121 further enhance accuracy to 92.13%. The proposed Gradient Boosted Decision Tree achieves 95.16%, SE-ResNet-34 network reaching 96.83% and a CNN-based deep learning technique achieving the highest accuracy of 98.23%. This progression highlights the superior performance of deep learning techniques, particularly in complex classification tasks.

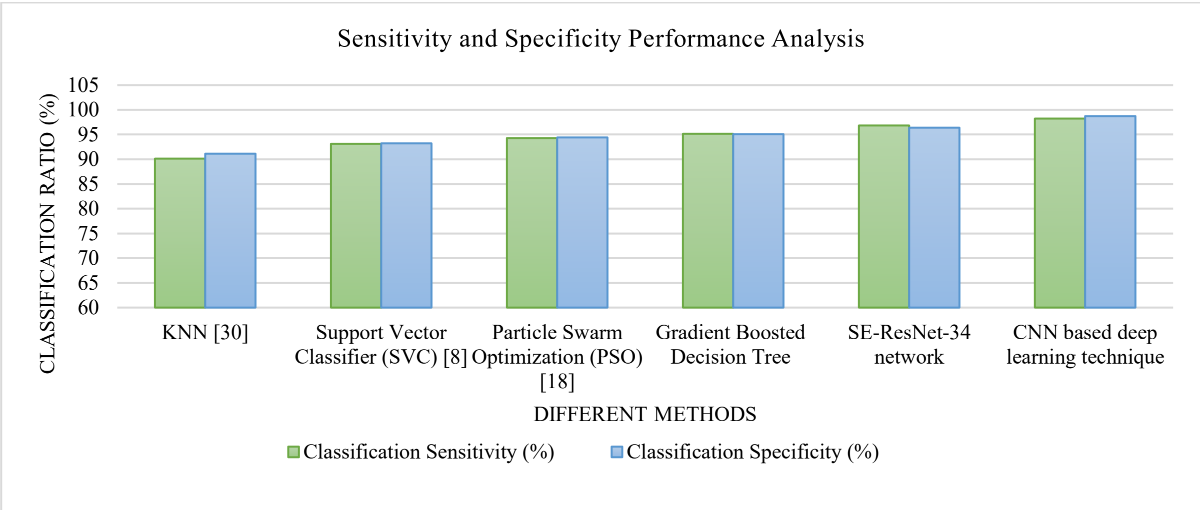

Figure 7. Comparing different performance metrics of sensitivity and specificity

Figure 7 Shows the Sensitivity and Specificity ratios for various models, showcasing their ability to identify positive and negative cases. The K-Nearest Neighbors (KNN) achieves 90.13% sensitivity and 91.13% specificity, reflecting solid but relatively lower performance. The Support Vector Classifier (SVC) improves these values to 93.13% and 93.21%. Particle Swarm Optimization (PSO) further enhances sensitivity to 94.29% and specificity to 94.41%. The proposed Gradient Boosted Decision Tree achieves 95.16% sensitivity and 95.08% specificity, showing a balanced improvement. The SE-ResNet-34 network, a deep learning approach, sensitivity to 96.83% and specificity to 96.39%. Finally, the review that CNN-based deep learning technique outperforms all models with the highest sensitivity of 98.23% and specificity of 98.73%, underscoring its improved performance in accurately identifying both positive and negative cases.

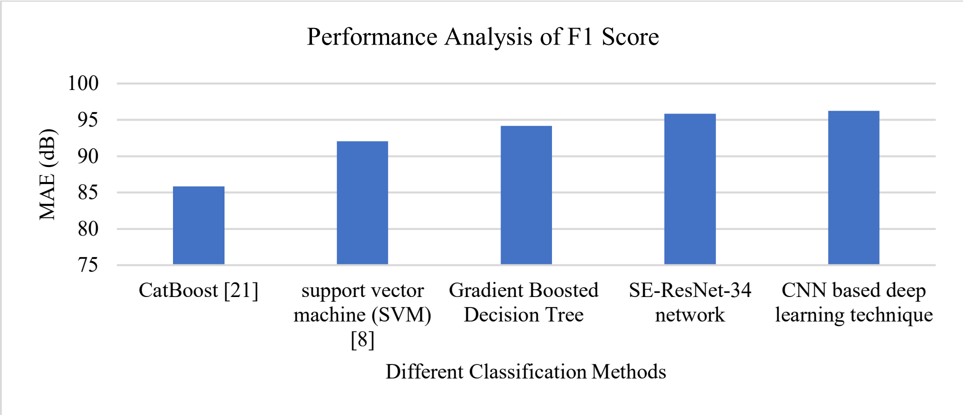

Figure 8. Comparing different performance metrics of F1 score

Figure 8 shows the Classification F1 Score (%) for various models, reflecting their balance between precision and recall. CatBoost achieves a moderate F1 score of 85.86%, while SVM further enhances the F1 score to 92.06%, indicating better performance. The Gradient Boosted Decision Tree continues this evaluate with an F1 score of 94.16%, showing it improve capability for classification tasks. Deep learning models outperform these approaches, with the SE-ResNet-34 network achieving 95.83% and the CNN-based deep learning technique delivering the highest F1 score of 96.23% which indicates the performance Metrix

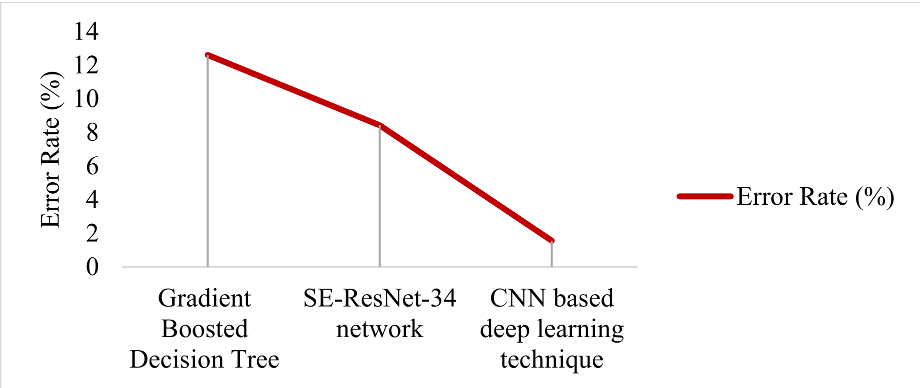

Figure 9. Comparing different performance metrics of error rate analysis

Figure 9 shows the Error Rate (%) of different models, indicating their misfeatures ratio. The Gradient Boosted Decision Tree has the highest error rate at 12.6%, followed by the SE-ResNet-34 network with 8.41%, while the CNN-based deep learning technique achieves the lowest error rate of 1.55%, demonstrating its superior accuracy and minimal errors.

CONCLUSION

This study reviewed and theoretically evaluated various methods for detecting Endometriosis disorder, with a particular focus on neural network algorithms. It provided a detailed description of previous research algorithms, highlighting their features, women health care data, analysis procedures, and outcomes. Additionally, the ultrasound datasets used in these algorithms were briefly discussed. The limitations identified in this review include a small number of datasets, imbalanced datasets, low detection rates, and the absence of additional feature selection techniques. Furthermore, performance metrics were used to evaluate three key approaches: CNN-based deep learning, SE-ResNet-34 network, and gradient-boosted decision trees. In the initial study, when ovarian cyst types were classified using a CNN-based deep learning technique, the accuracy of the classification models improved 98% with low error rate 1.55%. This demonstrates that the enhanced performance directly contributes to improved classification outcomes.

Future Scope

Future research must focus on collecting extensive datasets to refine the augmentation techniques and ensure the production of more accurate and reliable findings. In the context of polycystic ovarian syndrome detection, advanced deep learning methods offer significant potential. Bridging the gap between informatics and medical experts is crucial this can be achieved by aligning the model's development with the specific needs of healthcare challenges, rather than solely focusing on the machine learning aspect. Additionally, establishing clinical practice guidelines that leverage AI/ML models to predict histological types of ovarian lesions could revolutionize patient care. Furthermore, ongoing research into AI/ML techniques has already demonstrated improved predictive accuracy for ovarian borderline disease, laying the groundwork for more precise and effective diagnostic tools**.**

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