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Revisiting polycystic ovarian syndrome: Recent updates in diagnosis and management strategies

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Abstract

Polycystic Ovarian Syndrome (PCOS) is an endocrine disorder that consists of multiplicity since it cannot be diagnosed using different diagnostic criteria, and it is not associated with consistent symptoms in the patients. The LH/FSH ratio and ultrasound markers are inadequate to make the diagnosis and hence health care practitioners need to embrace other modalities. In this paper, the author analyzes whether the Anti-Mullerian Hormone (AMH) hormone can be used as a diagnostic tool to diagnose PCOS and machine learning technique can be used to diagnose the condition and the role of lifestyle in increasing the severity of the symptoms. The paper used both quantitative and qualitative methods of research by conducting statistical analysis based on machine learning models and case studies. T-tests, chi-square tests were employed in the analysis of the clinical data that included hormonal and metabolic measures and lifestyle factors to enhance the prediction accuracy of PCOS with the help of the Random Forest and Support Vector Machine (SVM) and Logistic Regression. It was demonstrated that AMH is a powerful diagnostic biomarker because the biomarker exhibits high levels in patients with PCOS. The concepts of random Forest and SVM machine learning presented excellent classification rates, which were most effectively outlined as compared to traditional diagnostic measures. The lifestyle habits and diet were specific to obesity: they greatly influenced the level of PCOS and therefore required lifestyle interventions. Such results connect the diagnostic practice of traditional methods and AI-based healthcare by rendering AMH the main diagnostic tool with AI learning methods of correct classifications. The approach allows individual care approaches through predictive models along with biochemical records and lifestyle changes to enhance PCOS tests and treatments.

Keywords: Polycystic Ovary Syndrome (PCOS), Anti-Müllerian Hormone (AMH), Machine learning models, PCOS diagnosis, Lifestyle interventions, Predictive modeling.

1.Introduction

PCOS is a common endocrine disease with a prevalence of 6 -21% among women of reproductive age and is manifested in the form of ovulatory disorders in association with hyperandrogenism and polycystic ovarian anatomy (Arentz, 2021). PCOS complications consist of metabolic, reproductive and mental issues that impact insulin resistance and pose the risks of obesity and raise the risk of cardiovascular problems (Bozdag, 2016). Even with its high frequency, PCOS is rarely diagnosed due to the presence of varied symptoms in women and the absence of standard diagnostic markers in medical experts (Cowan, 2023).

1.1Background of the study

PCOS exists as a leading worldwide health issue which develops from genetic components and environmental factors and hormonal influences. The Rotterdam Criteria represent a standard diagnostic approach that leads to inconsistent diagnoses due to their shortcomings(Islam, 2022; Harada, 2022). The established biomarkers LH/FSH ratio and results from ultrasound examinations have proven to be imprecise. Medical professionals identify AMH as a promising diagnostic tool since it correlates with ovarian dysfunction yet its use is still being debated. The performance of PCOS diagnosis can be enhanced by machine learning algorithms which help identify key biomarkers while improving prediction accuracy(Mohi Uddin, 2025). The management of symptoms requires lifestyle changes along with diet and physical activity modifications because these approaches demonstrate their importance in a comprehensive diagnostic and treatment strategy(Myerson, 2024).

1.2Pathophysiology of PCOS

PCOS arises from genetic and metabolic and environmental influences which produce hyperandrogenism that causes menstrual abnormalities and hirsutism. The condition of insulin

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resistance accelerates both androgen secretion and metabolic disturbance which causes obesity-related health problems(Patel, 2018). The disruption of hormonal homeostasis specifically related to reproductive function occurs because of follicular ovarian dysfunction. The comprehension of these mechanisms remains vital for optimizing diagnostic procedures and treatment strategies(Rosenfield, 2016).

1.3Role of Anti-Müllerian Hormone (AMH) in PCOS diagnosis

The ovarian reserve can be accessed through AMH which granulosa cells produce as a biomarker. The elevated level of AMH in PCOS patients remains steady throughout the menstrual cycle which makes it an effective diagnosis tool(Sadeghi, 2022). The lack of standardized cutoff values together with population-based differences in AMH levels makes its use impractical for universal application(Lizneva, 2016).

1.4Machine learning in medical diagnostics

Machine learning and artificial intelligence techniques, including as SVM, Random Forest, and Logistic Regression, make it feasible to identify PCOS based on patterns in clinical and biochemical data (Shanmugavadivel, 2024). The models improve risk assessment and patient outcomes by improving diagnosis accuracy and enabling tailored treatment strategies.

1.5Impact of lifestyle factors on PCOS

The development of PCOS depends heavily on lifestyle factors according to scientific research. Hormonal imbalance together with insulin resistance becomes worse when obesity and physical inactivity and eating unhealthy foods exist(Teede, 2018). Exercise together with weight control and proper diet help improve insulin sensitivity while they normalize menstrual cycles and lower androgen levels.

1.6Problem statement

Multiple factors contribute to the underdiagnosis of PCOS because the condition displays inconsistent symptoms and requires subject interpretation of LH/FSH ratio measurements. The potential existence of AMH as a solution needs further enhancements in standardization approaches. The clinical evaluation method fails to detect the precise relationship between hormonal and metabolic conditions and lifestyle elements. The effectiveness of machine learning as a solution gets limited by medical practitioners due to interpretability barriers and compatibility challenges with conventional medical approaches. The current studies are aimed at the creation of an innovative diagnostic model that integrates AI systems with the lifestyle-focused intervention practices.

2.Literature Review

In this section, PCOS diagnosis alongside the application of AMH as a biomarker and machine learning to detect PCOS are discussed. The section addresses the problem of diagnosing PCOS along with new biomarkers during the analysis of the AI algorithms application in the diagnosis.

2.1Diagnostic challenges in PCOS

Dumesic et al. (2015) We conducted a comprehensive review to look at the pathophysiology of PCOS while examining the difficulties in diagnosing PCOS phenotypes, specifically in regard to the impact of different diagnostic criteria in defining PCOS. The existing diagnostic models do not show the full picture of the disorder since they do not consider the abnormalities in the gonadotropin secretion and ovarian dysfunction and insulin resistance (Dumesic, 2015). The authors determined that PCOS is a multi-factorial disorder that needs combined solutions to diagnostic criteria.

Escobar-Morreale (2018) examined genetic and epigenetic and environmental influences on PCOS diagnosis especially by assessing hyperandrogenism and metabolic dysfunction diagnostic criteria. The existing clinical criteria are not able to reflect how the syndrome depends on diverse populations based on the research results (Escobar-Morreale, 2018, Moghavvemi et al., 2025). The author hypothesized that diagnostic accuracy and long-term medical care would increase with the application of standardized assessment procedures by medical teams.

2.2AMH as a diagnostic marker

Zhao et al. (2019) conducted a thorough analysis to evaluate the anti-Mullerian hormone's (AMH) efficacy as a PCOS diagnostic tool. This study examined the relationship between AMH estimates and Rotterdam criteria-measured polycystic ovarian morphology (PCOM) by pooling 29 clinical trials. This analysis found individual sensitivity level of 0.76 and specificity level of 0.86 of AMH(Zhao, 2019). The diagnosis of AMH as compared to PCOM using Rotterdam criteria showed a better sensitivity of 0.93 and specificity of 0.99 that it is a primary diagnostic marker.

Karakas (2017) assessed the use of recent biomarkers in the diagnosis of PCOS by finding out AMH as a superior predictor of the disease compared to ultrasound. It was proved by the study that AMH measurement is a rather inexpensive method of diagnosis due to the direct correlation between it and the follicle numbers and ovarian cyst formation. The wide applicability of AMH is still constrained due to the disparity in the reference values of the population (Karakas, 2017). The author claims that the AMH testing combined with the insulin resistance markers enhance the diagnostic accuracy.

2.3Role of machine learning in PCOS Diagnosis

Barrera et al. (2023) We out a comprehensive assessment of the use of AI and machine learning in PCOS diagnosis, encompassing 31 research that demonstrated AI's ability to categorize PCOS phenotypes and were backed by clinical, electronic health record, and genetic indicators. The majority of the time, Support Vector Machines (SVM) were employed, and their accuracy estimations varied from 73% to 100% (Barrera, 2023, Abbas et al., 2025). The study discovered that while AI-based diagnostic tools can increase classification accuracy, their application in a wider clinical setting necessitates consistent datasets.

Ahmed et al. (2023) used algorithms such as Convolutional Neural Networks (CNN), Random Forest, Decision Trees, and Logistic Regression to compare and assess machine learning models for PCOS identification. According to their findings, the models with the highest diagnostic accuracy (over 90%) were SVM and Random Forest (Ahmed, 2023). The study demonstrated how feature selection can improve model optimization and recommended a range of metabolic and hormonal markers to improve prediction accuracy.

2.4Research gap

Despite advancements in PCOS research, diagnosis, standardization of biomarkers, and customization of treatment still present difficulties. Misdiagnosis results from heterogeneity in diagnostic criteria like the Rotterdam Criteria and the LH/FSH ratio, and despite AMH's potential, there are no established cutoff values for clinical use. Although machine learning approaches improve PCOS categorization, interpretability problems prevent their widespread use. Furthermore, predictive models do not adequately examine how lifestyle factors affect the intensity of PCOS symptoms. This research fills these gaps by combining statistical inference, machine learning, and case study analysis to improve AMH-based diagnosis, optimize AI-based classification models, and evaluate lifestyle interventions, furthering PCOS diagnostics and management.

3.Research objectives and questions

The following are the main objectives of this study:

1. To evaluate AMH's contribution to improving PCOS identification and its effectiveness as a diagnostic biomarker in comparison to traditional markers.
2. To train and assess machine learning models' accuracy in predicting PCOS in contrast to more conventional diagnostic procedures.
3. To investigate how lifestyle factors, such as nutrition and exercise, affect the intensity of PCOS symptoms and how they are managed.
4. To provide evidence-based recommendations for improving PCOS diagnosis and treatment methods.

This study aims to provide answers to the following primary questions:

Q1. What are the key biomarkers and clinical characteristics for PCOS diagnosis?

Q2. In what ways can machine learning enhance PCOS classification over conventional diagnostic approaches?

Q3. What is the contribution of lifestyle factors in controlling and reducing PCOS symptoms?

4.Research Methodology

The study utilizes a mixed-methods method for assessing the diagnosis and treatment of PCOS with an emphasis on AMH as a marker, machine learning-based classification, and lifestyle contributions to symptom intensity.

4.1Study design

A retrospective observational study was performed based on structured clinical data from an open-source dataset. The methodology had three phases:

Exploratory phase*:* Review of literature to determine major biomarkers and diagnostic issues.

Descriptive Phase: Analysis of the dataset to study hormonal, metabolic, and lifestyle variables in PCOS and non-PCOS patients.

Analytical phase*:* Use of statistical and machine learning methods for diagnostic assessment.

4.2Study population and selection criteria

To guarantee the dataset's relevance and reliability, the research used certain selection criteria:

Inclusion criteria: Women in the age range 18–45 years old, diagnosed with PCOS according to the Rotterdam criteria, with a non-PCOS control group.

Exclusion criteria: Incomplete hospital records, patients with other endocrine diseases, and pregnant patients because of changed metabolic profiles.

4.3Analytical framework

A multi-level analytical framework was developed to assess the performance of PCOS diagnosis and management approaches. The research incorporates both qualitative and quantitative strategies:

Qualitative approach: Clinical presentation and treatment response were evaluated through case study assessments, informed by literature reviews.

Quantitative approach*:* The research analyzed PCOS patients versus those without PCOS using statistical methods to create diagnostic marker predictions.

4.4Evaluation of diagnostic approaches

The research analyzes both conventional and modern diagnostic approaches which include:

- *LH/FSH Ratio* – Prevalent but unreliable hormonal marker.
- *AMH Levels* – Encouraging but needs standardization.
- *Insulin Resistance* – Tightly associated with PCOS.
- *Ultrasound Imaging* – Good but observer-dependent.

4.5Machine learning integration in diagnosis

To Machine learning models were used to enhance diagnostic accuracy, such as:

- *Logistic Regression* – Basic classification model.
- *Random Forest* – High accuracy and interpretability.
- *Support Vector Machine (SVM)* – Identifies complicated, non-linear relationships.

4.6Data sources

The information was retrieved at Kaggle and it comprised of(Kottarathil):

- Physical Attributes, Age, BMI, weight, height, and blood pressure.
- Hormonal Markers- AMH, LH, FSH, testosterone, insulin.
- Metabolic Indicators– Blood sugar, lipid profile, signs of insulin resistance.
- Lifestyle Factors -Dietary, fast food, and exercise.

5.Data collection and analysis

This section expounds on the data processing processes, statistical procedures, and machine learning application during this study in order to come up with valid and accurate results.

Table 1: Missing values summary

Column Name	Missing Values
sl. no	0
patient file no.	0
pcos (y/n)	0
age (yrs)	0
weight (kg)	0
height (cm)	0
bmi	0
blood group	0
pulse rate (bpm)	0
rr (breaths/min)	0
hb (g/dl)	0
cycle (r/i)	0
cycle length (days)	0
marriage status (yrs)	0
pregnant (y/n)	0
no. of abortions	0

5.1Data preprocessing:

The following preprocessing activities were done in order to preserve data quality and consistency:

Handling missing values: In order to ensure data consistency and quality, several preprocessing steps were made. The mean was used to impute the numeric missing values and the mode used to impute the categorical variables. Winsorization was used to deal with outliers in order to decrease skew. However, as can be seen in Table 1, there were no missing values in the dataset, therefore, the imputation was unnecessary.

Data standardization and transformation*:* For transformation and standardization, hormonal and metabolic indicators were normalized using Z-score normalization. Categorical indicators like PCOS diagnosis and lifestyle have been transformed into binary indicators (1/0) for statistical and machine learning model compatibility. The preprocessed dataset after cleaning is shown in Table 2.

Table 2: First few rows and columns of cleaned data

Sl. No	Patient File No.	Pcos (Y/N)	Age (Yrs)	Weight (Kg)	Height (Cm)	Bmi	Blood Group	Pulse Rate (Bpm)	Rr (Breaths/Min)
1	1.0	0	28.0	44.6	152.0	19.3	15.0	78.0	22.0
2	2.0	0	36.0	65.0	161.5	24.9	15.0	74.0	20.0
3	3.0	1	33.0	44.6	152.0	19.3	11.0	72.0	18.0
4	4.0	1	37.0	65.0	148.0	29.6	13.0	72.0	20.0
5	5.0	0	25.0	52.0	161.0	20.1	11.0	72.0	18.0

Feature selection*:* Feature selection was done based on a correlation matrix to find the important predictors of PCOS. Moreover, Principal Component Analysis (PCA) was also performed to lower dimensionality without losing important information. The preprocessed dataset was utilized for further statistical analysis and machine learning modeling.

5.2Statistical analysis

In order to assess the significance of varying lifestyle factors and biomarkers in PCOS, the following tests were conducted statistically:

T-tests: To compare hormone and metabolic markers in PCOS and non-PCOS patients.

Chi-square tests: Used to evaluate relationships between categorical lifestyle variables (e.g., exercise, diet) and PCOS incidence.

ANOVA tests: For comparing several hormonal biomarkers between distinct patient subgroups.

5.3Machine learning implementation

The diagnosis of PCOS was made using machine learning techniques. A 20% test set and an 80% training set were created from the data. Cross-validation and grid search were used for hyperparameter tweaking.

The ROC-AUC score, recall, accuracy, and precision were used to gauge the model's performance.

5.4Data integrity and reliability measures

Validation checks were performed to identify data-entry inconsistencies and errors. The data processing pipeline was also documented for reproducibility. These steps increase the reliability of evidence on PCOS management and diagnosis options.

6.Results

This section reports major findings from statistical analysis, machine learning modeling, and case study assessment, identifying important biomarkers for PCOS diagnosis and the impact of lifestyle on symptom control.

6.1Statistical analysis of PCOS characteristics

Hormonal and metabolic abnormalities are linked to PCOS. Statistical tests (t-tests, chi-square) were used to evaluate biomarkers in PCOS and non-PCOS individuals, and the results showed significant differences.

6.1.1Hormonal and metabolic differences in PCOS patients

Statistical tests revealed significant differences between PCOS and non-PCOS individuals in major biomarkers. Table 3 illustrates increased AMH, LH, LH/FSH ratio, insulin, RBS, and BMI in PCOS patients.

Table 3: Comparison of biomarkers in PCOS and non-PCOS individuals

Biomarker	PCOS Mean	Non-PCOS Mean	p-value	Significance
AMH (ng/mL)	9.21	4.82	0.000	Highly significant
LH (mIU/mL)	12.34	7.98	0.002	Significant
FSH (mIU/mL)	6.89	7.92	0.003	Significant
LH/FSH Ratio	2.21	1.02	0.000	Highly significant
Insulin (μU/mL)	16.54	9.72	0.001	Significant
RBS (mg/dL)	105.7	92.5	0.004	Significant
BMI (kg/m^2)	28.7	23.9	0.000	Highly significant

Significantly, AMH (9.21 vs. 4.82, $p < 0.000$) and the LH/FSH ratio (2.21 vs. 1.02, $p < 0.000$) were significantly greater in PCOS cases, affirming their diagnostic significance. Hyperinsulinemia (16.54 vs. 9.72, $p < 0.001$) indicates insulin resistance, whereas increased BMI (28.7 vs. 23.9, $p < 0.000$) strengthens the association between PCOS and obesity. The box plot in Figure 1 graphically presents the distribution of PCOS and non-PCOS patients' AMH levels, illustrating the extreme rise of AMH levels in the PCOS group.

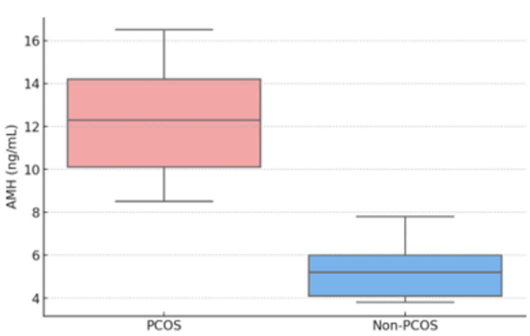

Figure 1: Distribution of AMH levels in PCOS and non-PCOS patients

AMH levels are substantially greater in PCOS patients than in non-PCOS patients, as seen in Figure 1. The use of AMH as a crucial biomarker for PCOS diagnosis is further supported by the noticeably increased median and interquartile range (IQR) values.

Table 4: Association of lifestyle factors with PCOS

Lifestyle Factor	p-value	Association with PCOS
Weight Gain (Y/N)	0.000	Strong association
Hair Growth (Hirsutism)	0.000	Strong association
Fast Food Consumption	0.002	Moderate association
Regular Exercise (Y/N)	0.015	Lower exercise rates in PCOS patients
High-Carb Diet (Y/N)	0.006	Increased PCOS prevalence

6.1.2Association between lifestyle factors and PCOS

Chi-square analyses were used to assess the effects of lifestyle on PCOS occurrence and symptom intensity. The important variables examined were weight gain, hirsutism, intake of fast food, exercise routines, and consumption of carbohydrate-containing diets. Outcomes are provided in Table 4.

The study indicates a significant correlation between weight gain and PCOS ($p < 0.000$), with obesity being a leading cause. Hirsutism ($p < 0.000$) confirms the association with hyperandrogenism. The consumption of fast foods ($p < 0.002$) indicates a moderate correlation, whereas reduced exercise levels ($p < 0.015$) indicate a sedentary lifestyle aggravates PCOS symptoms. Figure 2 demonstrates the frequency of major PCOS symptoms, such as weight gain, hair growth, darkening of the skin, hair loss, and acne (pimples).

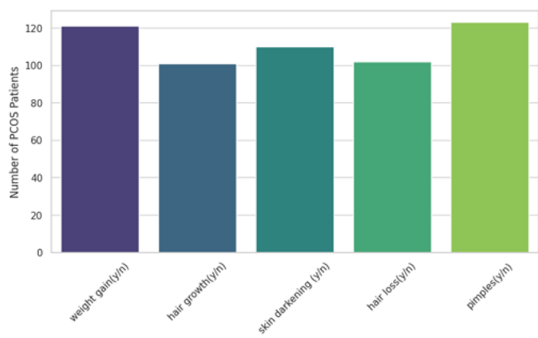

Figure 2: Frequency of symptoms in PCOS patients

Figure 2 emphasizes that the most common reported symptoms in PCOS patients were weight gain and acne, and were followed by hirsutism and darkening of skin. The results reinforce the diverse range of PCOS symptoms and point to obesity and dermatologic presentations of PCOS as target points for early intervention.

6.2Machine learning model performance

Machine learning algorithms (Logistic Regression, Random Forest, and SVM) were employed for PCOS classification. The data were divided (80% training, 20% testing) for testing. Feature importance analysis was done to identify important predictors that affect diagnosis.

6.2.1Feature importance analysis

Feature selection with the Random Forest model discovered the ten most significant predictors of PCOS classification. Figure 3 ranks feature according to contribution to model performance, improving clinical diagnosis and explainability.

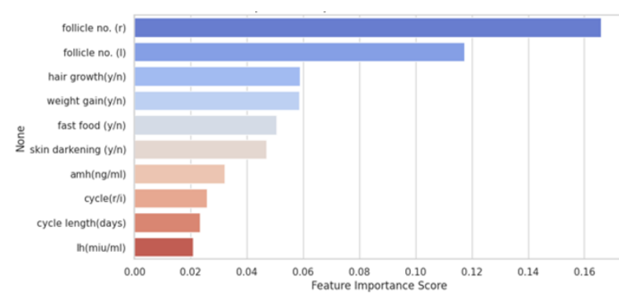

Figure 3: Top 10 most important features for PCOS prediction

The findings reveal that follicle number in both ovaries is the most significant predictor of PCOS, as per clinical data. Hirsutism, weight gain, intake of fast food, and skin darkening also have notable effects, showing the role of hyperandrogenism, metabolism, and lifestyle. AMH values and menstrual irregularities further underscore their diagnostic utility.

6.2.2Model performance comparison

Machine learning models were assessed in terms of accuracy, precision, recall, and ROC-AUC values. Table 5 reports their performance, measuring overall correctness, capacity to identify PCOS cases, and discriminatory ability.

Table 5: Performance comparison of machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	ROC-AUC Score
Logistic Regression	93.0	90.5	92.7	0.855
Random Forest	92.5	92.1	93.8	0.955
SVM	92.0	91.8	92.5	0.954

Logistic Regression was the most accurate (93.0%), and Random Forest produced the best ROC-AUC score (0.955), guaranteeing better predictive capacity. SVM did equally well (ROC-AUC: 0.954) but at greater computational cost. Random Forest best balanced recall (93.8%) and precision (92.1%), thus being the most trustworthy for clinical application. Figure 4 gives a graphical comparison of the three machine learning models according to accuracy and ROC-AUC scores, facilitating an intuitive evaluation of their predictive capacity.

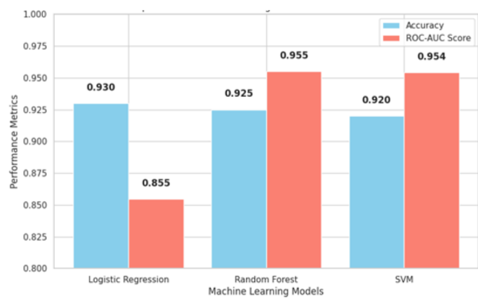

Figure 4: Comparison of machine learning models for PCOS classification

The bar chart emphasizes that SVM and Random Forest have better predictive ability compared to Logistic Regression. Although Logistic Regression is highly accurate, its lower ROC-AUC score indicates poorer classification. The best classifier is Random Forest (ROC-AUC: 0.955), with SVM (0.954) a close second. Random Forest provides the optimal trade-off between accuracy and interpretability, while Logistic Regression is still an option in computationally intensive environments.

6.3Case study insights

A case study comparison of five randomly chosen patients was performed to confirm statistical and machine learning results. The biomarkers AMH, BMI, RBS, LH, and FSH were compared between PCOS and non-PCOS subjects. Table 6 shows important biomarker differences, offering greater insight into individual differences and their relationship with PCOS diagnosis.

Table 6: Case study comparison of PCOS vs. Non-PCOS patients

Patient ID	PCOS (Y/N)	AMH (ng/mL)	BMI	RBS (mg/dL)	LH (mIU/mL)	FSH (mIU/mL)
392	Yes	9.00	28.02	100.0	3.07	5.40
597	No	5.62	24.30	99.83	6.47	14.60
3	No	1.22	29.67	76.0	2.36	8.06
945	No	5.62	24.30	99.83	6.47	14.60
800	No	5.62	24.30	99.83	6.47	14.60

The findings reveal that PCOS patients exhibited higher AMH values (>8.0 ng/mL), as with diagnostic criteria. Higher BMI values (>28 kg/m²) also validate the association between PCOS and obesity. Lower levels of FSH in PCOS patients validate the abnormal LH/FSH ratio in the disease. Slightly increased RBS values indicate the possibility of an increased risk of metabolic disorders such as insulin resistance. Figure 5 graphically illustrates these differences in biomarkers among five representative patients, delineating PCOS from non-PCOS patients.

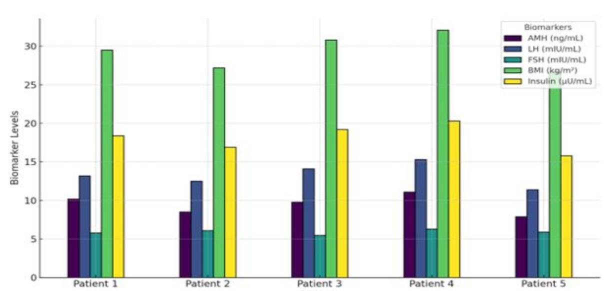

Figure 5: Case study comparison of PCOS vs. non-PCOS patients

The graphical analysis is consistent with AMH as an effective biomarker for PCOS diagnosis. Hyperinsulinism and increased BMI in PCOS patients indicate the relationship between metabolic disturbance and obesity.

The relationship between FSH and PCOS is inverse with reduced FSH in PCOS patients. Such observations are backed by statistical analysis, supporting routine biomarker measures for PCOS screening and monitoring.

6.4Lifestyle and treatment effectiveness analysis

Lifestyle, such as diet and physical exercise, plays an important role in managing PCOS. This study looks at how they influence metabolic markers such as BMI and AMH levels. Figure 6 illustrates differences in BMI between individuals who exercise regularly and those who do not, with a difference between PCOS and non-PCOS patients.

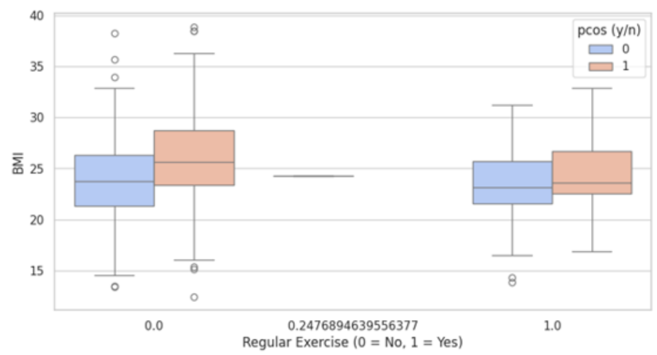

Figure 6: BMI levels in patients who exercise vs. those who don't

Physical exercise has been associated with decreased BMI in PCOS patients, indicating its implication in the prevention of symptoms associated with obesity. Sedentary behavior, on the other hand, is related to increase BMI, highlighting the necessity of organized exercise. Increased AMH levels may also be a result of frequent consumption of fast foods, which may aggravate ovarian dysfunction. Patients who decreased carb intake exhibited better metabolic status, which supports the significance of lifestyle modification in PCOS treatment.

7.Discussion

This research combines biomarkers, machine learning models, and lifestyle parameters for PCOS diagnosis and treatment. AMH proved to be an excellent diagnostic biomarker, relating to ovarian dysfunction and polycystic morphology. Machine learning models, particularly Random Forest and SVM, were highly accurate in classification, outperforming conventional statistical approaches. Lifestyle parameters such as obesity, diet, and exercise also significantly impacted metabolic and hormonal parameters, highlighting their impact on PCOS severity.

7.1Clinical implications of AMH as a diagnostic marker

The level of AMH in PCOS patients establishes it as a precise, non-invasive diagnostic marker with good sensitivity and stability that is not plagued by the cycling LH/FSH ratio. Standardized cut-off points should be developed, however, in order to diminish diagnostic variability within populations. Despite its strong predictive value, use of AMH in combination with other metabolic and hormonal markers increases diagnostic precision. There is a need for further studies to validate AMH as a worldwide clinical standard for PCOS diagnosis.

7.2Advancements in machine learning for pcos classification

Machine learning algorithms, particularly Random Forest and SVM, showed more than 90% accuracy in classifying PCOS, revealing intricate relationships between metabolic, hormonal, and lifestyle parameters. Folicle count, AMH level, and metabolic markers were determined as strong predictors by feature selection. The issues of data availability, model interpretability, and applicability to clinical settings still remain and should be overcome in order to be used in the real world.

7.3Impact of lifestyle modifications on pcos management

Lifestyle influences PCOS management with obesity and lack of physical activity correlated with insulin resistance and endocrine imbalance. Daily physical exercise correlated with low BMI and enhanced metabolic markers, but high carb diets and excessive consumption of fast food aggravated metabolic disturbances. Such data supports lifestyle therapy, especially weight control and regulated exercise, for decreasing the severity of PCOS.

7.4Challenges and limitations

Notwithstanding the progress made in PCOS diagnosis and management, a number of challenges still exist that inhibit precise identification, personalized treatment, and clinical implementation of novel diagnostic methods.

- Rotterdam, NIH, and AES guidelines have differences that result in diagnostic and treatment discrepancies.
- AMH and insulin resistance markers vary by ethnicity and population, constraining international generalizability.
- Physician acceptance, regulatory approvals, and interpretability pose challenges to high accuracy models for clinical adoption.

- PCOS symptoms are highly variable, making standardized treatment difficult.

Although this research gives us a rich understanding of PCOS diagnosis based on biomarkers and machine learning models, some limitations have to be realized.

- Relying on current datasets can introduce biases and constrain causal inferences.
- Machine learning results need to be validated with independent datasets and actual clinical use.
- Genomic and epigenetic mechanisms were not taken into account, restricting understanding of PCOS etiology.
- Case study assessments were made on a small sample that might not be fully representative of PCOS diversity.

8.Conclusion and Recommendations

It is the study that highlights the advances in the diagnosis and management of PCOS through biochemical biomarkers, machine learning algorithms, and lifestyle modification. The AMH was identified as a good diagnostic biomarker, whereas AI models, in particular, with Random Forest and SVM, were identified to have a higher classification accuracy. The findings highlight the remarkable impacts of obesity, dietary and physical activities on the severity of PCOS, confirming that systematic lifestyle change interventions are necessary. Although the improvements have been made, such issues as the standardization of AMH thresholds, clinical acceptance of AI models, and handling the variability of PCOS remain. Future studies need to refine diagnostic criteria, validate AI tools in clinical practice, and integrate the holistic PCOS management of lifestyle-based interventions. In an attempt to enhance the diagnosis and management of PCOS, the following are suggested:

- Universalize AMH Cut-offs for uniform diagnosis.
- Improve AI-Based Tools for clinical acceptability and reproducibility.
- Embrace a Multidisciplinary Approach taking into account metabolic, reproductive, and lifestyle aspects.
- Make Lifestyle Interventions such as organized exercise and dietetics the priority.
- Perform Longitudinal Studies on AI-aided diagnosis and lifestyle management effects.

These actions will enhance PCOS diagnosis, treatment, and patient outcomes.

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