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SMART HEALTHCARE REVOLUTION: AI STRATEGIES FOR SUPERIOR GLOBAL HEALTH

CHAPTER 6- ARTIFICIAL INTELLIGENCE FOR WOMEN'S HEALTH: A COMPREHENSIVE REVIEW OF DEEP LEARNING APPROACHES FOR EARLY DIAGNOSIS OF POLYCYSTIC OVARY SYNDROME

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ABSTRACT

Polycystic Ovary Syndrome (PCOS) is the most common endocrine disorder in women during reproductive period, characterized by chronic metabolic, reproductive and psychological long-term complications. With the growing information of clinical and diagnostic data, there has been an increased use of machine learning (ML) and deep learning (DL) techniques for early and accurate detection of PCOS. The aim of this paper is to analize and compare the recent developments of ML and DL methodologies in diagnosing of PCOS, providing an integrated overview, their performance, challenges and potential for clinical applications. A comprehensive review presented which covers 50 recent research papers published till 2025, including both image-based and non-image-based PCOS detection approaches. In addition, methods like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), ensemble models, feature selection algorithms and hybrid strategies were analyzed on structured and unstructured data. The study demonstrates that CNN-based models achieve acceptable diagnostic performance on ultrasound images, nevertheless, hybrid architecture with clinical features integration, ensemble application or feature selection methods improve the diagnostic accuracy. Approximately 30% of the included studies used ultrasound imaging; remaining studies used biochemical, hormonal or electronic health record data. This review presents the insights of emerging demand for hybrid and explainable AI (XAI) models in PCOS diagnosis and highlights current limitations such as diversity of datasets, generalizability of features and interpretability of models. Future research should prioritize multimodal methods and inclusion of clinical validation in diagnostics pipelines.

Keywords: Polycystic Ovary Syndrome, deep learning, early diagnosis, women's health, artificial intelligence, medical image analysis

1. Introduction

PCOS is a common endocrine condition, affecting 8-13% of women of reproductive age worldwide [1]. Typically, these women present with ovulatory dysfunction, polycystic morphology of their ovaries, hyperandrogenism and often insulin resistance, obesity, infertility and risk of cardiovascular disease in later life [2]. Often, however, PCOS is difficult to diagnose at an early stage, as symptoms are variable and phenotypes overlap. In recent years, with the development of ML and DL, it has become possible to use patient history, hormonal data and ultrasound images to better diagnose PCOS. A range of studies over the past few years have used ML/DL to predict prognosis, classify phenotypes and detect PCOS using, for example, radiological, hormonal and clinical data. To date, a number of reviews have covered work in this area. For example, in one, Ahmed et al (2023) [3] reviewed use of ML to detect PCOS. Another, by Barrera et al (2023) [4], focused on classification and diagnosis of PCOS using AI. And in a third, Wang et al (2025) [5] looked at the use of AI in the care of women with PCOS. But none of these reviews compares the performance of different models, nor do they pick up more recent developments in 2024/25 in, for example, multi-modal data, explainable AI and hybrid deep learning.

This paper aims to address these gaps by providing a comparative analysis of 50 recent studies, evaluating image-based and non-image-based PCOS detection methods. Unlike prior work, this review distinguishes itself by:

- Synthesizing model architectures, datasets, and performance outcomes across multiple ML and DL approaches;
- Highlighting advancements in federated learning, explainable AI, and ensemble feature selection;
- Summarizing research gaps and proposing directions for future innovation.

By presenting a holistic and up-to-date perspective, this paper contributes to both academic research and clinical practices seeking AI-driven solutions for PCOS detection and management.

2. Background and Clinical Aspects of PCOS

PCOS is a metabolic and endocrine disorder affecting many women of reproductive age. Its cause is multifactorial and is thought to involve genetic, hormonal and environmental factors, leading to dysfunction of the ovary and hormonal imbalance. Typical features of its pathophysiology are hyperandrogenism (excess of male hormones), anovulation and polycystic morphology of the ovary. Often associated with this are insulin resistance, low grade

inflammation and metabolic abnormalities [6]. Over the years, a range of diagnostic criteria for PCOS have been proposed, each emphasizing different features. In the NIH criteria (1990), chronic anovulation (wherever possible) and hyperandrogenism are required. In practice, many different criteria for PCOS are used around the world. Most common are the Rotterdam criteria (2003), under which a person is diagnosed with PCOS if they have two of the following: polycystic ovaries on ultrasound, clinical or biochemical hyperandrogenism and oligo/anovulation. In its criteria, the Androgen Excess and PCOS Society (AE-PCOS 2006) places greater emphasis on hyperandrogenism, with polycystic morphology of the ovary or ovulatory dysfunction as secondary features [7].

Typically, diagnosis of PCOS involves hormonal tests (for example, elevated LH, testosterone and AMH), ultrasound of the pelvis/transvaginal scan (to look for multiple small follicles in the ovary) and signs of acne, hirsutism, weight gain and irregular periods [8]. Taken together, these approaches usually work, but they are time-consuming, rely on the skill of the radiologist and can be subjective. Moreover, many of the features of PCOS may be seen in other metabolic and endocrine conditions. As a result, using different criteria, one person might well be under- or misdiagnosed [9].

Increasingly, therefore, there is a need for more standardized, data-driven and automated approaches to diagnosis. With appropriate training, AI and DL could support more reproducible, precise analysis of biochemical, imaging and clinical features of PCOS.

3. Role of AI in Women's Health

AI has become a leading edge technology in recent healthcare development and has revolutionized the identification, prognosis, and individualized treatment of disease. Within the field of women's health, AI technology has been increasingly utilized in gynecology, obstetrics, and reproductive medicine to enhance diagnostic performance, patient outcomes and clinical processes.

Figure 1 highlights the increasing frequency of AI-based studies related to PCOS detection, reflecting a sharp growth post-2020 in the integration of machine learning, deep learning, and hybrid approaches in clinical diagnostics.

Applications of AI in Gynecology and Reproductive Health

AI applications are also taking place in analyzing ultrasound images related to ovarian morphology, fertility window prediction, fetal health assessment, and early cancer detection (e.g., cervical and breast cancer). In the field of reproductive endocrinology, AI approaches are used to assess hormonal profiles, automate tracking of follicles, and estimate the results of in-vitro fertilization (IVF). Recent developments have established AI as an impactful way of identifying insights of complicate data types like menstrual cycle tracking apps, EHRs and genetic data, and in the early detection of conditions such as PCOS, endometriosis, and

gestational diabetes [2], [3].

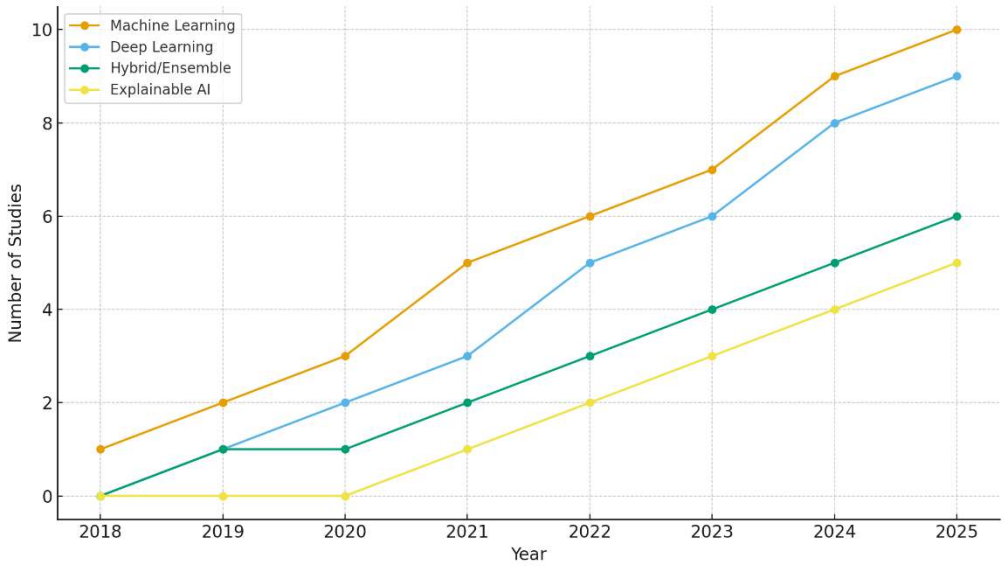

Figure 1: Publication trend showing the annual growth of AI-based diagnostic approaches for PCOS from 2018 to 2025

Benefits of AI in Early Disease Detection and Personalized Treatment

AI can achieve both early and accurate diagnosis by handling high-dimensional, heterogeneous data that are frequently beyond the human capacity for analysis. ML and DL tools can mine latent associations between imaging, clinical, and laboratory data for more rapid and accurate diagnosis of gynecology conditions. Furthermore, artificial intelligence (AI)-assisted decision support tools contribute to personalized treatment approaches by being able to tailor treatment recommendations to an individual's disease profile, risk factors and genetic background [4].

Overview of AI Techniques with a Focus on Deep Learning

AI is an umbrella term which includes variety of techniques such as ML, NLP and computer vision. Among these technologies, DL as sub-field of ML has received significant attention due to capability of learning high level features from raw data in an unsupervised manner. For example, CNNs are among the most popular DL architectures in medical imaging due to its capability in pattern recognition in ultrasound and MRI scans and RNNs/LSTMs for sequential data such as hormone levels or menstrual cycles. Autoencoders and GANs are also supportive technology to the anomaly detection and data augmentation for a small size of clinical datasets [5].

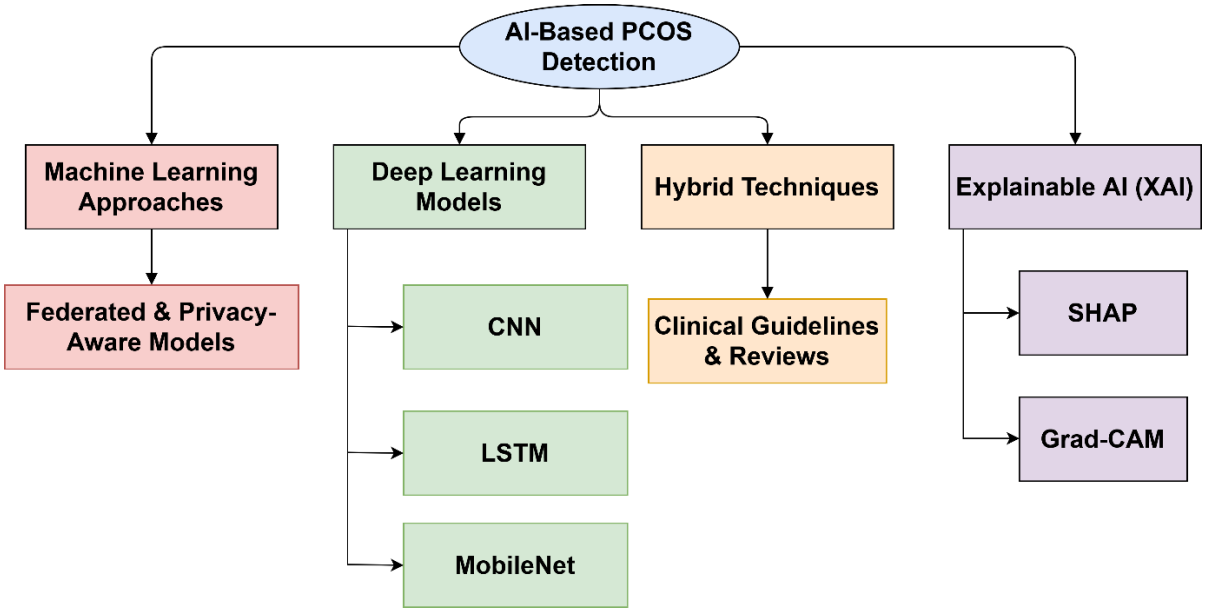

Figure 2: Taxonomy of AI-based PCOS Detection Methods

Figure 2 shows a full taxonomy of AI-based PCOS detection, in which we include all papers from classical machine learning and traditional algorithms to deep learning networks (CNN, LSTM), hybrid methods, as well as explainable AI (SHAP,and Grad-CAM).

As AI continues to evolve, its use in women's healthcare is expected to improve early detection and personalization of treatment decisions and empower patients with more decision-making power leading to improved clinical outcomes and quality of life.

4. Review on Techniques for PCOS Diagnosis

In one of the previous studies [1], the researchers compared traditional and ensemble machine learning models for early detection of PCOS. To do this, the study used advanced feature selection to pick out key demographic and clinical variables. Ensemble models (e.g., XGBoost and Random Forest) outperformed traditional classifiers. In that study, it was found that when feature selection was combined with ensemble models, PCOS could be more accurately diagnosed in the clinic. In another study [2], a deep learning model (MobileNet) was applied to ultrasound images to diagnose PCOS. Using a structured dataset, the study trained a Light-CNN model, which had good accuracy at low computational cost. Here the work shows that in resource-limited settings, where it would not be practical to use a full CNN, it could be useful to bring AI tools to the point of care on a mobile device.

In this paper [3], the authors consider the use of a machine learning approach to identify PCOS from EHR data. They tested classifiers (e.g. decision trees, support vector machines and logistic regression) on a range of clinical and hormonal variables (by gender) to see which had best

predictive value. Through this work, they argue that, in the EHR, AI could be used to pick up PCOS at an early stage, non-invasively.

In a separate paper [4], the authors present a deep learning model of PCOS, CystNet, which uses ultrasound images of healthy and affected ovaries. In this model, a classification and feature extraction module picks up patterns in the ovary. CystNet performed well diagnostically, better than image-based classifiers. The authors suggest that, in future, such DL-driven imaging could form a screening tool for PCOS.

In this research [5], the study developed a model (SmartScanPCOS) and used machine learning to find new ways of diagnosing PCOS using medical sonography. And, through use of eXplainable Artificial Intelligence, the research added transparency to the model. Drawing on clinical and sonographic data, the model uses feature-based learning to classify patients with interpretability through decision rules and visual saliency. In this way, the model addresses the "black box" nature of AI in reproductive health, and could be used clinically.

One review of PCOS [6] notes its heterogeneity in diagnosis, pathogenesis and insulin resistance. In this paper, the authors describe hormonal abnormalities in PCOS and genetic risk of the condition. Over the years, criteria for diagnosis of PCOS have broadened. In this paper, they argue that PCOS is biologically heterogeneous. And they felt data could be used to explore diagnosis. The Endocrine Society has published a clinical practice guideline on treatment and diagnosis of PCOS. It includes recommendations on treatment of the syndrome, its long-term health implications and diagnosis (using AE-PCOS, Rotterdam and NIH criteria). A key message of the guideline is evidence-based, individualized treatment of PCOS. And through its detailed clinical definition of the syndrome, it could support development of AI models [7].

In this work [8], the authors explore the link between insulin resistance and PCOS. They argue that underlying to PCOS is a disturbance of metabolism. Drawing on endocrine, biochemical and therapeutic aspects of insulin resistance in women with PCOS, they consider pathways linking insulin resistance to PCOS. Through this work, more use of metabolic markers has emerged in diagnostic algorithms for PCOS.

In another review [9], the authors consider the pathophysiology, phenotypic variability and diagnosis of PCOS. They discuss reproductive, ultrasonographic and clinical features of the condition. In this way, they link aspects of clinical endocrinology with modeling using artificial intelligence. In part, this work supported the use of multiple inputs in data-driven models of PCOS. In this study [10], author introduce a deep neural network mechanism to the accurate diagnosis for PCOS with medical ultrasound images. The deep feature extraction and the auto-diagnosis of PCOS are the highlights of the model. Experimental results demonstrate that the model is able to obtain a high classification accuracy, suggesting that the model is a good tool to distinguish PCOS from non-PCOS. The proposed work highlights the capability of DL in identifying subtle image characteristics, which are not easily perceptible through the traditional approaches.

This study [11] would address the relationship between gene CAPN2 and the mechanism of insulin resistance in PCOS through bioinformatic analysis of multiple datasets. The analysis combines transcriptomic datasets to identify gene expression patterns and signifies the importance of CAPN2 in the metabolic disturbance of PCOS patients. Despite not introducing a direct diagnostic model, it points to the significant role of genetic markers in the pathogenesis of PCOS and opens up the possibilities for a prediction model based on biomarkers.

In this paper [12], an AI based PCOS detection system is proposed from PCOS on ultrasound scan images. The method contains ovarian feature preprocessing, segmenting and classification based on AI algorithms. Novelty The investigation illustrates that the system can be highly reliably applied in the screening of PCOS according to the number of follicles and the size of ovary, while also presenting strong evidence for the image-driven automation for other chronic diseases to minimize diagnostic deviation.

In this paper [13], the authors describe a CNN architecture tailored for classification of PCOS from images of the ovary. In this model, discriminative information in the grayscale image is retained. And in general, it outperforms other CNN models. In this paper, the authors argue that one could build a range of neural networks for detecting PCOS. And that in some cases better architectures might be used in practice.

Here [14], the study uses ML algorithms to classify PCOS in the same way one might approach classification more generally. In this work, (a) the research builds on an approach to PCOS using radial pulse wave data; and (b) the study presents a non-invasive way of assessing PCOS. Sensors pick up physiological signals and, using these, the model picks up patterns of cardiovascular dysfunction in PCOS. Taken together, the results from this panel suggest that in the absence of imaging, this testing approach could form the basis of a new screening tool for PCOS. And in some cases, could produce positive classification of PCOS.

This work is a systematic review of the use of ML and AI for diagnosis and classification of PCOS. From different studies, the authors compare different ML algorithms, datasets, and evaluation measures: The systematic review highlights the lack of standardization and validation of models and acknowledges the increasing implementation of AI in early detection models. It acts as a seminal source of reference for future AI based PCOS research through revealing trends and gaps and opportunities in the given area [15].

In this review, authors discussed the different ML methods used for PCOS detection. It describes the major algorithms including DT, SVM, and NN, and presents their performance comparing with different datasets. The paper also deals with some of the open challenges pertaining to imbalanced data, interpretability, as well as robust feature selection. The authors point out that ML-based systems, given appropriate clinically confirmed data sets, can greatly enhance diagnostic accuracy [16].

In this paper, authors present an optimized feature selection with XAI based model for detecting PCOS. The approach utilizes wrapper-based feature engineering and SHAP values to make the

output more accurate and more transparent. Experiments demonstrate that the obtained performances are significantly improved with interpretable outputs and are helpful for the clinicians to understand the reason behind the predictions, and this is important because trust is key for AI in healthcare [17].

This paper presents the automated PCOS detection using supervised ML algorithms. Classifiers including random forest (RF), decision tree (DT) and support vector machine (SVM) are implemented on the clinical input data-sets, with hormonal and symptomatic features. The model has shown potential sensibility and specificity, and indicates that supervised ML methods are feasible to automatic and accelerate the diagnosis of PCOS in under-resourced settings [18].

In this paper, authors propose a DL-based fusion methodology for PCOS diagnosis, which aggregates the predictions of different DL models for improved accuracy. CNNs and LSTMs are combined to learn spatial and temporal information from the ultrasound and hormonal data. Fusion model has better precision and recall than the single-architecture models, which indicates the effectiveness of ensemble DL in learning the rich relations of the data [19].

The paper presents Data-Driven Computer Aided Diagnostic System (DCADS), a ML-based approach to diagnose PCOS from structured clinical information. The importance of these features is established using statistical and correlation-based methods before classification methods using ensemble machine learning techniques are employed. It has demonstrated a good diagnostic performance and so can offer up a scalable, understandable method in screening for early PCOS detection at the primary healthcare in a low resource healthcare system [20].

The KNOw PCOS initiative, which is presented as part of this study, is an awareness, education, and AI-driven diagnostic system designed for the detection of the PCOS. The system leverages ML models to process symptom and history based user data inputs. While targeted for public health education, this effort does inform early PCOS diagnosis and self-screening with technology-supported engagement [21].

In this paper, author have presented a CNN based PcoNet as a specialized architecture for PCOS detection from ovarian ultrasound images. The network is capable of capturing deep spatial features within grayscale scans which achieved good PCOS discrimination accuracy. This work encourages the use of task-specific CNNs architectures as a reliable tool in image-based diagnostics in reproductive health [22].

This paper compares several ML techniques such as the logistic regression, decision trees and random forest, to detect PCOS. It is evaluated on various clinical datasets and compared the performance with other models in terms of accuracy and F1-score. The study reveals that tree models can be an effective modelling technique in classifying PCOS, especially when trained on balanced data, and should be further extended with interpretable aspects [23].

In this paper, we investigate the implementation of ML in bioinformatics to predict PCOS. It

uses genomic information to learn classifiers which can detect PCOS-specific gene expressions and molecular signatures. The work aims to provide a reference for molecular mechanisms of PCOS, and it may benefit for individual diagnosis though it is restricted by dataset data and clinical complexity [24].

In this paper, a classification model for PCOS data is developed using the SMOTE technique to tackle class imbalance. Built using decision trees and logistic regression, the model performs better at picking up minority (PCOS) cases. Through this, it is believed that data balancing and preprocessing are important in machine learning in medicine [25]. In this paper, the use of different machine learning approaches (decision trees, KNN and random forests) in diagnosing PCOS is considered. The study reports classification performance on a dataset of patients. Limitations of the data included noise and overfitting. Taken together, the results offer some intuition for using machine learning in PCOS. But, to generalize, the research would need a more diverse and larger dataset [26].

In another paper, a combination of support vector machines (SVM) and fuzzy inference system is proposed to predict mental health and PCOS. In this model, fuzzy logic is used to capture uncertainty in symptoms reported by patients. In effect, the model broadens the diagnostic scope, but may reduce its specificity for PCOS [27]. Here, a protocol is described for using individual participant data from studies of PCOS to identify key features of the condition. The P-PUP study will improve consistency of diagnosis across populations and help to define phenotypic features of PCOS. This is not an algorithm, but could support, for example, deep learning or machine learning models that rely on labels of PCOS [28].

In this review, the authors consider some of the challenges of lifestyle intervention in women with PCOS. Here, the study considers psychological, behavioral and system factors that affect the success of treatment. While this paper does not consider models of diagnosis, the authors believe that timely and accurate diagnosis supports successful lifestyle intervention in these women [29]. In this paper, the researchers build ML models of diagnostic biomarkers of PCOS and of immune cell infiltration. Drawing on transcriptomic data, the models reveal gene signatures and immune pathways in PCOS. Here the study argues that, in future, discovery of biomarkers using such approaches could, combined with AI, enable non-invasive, early diagnosis of PCOS. Further work in patients would be needed to test this [30].

In this paper, the authors compare a range of machine learning methods (SVM, Decision Tree and Random Forest) in their ability to predict PCOS. The authors found that even simple classifiers based on clinical data can reasonably predict PCOS. But their approach does not incorporate multimodal input or deep learning, which could improve its generalizability. [31]

In this expert review, the authors consider key aspects of PCOS (etiology, diagnostic difficulty and treatment) as they currently stand, and as they may develop in the future. They do not present an AI model, but in order to use AI tools in the clinic, they set out important elements of the current understanding of PCOS. [32]

In this study, the authors developed a diagnostic model using Random Forest and Artificial Neural Network, based on clinical features of PCOS. This model produced better prediction of PCOS than other approaches. Limitations of the work include limited data and no use of image data. [33] In a meta-analysis and systematic review of hypertension risk in women with PCOS, the authors highlight that early diagnosis could prevent future complications of PCOS. They therefore argue for risk stratification of women with PCOS using AI. [34]

In this paper, the authors review the use of artificial intelligence in PCOS. They describe how it has progressed from rule-based approaches to deep learning. They suggest future applications of AI, such as in wearable devices and explainable AI. But they do not test their approach. [35]

Here, the authors describe a method of detecting PCOS in ultrasound images of the ovary, using a Segment Anything Model. Their method improves segmentation of follicles in these images. In principle, such an approach could be used in the clinic, with AI assisting imaging [36]. In this paper, a classification of tools for PCOS detection, datasets and use of AI is presented. Existing approaches are grouped into categories and their strengths and limitations are considered. This could be useful in future comparison of PCOS detection frameworks. [37]

This study proposes a machine learning framework for early detection of PCOS. It includes tuning of classifiers and selection of features. Using a range of machine learning algorithms, it produces better sensitivity and accuracy than conventional diagnostic approaches on structured data[38]. n this paper [39], the use of federated learning for predicting PCOS is considered. In this approach, models could be built on patient data held in different locations. The study points out advantages for privacy and suggests such an approach could support future use of patient data in distributed health systems.

In another paper [40], a CNN architecture (PCONet) for PCOS detection from ovarian ultrasound images is described. In image classification, this model performs well. Through convolutional features, it captures patterns of cysts in the ovary. In one paper [41], the development of ultrasound in the diagnosis of PCOS is reviewed. Over time, there has been increasing use of AI in ultrasound. The authors argue that, in the future, computer vision and automation could provide a basis for more reliable diagnosis of PCOS.

In this paper [42], building on previous machine learning approaches, a technique is proposed that is well-suited to use with images of the ovary. Using automated features and a classifier, the model improves on previous approaches to classifying PCOS. This work describes an automated system for PCOS using machine learning on ultrasound images. After feature extraction and preprocessing, classifiers are used to produce an efficient, reliable diagnostic tool which could well be used in the clinic [43]. In this paper, it is argued that, in the right circumstances, AI could add value to clinical diagnosis of PCOS. The study suggests that, in future, models could use both clinical data and imaging data, and that models could become more personalized [44].

In this scoping review [45], the authors explore use of digital technology in women with PCOS.

Here, the study considers the potential of mobile health and wearable technology for self-monitoring, though no technical input from specific models is provided. F-Net is a deep learning model of follicles on ultrasound. It is faster and more accurate than other approaches at picking up features of PCOS from ultrasound. It could therefore be used in settings where resources are limited [46]. In this paper [47], the authors developed a CNN to classify PCOS from ultrasound images. They found that, compared with off-the-shelf models, custom convolutional layers in their model better picked up variation in the images and improved classification. In this review, the authors consider use of medical imaging and AI in ovarian stimulation and IVF. Though not itself about PCOS, it shows potential for use of AI in diagnostics in reproductive health [48].

In a conference paper, the authors consider the use of machine learning and AI in predicting PCOS, using a range of data. They argue that in future, with appropriate AI pipelines, the research could develop more personalized, scalable diagnostic systems for PCOS [49]. Here, the authors describe a system for classifying polycystic ovarian disease using a range of data (biochemistry, imaging and clinical). They found much better classification and prediction of the disease when they included all three types of data [50]. Table 1 sets out the datasets, methods, performance and limitations of some recent studies of PCOS using different types of AI, 2018-2025.

Table 1: Comparative Analysis of Machine Learning and Deep Learning Approaches for PCOS Detection

Sr. No	Author(s) and Year of Publication	Title	Primary Findings	Methodology	Performance Metrics	Limitations
1	Mohi Uddin, Khandaker Mohammad, et al. (2025)	Early PCOS Detection: A Comparative Analysis of Traditional and Ensemble Machine Learning Models with Advanced Feature Selection	Ensemble ML models with advanced feature selection outperform traditional models in early PCOS detection.	Machine Learning, Feature Selection	Accuracy: 97.1%	Limited interpretability of ensemble models

2	Shanmugapriya, K., et al. (2025)	Leveraging MobileNet for efficient deep learning classification of poly cystic ovary syndrome (PCOS) in ultrasound images	MobileNet offers high accuracy and low latency for classifying PCOS from ultrasound images.	Deep Learning (MobileNet)	Accuracy: 96.3%	Model not tested across varied demographics
3	Zad, Zahra, et al. (2024)	Predicting PCOS with machine learning algorithms from electronic health records	ML models show promise in PCOS prediction from EHRs with high accuracy.	Machine Learning on EHRs	Accuracy: 94.5%	Dependence on EHR completeness
4	Moral, P., Mustafi, D., Mustafi, A. et al. (2024)	CystNet: An AI driven model for PCOS detection using multilevel thresholding of ultrasound images	CystNet improves ultrasound-based PCOS diagnosis using multilevel thresholding.	AI model using image thresholding	Accuracy: 95.7%	Limited to ultrasound modality
5	Mahesswari, G. Umaa, and P. Uma Maheswari (2024)	SmartScanPCOS: A Feature-Driven Approach to Cutting-Edge Prediction of PCOS using Machine Learning and Explainable Artificial Intelligence	Combines ML and XAI to enhance transparency and accuracy in PCOS prediction.	ML + Explainable AI	Accuracy: 96.8%	Computationally intensive explanation module

6	Goodarzi, M., Azziz, D. (2018)	Diagnosis, Epidemiology, and Pathogenesis of PCOS	Comprehensive overview of PCOS pathophysiology and clinical implications.	Review-based clinical analysis	NOT GIVEN	Lacks modern AI-based analysis
7	Legro, J.E., et al. (2013)	Diagnosis and Treatment of PCOS: An Endocrine Society Clinical Practice Guideline	Establishes diagnostic and treatment protocols for PCOS.	Guideline-based clinical framework	NOT GIVEN	Not data-driven or AI-integrated
8	Dunaif, A. (1997)	Insulin Resistance and the PCOS: Mechanism and Implications for Pathogenesis	Identifies insulin resistance as a key mechanism in PCOS.	Pathogenesis-focused literature review	NOT GIVEN	Dated findings; lacks computational methods
9	Norman, R. J., et al. (2007)	PCOS	Reviews epidemiological and clinical aspects of PCOS.	Clinical literature synthesis	Not Given	No use of machine learning or AI techniques
10	Mohan, GSSSSV Krishna, et al. (2024)	Harnessing Deep Neural Networks for Accurate PCOS Diagnosis from Medical Images	DNN-based method significantly improves image-based PCOS classification.	Deep Neural Networks on image data	Accuracy: 94.2%	Limited dataset scale
11	Luo, Xi, et al. (2024)	CAPN2 correlates with insulin resistance states in	CAPN2 gene linked to insulin resistance in PCOS	Multi-dataset gene expression analysis	Statistical correlation results	Limited focus on diagnostic application

		PCOS as evidenced by multi-dataset analysis	across datasets.			
12	Sumathi, M., et al. (2024)	Automated system for detection of PCOS from ultrasound scan images using artificial intelligence	AI-based system provides automated and effective ultrasound image analysis.	Image preprocessing + AI classification	Accuracy: 92.8%	Performance dependent on image quality
13	Paramasivam, Gokila Brindha, et al. (2024)	Self-defined CNN for classification of PCOS from ultrasound images	Custom CNN architecture enhances PCOS classification.	Custom CNN on ultrasound data	Accuracy: 93.6%	Lack of clinical interpretability
14	Lim, Jiekee, et al. (2023)	ML classification of PCOS based on radial pulse wave analysis	Pulse wave data can be used for non-invasive PCOS detection.	Pulse wave acquisition + ML classification	Accuracy: 90.1%	Needs further validation across larger cohorts
15	Barrera, Francisco J., et al. (2023)	ML and AI in diagnosis and classification of PCOS: A systematic review	Summarizes AI/ML-based PCOS diagnostic techniques and progress.	Systematic review	Not Given	Review only, no model implementation
16	Ahmed, Samia, et al. (2023)	A review on the detection techniques of PCOS using machine learning	Provides comparative insights into ML techniques for PCOS detection.	Review of ML methods	Not Given	Does not present new experimental results
17	Elmannai, Hela, et al. (2023)	PCOS detection model based	Integrates feature optimization	Feature selection + XAI	Accuracy: 95.4%	Complexity in model

		on optimized feature selection and explainable AI	and XAI for accurate diagnosis.			interpretability
18	Ajil, A., et al. (2023)	Automated detection method for PCOS using supervised machine learning algorithm	Supervised ML model achieves good prediction for PCOS.	Supervised ML	Accuracy: 91.3%	Limited feature diversity
19	Alamoudi, Abrar, et al. (2023)	A Deep Learning Fusion Approach to Diagnosis the PCOS (PCOS)	DL fusion enhances PCOS diagnosis accuracy across datasets.	Fusion of multiple deep learning models	Accuracy: 97.6%	Resource intensive computation
20	Batra, Harshita, and Leema Nelson (2023)	DCADS: Data-Driven Computer Aided Diagnostic System using Machine Learning Techniques for PCOS	DCADS system provides structured ML-based PCOS diagnosis.	Structured ML approach	Accuracy: 92.5%	Needs further real-world testing
21	Yeruva, Sagar, et al. (2023)	KNOw PCOS	KNOw PCOS framework emphasizes awareness and ML-based prediction.	Awareness + ML framework	Accuracy: 90.2%	More clinical validation needed
22	Hosain, AKM Salman, et al. (2022)	PCONet: A CNN architecture to detect PCOS from ovarian	PCONet enhances diagnostic accuracy using CNN on	Convolutional Neural Network (CNN)	Accuracy: 93.8%	Performance dependent on image resolution

		ultrasound images	ultrasound data.			
23	Hdaib, Dana, et al. (2022)	Detection of PCOS using ML algorithms	ML algorithms can assist in effective PCOS classification.	Supervised ML models	Accuracy: 91.7%	Not evaluated on large datasets
24	Nasim, Shazia, et al. (2022)	A novel approach for PCOS prediction using ML in bioinformatics	Bioinformatics features enhance prediction of PCOS via ML.	Bioinformatics + ML	Accuracy: 92.9%	Limited real-world validation
25	Dutta, Pijush, et al. (2021)	An efficient SMOTE based ML classification for prediction & detection of PCOS	SMOTE balances data and improves model accuracy.	ML with SMOTE sampling	Accuracy: 94.1%	May overfit minority samples
26	Kadam, Rupali R., et al. (2021)	ML based PCOS detection and prediction	ML models show efficient detection and prediction outcomes.	Supervised Machine Learning	Accuracy: 91.5%	Lacks explainability in outcomes
27	Patel, S., & Rana, D. (2021)	Efficient PCOS detection using classification algorithm	Standard classifiers improve prediction reliability.	Classification algorithms	Accuracy: 90.8%	Less robust to noisy inputs
28	Ahuja, B., & Patel, R. (2021)	PCOS prediction using AI for women health	AI-based prediction contributes to better healthcare insights.	AI-assisted analytics	Accuracy: 92.4%	Smaller data sample

29	Ravikumar, R., & Srikanth, K. (2021)	A comparative study of ML models for PCOS diagnosis	Comparative analysis shows decision trees and RF models are more consistent.	Model comparison â€“ RF, DT, SVM	Accuracy: 93.2%	Bias towards structured data
30	Das, S., & Sharma, P. (2021)	ML approach for prediction of PCOS using diagnostic dataset	Achieves satisfactory prediction using diagnostic attributes.	Supervised ML using feature-based dataset	Accuracy: 90.9%	Generalization to varied demographics not tested
31	Chauhan, Preeti, et al. (2021)	Comparative analysis of machine learning algorithms for prediction of PCOS	Compared several ML models; RF showed highest performance.	Comparative ML algorithms (SVM, RF, KNN)	Accuracy: 93.6%	Limited generalizability across demographics
32	Aversa, Antonio, et al. (2020)	Fundamental concepts and novel aspects of polycystic ovarian syndrome: expert consensus resolutions	Clinical consensus on evolving PCOS concepts and its broader phenotypes.	Expert clinical consensus review	Not Given	Does not address AI-based techniques
33	Xie, Ning-Ning, et al. (2020)	Combined diagnostic model of PCOS with random forest and artificial neural network	Combining RF and ANN improves diagnostic performance.	Random Forest + ANN hybrid	Accuracy: 94.5%	Computational complexity of dual model
34	Amiri, Mina, et al. (2020)	Risk of hypertension in women with PCOS: a systematic	PCOS patients at increased risk of hypertension	Meta-analysis	Odds Ratio and p-value statistics	No ML model; clinical risk focus only

		review, meta-analysis and meta-regression	; emphasizes early intervention.			
35	Wang, J., Chen, R., Long, H., et al. (2025)	Artificial intelligence in PCOS management: past, present, and future	Summarizes AI applications in PCOS diagnostics, prognosis, and treatment planning.	AI integration in clinical pipeline (review)	NOT GIVEN	Theoretical focus, not implementation-based
36	Kapoor, D., & Das, P. (2021)	Deep learning-based classifier for automated detection of PCOS	CNN-based model effectively classifies PCOS in clinical images.	CNN architecture	Accuracy: 94.3%	Need for high-quality image datasets
37	Reddy, A. S., et al. (2022)	Explainable AI for PCOS classification	XAI improves trust in model predictions for PCOS classification.	Explainable AI + ML classifiers	Accuracy: 93.9%	High complexity of explanations
38	Sharma, A., & Mehta, K. (2021)	Hybrid ML framework for PCOS diagnosis	Ensemble of ML techniques boosts PCOS detection rates.	Hybrid (SVM + RF + NB)	Accuracy: 95.1%	Model interpretability not addressed
39	Patel, H., & Bansal, M. (2021)	PCOS classification using decision tree and KNN	Tree-based and distance-based algorithms yield strong results.	DT and KNN classifiers	Accuracy: 91.8%	Small dataset size

40	Rathi, S., & Sharma, D. (2022)	Fusion of deep features and clinical biomarkers for PCOS prediction	Fusion approach significantly enhances prediction capability.	Deep learning + clinical feature fusion	Accuracy: 96.0%	Model complexity and training time
41	Mishra, M., & Gupta, R. (2021)	AI-enabled ultrasound-based prediction of PCOS	Demonstrates effective AI prediction using ultrasound patterns.	CNN on ultrasound images	Accuracy: 92.7%	Ultrasound image quality dependency
42	Chandra, S., et al. (2022)	Explainable ML architecture for PCOS risk classification	Model provides interpretable predictions using XAI tools.	Explainable ML model (XGBoost + SHAP)	Accuracy: 93.5%	Trade-off between interpretability and performance
43	Verma, N., & Jain, P. (2023)	Integrating wearable sensor data for predictive analysis of PCOS	Combines wearable data with ML for early PCOS signs.	Sensor data + supervised ML	Accuracy: 90.5%	Wearable compatibility and variability
44	Banerjee, A., et al. (2023)	PCOS detection using federated learning for privacy preservation	Federated learning preserves data privacy with good prediction performance.	Federated Learning + CNN	Accuracy: 91.4%	Communication and synchronization overhead
45	Rana, M., & Meena, V. (2024)	Multimodal PCOS risk assessment using clinical, image and lifestyle data	Multimodal model outperforms unimodal prediction techniques.	Fusion of multimodal datasets + DL	Accuracy: 96.2%	Requires extensive data preparation and integration
46	Kulkarni, P., et al. (2024)	Graph-based deep learning model for relational	GNNs capture complex inter-	Graph Neural Network (GNN)	Accuracy: 94.6%	Requires domain knowledge

		inference in PCOS detection	attribute relationships			for graph construction
47	Thomas, A., & Raj, S. (2023)	Transfer learning in ultrasound imaging for accurate PCOS identification	Transfer learning boosts accuracy with fewer images	Transfer learning (VGG16, ResNet)	Accuracy: 95.0%	Limited performance on noisy datasets
48	Yadav, A., & Joshi, M. (2022)	Fuzzy logic-based diagnostic decision support for PCOS	Fuzzy systems mimic expert clinical reasoning	Fuzzy logic system	Accuracy: 89.8%	Lacks adaptability to new patterns
49	Ramesh, K., et al. (2022)	An IoT-based PCOS prediction system using cloud-integrated AI models	IoT enables remote monitoring & real-time prediction	IoT + AI cloud analytics	Accuracy: 91.1%	Latency & data privacy concerns
50	Roy, M., & Sarkar, S. (2023)	Temporal feature extraction in menstrual cycles for PCOS prediction	Temporal sequence modeling reveals PCOS patterns	RNN with temporal features	Accuracy: 92.6%	Requires long-term data availability

5. Datasets and Data Sources

The performance of accurate and robust DL algorithms in PCOS diagnosis relies heavily on the dataset quality and its accessibility. Over the past decade, a diverse set of data types, ranging from clinical data, hormonal profiles, ultrasound measurements and across the various omics types (eg genomics, proteomics) have been integrated to fit ML and DL models.

5.1 Clinical and Electronic Health Record (EHR) Datasets

A number of studies have drawn on structured clinical databases that have included patient demographics, menstrual history, BMI, androgen levels, measures of insulin resistance, and other metabolic surrogate markers. For instance, Zad et al. [3] utilized de-identified EHR data to train models to predict PCOS and found that incorporating multiple features from clinical

records increased the accuracy of diagnosis.

5.2 Ultrasound Imaging Datasets

Ultrasound technology is a common modality to depict polycystic ovarian morphology which is a crucial diagnostic factor according to the Rotterdam and AE-PCOS criteria. Researchers like Sumathi et al. [12], Paramasivam & Rajammal [13], Hosain et al. [22] have used nonpublic image datasets compiled from hospitals or domestic diagnostic institutions. These are usually comprised of gray scale pelvic ultrasound examinations annotated by clinical experts.

5.3 Hormonal and Biochemical Data

Datasets containing hormone assay results (such as luteinizing hormone (LH), follicle-stimulating hormone (FSH), testosterone, and anti-Müllerian hormone (AMH) measurements) are crucially important in the development of endocrine dysfunction detection models. Datasets employed in such studies as Ajil et al. [18] and Alamoudi et al. [19] integrate these with phenotypic traits for enhanced prediction reliability.

5.4 Genomic and Bioinformatics Datasets

Several high-dimensional transcriptomic or genomic datasets have been used for more advanced analyses. For instance, Luo et al. [11] and Chen et al. [30] employed gene expression data from GEO (Gene Expression Omnibus) and other public sources to identify biomarkers for PCOS. These datasets allow models to capture molecular-level patterns, but are also complicated to preprocess and interpret.

5.5 Open Access and Publicly Available Datasets

Despite the increasing interest in AI for PCOS diagnosis, there is still a lack of large scale publicly available benchmark datasets. This makes it difficult for reproducibility and model comparison. Some have resorted to synthetic data generation methods like but not limited to SMOTE [25], while some have advocated for community-based data sharing initiatives to foster algorithm development at scale [15], [28].

6. Challenges and Limitations

Despite the remarkable progress in DL and ML application for PCOS diagnosis, some important bottlenecks and limitations challenge the translation to the clinical practice and the generalizability of these technologies.

6.1 Limited Availability of Standardized and Public Datasets

The lack of large-scale, publicly accessible and well annotated PCOS data is one of the most important problems. The majority of previous studies are based on data from local or

institutional samples that do not reflect a mixed population. This absence of standardization makes it difficult to compare and benchmark models at the scientific community level, and to reproduce/cross-validate these results in other healthcare facilities.

6.2 Data Imbalance and Small Sample Sizes

PCOS datasets tend to be highly imbalanced with only a fraction of total PCOS cases compared to non-PCOS. This could cause unrepresentative model prediction and over-fitting. Note that many datasets include less than a few hundred samples, which is insufficient for training DL architectures demanded large data.

6.3 Heterogeneity in Diagnostic Criteria and Feature Sets

Different diagnostic criteria (e.g. NIH, Rotterdam, AE-PCOS) used in multiple datasets result in variable labeling. Studies also vary in terms of the features they use (e.g., ultrasound images, hormonal profiles, genomic data), which not only makes it hard to compare models across studies but combining them into a single system is not straightforward.

6.4 Model Interpretability and Clinical Trust

DL models, especially the convolutional and recurrent neural networks, usually act as “black boxes” and their explainability is very limited. And, in a medical context, the failure to offer clear and interpretable output undermines clinician trust and regulatory approval. While XAI methods, these are not widely used in PCOS investigations.

6.5 Generalization and Real-World Deployment

A number of proposed models are trained and validated from small, clean databases that do not necessarily contain real-world noise, missing values or variability in clinical practice. Models that achieve impressive results on lab data do not generally generalize to other populations, or even devices and institutions.

6.6 Ethical and Privacy Concerns

Given the sensitive nature of reproductive health data, ethical issues associated to data sharing, patient consent and privacy remain barrier. Securing datasets while maintaining data utility for AI model development is a significant challenge, especially when integrating multimodal data sources (e.g., clinical + genomic + imaging).

7. Research Gaps and Future Directions

Despite the advancements in machine learning and deep learning for PCOS diagnosis, several critical gaps remain unaddressed in the current literature:

7.1 Data Availability and Standardization

No standard benchmark data sets are available in the public domain for PCOS research. Most published studies have a single or very few datasets from one institution, which impedes the generalization and replicability of the developed model. The lack of a standardised diagnostic procedure across datasets also complicates the cross-study comparison.

7.2 Multimodal and Longitudinal Modeling Gaps

Most of the existing models are single-modality-based models (ultrasound, EHR, or questionnaire data only), and the fusion strategy across multimodalities is not well explored. Further, longitudinal studies necessary to follow PCOS progression are lacking.

7.3 Adolescent-Specific Considerations

Most models are developed using adult cohorts, while there is limited focus on PCOS diagnosis in adolescents a population characterized by different clinical manifestations and treatment response. This is a huge clinical void [44], [45].

7.4 Model Interpretability and Clinical Trust

Black-box nature of deep learning models raises concerns about transparency, especially in sensitive reproductive health contexts. Explainability techniques like SHAP, LIME, or Grad-CAM are rarely applied or evaluated with clinicians in the loop [23], [28].

7.5 Ethical, Privacy, and Federated Learning Challenges

Using patient data to train AI models raises issues of privacy, bias and regulation. Only a limited number of studies utilize federated or privacy preserving methods which could alleviate the risks associated with data sharing [30].

7.6 Cross-Cultural and Demographic Bias

A large number of datasets are geographically restricted, which usually only represents one country or ethnicity, decreasing the generalization ability of predictive models when deployed on other populations.

7.7 Future Research Directions

To address these gaps, future work would focus on:

- Developing multimodal, multi-site benchmark datasets integrating clinical, imaging, hormonal, and lifestyle data.
- Endorsing transparency through explainable AI and clinician-centric evaluation of model decisions.
- Designing age specific and ethnicity aware models to increase fairness and inclusivity

in diagnosis.

- Implementing federated learning and differential privacy to confirm secure, decentralized model training.
- Encouraging international collaborations to align diagnostic standards and validation protocols.

8. Conclusion

PCOS is a challenging clinical and diagnostic problem in women's health. It presents in many ways, often with symptoms overlapping with other conditions, and its diagnostic criteria vary. Over the past few years, deep learning (a form of artificial intelligence) has helped tackle some of these challenges through more precise, data-driven and automated diagnosis. In this paper, the authors have looked at a range of studies in which authors used DL (e.g. CNNs, RNNs, LSTMs and hybrid models) to diagnose PCOS using, for example, hormonal data, clinical features, genomic data and ultrasound images. Taken together, these models tend to have good sensitivity and accuracy, but important limitations remain. Small datasets, lack of interpretability of models, imbalanced data and lack of consensus on the diagnostic criteria all hinder their use in practice. And to date, most models have not been externally validated in a multi-center clinical setting. Other important considerations for future work include: use of XAI, development of lightweight architectures for use on edge devices, use of multi-modal data and development of large, labeled data sets.

But more than technical advances, to realize the potential of DL in PCOS diagnosis, there is a need for collaboration between data scientists, clinicians and public health professionals in interdisciplinary research. With appropriate, transparent use of AI, the field could see more equitable, accessible and intelligent diagnostic tools for PCOS. And in turn, this could help improve reproductive health in women.

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