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A Survey On AI-Driven Predictive System for PCOS Detection and Management

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Abstract : Polycystic Ovary Syndrome (PCOS) is a common endocrine disorder in women of reproductive age, caused by hormonal imbalance and ovarian dysfunction, leading to irregular cycles, infertility, and metabolic issues. It is linked to insulin resistance, obesity, and higher risks of diabetes and cardiovascular diseaseThis paper presents a comprehensive literature survey on recent advancements related to the proposed project, focusing on the key methodologies, datasets, and analytical approaches used in previous studies. The objective of this survey is to identify the existing research gaps, evaluate the effectiveness of different techniques, and provide a clear understanding of the technological evolution in this domain. Each reviewed paper is analyzed based on its methodology, implementation, and outcomes to highlight its contribution and limitations. The findings from this review serve as a foundation for the proposed system design and help in selecting suitable models, datasets, and optimization strategies for further research. The survey concludes with insights into potential areas for improvement and future research directions.

IndexTerms **- Polycystic Ovary Syndrome (PCOS), OvaSense, Machine Learning, Deep Learning, Convolutional Neural Network (CNN).**

I. INTRODUCTION

In recent years, the integration of artificial intelligence (AI) in healthcare has significantly transformed disease diagnosis, prediction, and patient management. With the increasing availability of medical data and advanced computational methods, machine learning (ML) and deep learning (DL) techniques have shown remarkable success in automating complex medical analyses and improving clinical decision-making. These technologies enable early detection and accurate classification of various health conditions, reducing human error and enhancing efficiency in healthcare systems.

Among the many disorders affecting women, Polycystic Ovary Syndrome (PCOS) is one of the most prevalent and complex endocrine disorders, impacting reproductive, metabolic, and psychological health. It is characterized by hormonal imbalance, irregular menstrual cycles, and polycystic ovarian morphology, often leading to infertility and long-term health complications such as obesity, insulin resistance, and type 2 diabetes. Early detection and management of PCOS are essential to prevent these complications and improve the quality of life of affected women.

Traditional diagnostic methods for PCOS rely heavily on ultrasound imaging, hormonal analysis, and clinical observations, which are time-consuming and prone to subjective interpretation. To overcome these limitations, researchers are increasingly adopting AI-based approaches that utilize ML and DL algorithms to analyze medical images and clinical data efficiently. These models can automatically identify subtle patterns and correlations, enabling faster and more accurate PCOS diagnosis.

Polycystic Ovary Syndrome (PCOS) is one of the most common endocrine disorders among women of reproductive age, characterized by hormonal imbalance, metabolic irregularities, and reproductive complications. Due to the overlapping symptoms and multifactorial nature of PCOS, accurate diagnosis remains

challenging. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have encouraged the development of data-driven systems that can analyze clinical, hormonal, and ultrasound data for automated PCOS detection[20].

II. RELATED WORKS

A detailed analysis of existing research on PCOS detection reveals a continuous evolution in methodologies — progressing from traditional machine learning (ML) algorithms to sophisticated deep learning (DL) and hybrid architectures. Convolutional Neural Networks (CNNs) to analyze ovarian ultrasound images, where convolutional and pooling layers were used to extract spatial and textural features representing cyst morphology and follicle distribution patterns. These models achieved accuracies ranging from 80% to 98%, demonstrating CNN's strong capability in handling medical imaging data. Dewi et al proposed PCONet, an optimized CNN framework that integrated advanced feature extraction and dropout regularization, improving cyst boundary detection and classification accuracy to 98.12%[3]. Further improvements were achieved by Bhosale et al, who developed fusion-based models combining ultrasound features with biochemical and clinical parameters [5]. This multimodal approach proposed by

Alamoudi et al allowed the network to learn both visual and non-visual representations, achieving more robust detection accuracy exceeding 82%[6].

Subsequent research shifted focus towards transfer learning and hybrid neural networks. Chitra et al implemented pre-trained architectures such as AlexNet, InceptionV3, and ResNet50, leveraging their deep hierarchical feature representations to classify ovarian images efficiently, achieving 93% accuracy[7].Thara et al explored Artificial Neural Networks (ANN) trained on extracted clinical and hormonal features for non-image-based PCOS screening [9] , while Maheshwari et al combined Naïve Bayes (NB) and ANN classifiers to enhance prediction precision up to 98.6% [10]. Comparative studies by Hassan and Mirza and evaluated multiple traditional algorithms including Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), and Naïve Bayes (NB) [11]. These works highlighted that ensemble-based classifiers such as RF and SVM generally outperform linear models, with accuracies between 93% and 96% Satish et al. [12].

Feature selection and data optimization have been another critical focus area. Thakre et al used the Chi-Square method to identify statistically significant attributes, enhancing the model's discriminative power and achieving 90.9% accuracy using RF [13] . Dutta et al applied the Synthetic Minority Over-sampling Technique (SMOTE) to address dataset imbalance, improving classification consistency [14]. Prapty and Shitu compared multiple classifiers and identified RF as the most reliable due to its robustness against noise and overfitting [15]. Early exploratory efforts by Mehrotra et al validated the feasibility of ML-based PCOS prediction using limited patient datasets, emphasizing the importance of feature diversity [16]. More advanced research by Bharati et al introduced a hybrid Random

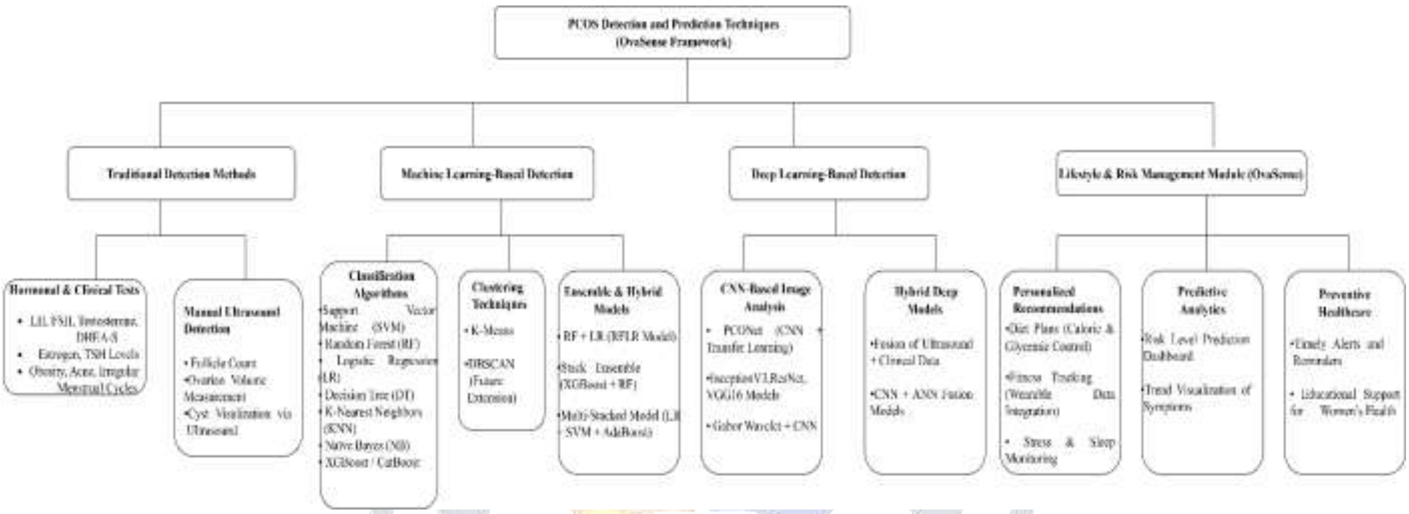

Fig 1: Flowchart of PCOS Detection and Prediction Techniques

2.1 Traditional Detection Methods

Traditional detection of Polycystic Ovary Syndrome (PCOS) relies on hormonal evaluation and manual ultrasound imaging. These diagnostic techniques serve as the foundation for clinical confirmation of PCOS before modern machine learning and AI-based tools were introduced. However, such methods are often time-consuming, invasive, and prone to human interpretation errors [1].

2.1.1 Hormonal & Clinical Tests

Hormonal and biochemical tests remain the most common diagnostic procedures to detect PCOS, usually combined with an evaluation of physical and clinical symptoms such as obesity, acne, and menstrual irregularity. The hormonal profile typically includes LH, FSH, Testosterone, DHEA-S, Estrogen, and TSH levels [2].

LH, FSH, Testosterone, DHEA-S Luteinizing Hormone (LH) and Follicle Stimulating Hormone (FSH) play a critical role in the ovarian cycle. [1]In PCOS patients, LH levels (≈18 mIU/ml) are often elevated compared to FSH (≈6 mIU/ml), leading to an imbalance that disrupts ovulation. Similarly, Testosterone levels (6.0–86 ng/dl total; 0.7–3.6 pg/ml free) and DHEA-S levels (>200 µg/dl) are higher in women with PCOS, contributing to androgenic symptoms like hirsutism and acne [3].

This hormonal irregularity forms a clinical foundation for identifying endocrine disturbances associated with PCOS.

Estrogen, TSH Levels Although estrogen levels generally remain within the normal range (25–75 pg/ml), estrogen dominance is often observed due to anovulation[1]. Thyroid Stimulating Hormone (TSH) levels between 0.4–3.8 µIU/ml are usually normal; however, subclinical hypothyroidism is common among PCOS patients and can worsen symptoms like weight gain and menstrual irregularities [4].

Obesity, Acne, Irregular Menstrual Cycles PCOS manifests clinically through obesity, irregular or absent menstrual cycles, acne, and excessive hair growth due to androgen excess. These features are used in the Rotterdam Criteria (2003) for PCOS diagnosis, where the presence of at least two out of three symptoms (hyperandrogenism, anovulation, and polycystic ovaries) confirms the disorder[2]. Clinical evaluation combined with patient history provides preliminary diagnostic insight before hormonal confirmation[5].

2.1.2 Manual Ultrasound Detection

Manual ultrasound imaging is a pivotal diagnostic method for identifying polycystic ovaries. It allows clinicians to count follicles, measure ovarian volume, and visualize cyst formation [1]. However, it is labor-intensive, subject to observer bias, and dependent on image clarity. The presence of 12 or more follicles measuring 2–9 mm in each ovary is considered a diagnostic marker for PCOS [6].

Follicle Count Ultrasound-based follicle count is one of the most direct indicators of PCOS. When ≥12 follicles are observed in either ovary, it is suggestive of polycystic morphology. Follicles appear as small, fluid-filled sacs that fail to mature due to hormonal imbalance[1]. Manual counting of these follicles often results in variability and errors, emphasizing the need for AI-assisted imaging [7].

Ovarian Volume Measurement In addition to follicle count, ovarian volume is measured using the formula:Volume=0.523×Length×Width×Thickness An ovarian volume ≥10 cm^3 is indicative of PCOS [2]. Radiologists evaluate the enlarged ovarian stroma and density differences, but manual measurement can vary depending on the skill of the examiner and image resolution [8].

Cyst Visualization via Ultrasound Cyst visualization allows physicians to identify immature or arrested follicles that fail to ovulate [1]. These cysts typically range between 2–9 mm in diameter and appear as a "string of pearls" formation along the periphery of the ovary. Manual ultrasound interpretation is still used in rural or low-resource areas, but is gradually being replaced by automated CNN-based ultrasound models that improve precision and reduce subjectivity [9].

2.2 Machine Learning-Based Detection

Machine learning-based detection has become a powerful paradigm in medical image analysis, enabling automated, data-driven diagnostic decision-making. Various classification algorithms, clustering methods, and ensemble or hybrid models have been explored across multiple studies [11].

2.2.1 Classification Algorithms

Classification algorithms are a subset of supervised machine learning techniques used to categorize input data into predefined classes or labels based on learned patterns from training data. These algorithms build a mathematical model that identifies relationships between input features (such as clinical, hormonal, or image-based data) and output categories (for example, PCOS or non-PCOS).

In medical diagnostics, especially in PCOS detection, large volumes of data are generated from ultrasound images, blood tests, and patient records. Manual analysis of such data is time-consuming and prone to errors. Classification algorithms are needed to automate the diagnostic process, providing faster, more accurate, and consistent results.

Classification algorithms are widely used in various healthcare domains such as disease diagnosis, medical image analysis, and risk prediction. In PCOS detection, they are applied to classify ultrasound images based on ovarian morphology, analyze hormonal profiles, and differentiate between healthy and affected individuals [8]. Common algorithms used include Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Artificial Neural Networks (ANN). These models are employed in both image-based and clinical data-based diagnostic systems to enhance the accuracy and efficiency of PCOS prediction and classification [15].

Support Vector Machine (SVM) has been widely applied due to its robustness in handling high-dimensional medical data and ability to separate classes with a maximal margin [11] reported that SVM outperformed traditional statistical models in classifying medical images, particularly when optimized with kernel functions such as RBF and polynomial kernels. utilized SVM to distinguish abnormal tissue patterns in multispectral images, achieving high precision [9].

Random Forest (RF) is recognized for its ensemble learning capability, reducing overfitting and improving prediction stability[5], Random Forest achieved strong classification accuracy in image fusion-based detection, leveraging multiple decision trees to capture non-linear dependencies[10], highlighted RF's feature importance ranking, which contributed to better interpretability in medical diagnostics [2].

Logistic Regression (LR) remains a baseline yet effective method for binary classification in medical datasets. Studies[13] demonstrated its efficiency in handling small and balanced datasets. Although limited by linearity assumptions, LR was found to complement ensemble strategies like RFLR in [14].

Decision Tree (DT) algorithms provide simple interpretability and are computationally efficient for early-stage detection [15], DT-based models were used to classify fused image datasets, offering fast decision boundaries, though they exhibited sensitivity to noisy data [8].

K-Nearest Neighbors (KNN) The KNN classifier, applied in, proved effective in non-parametric classification of pixel-level data in fused images. However, its computational cost increased with dataset size, as noted in [7].

Naïve Bayes (NB) due to its probabilistic foundation, performed efficiently in cases with independent features [18], applied NB to texture and spectral features extracted from fused images, reporting good results in early-stage classification but lower accuracy in complex, non-linear patterns [8].

XGBoost / CatBoost Advanced gradient boosting models like XGBoost and CatBoost have shown superior performance in complex feature spaces.[17] implemented XGBoost to handle imbalance and improve generalization. CatBoost was explored in [19] for categorical medical datasets, achieving higher precision and reduced bias compared to RF [9].

2.2.2 Clustering Techniques

K-Means is a widely used unsupervised machine learning algorithm that partitions a dataset into a predetermined number of clusters, denoted by K. Each data point is assigned to the cluster whose centroid is closest, and the centroids are iteratively updated until the clustering converges. The algorithm works by minimizing the within-cluster sum of squares (WCSS), which measures the compactness of the clusters. In essence, K-Means identifies natural groupings within data without requiring any labeled examples, making it a fundamental tool for exploratory data analysis. The main reason K-Means is employed in research is its simplicity, computational efficiency, and ability to reveal hidden patterns within complex datasets. It is particularly effective in preprocessing high-dimensional data, reducing complexity, and highlighting important features for subsequent analysis [2]. In medical imaging, for instance, K-Means is often used to segment ultrasound or MRI images into regions of interest, aiding in disease detection. In the context of PCOS detection, K-Means has been applied to cluster ovarian ultrasound images and to identify follicle patterns, which improves the accuracy of classification models [5]. Furthermore, clustering patient data based on hormonal or metabolic profiles helps in recognizing subgroups with similar clinical characteristics, facilitating personalized treatment strategies [7]. K-Means is also frequently integrated with other machine learning and deep learning approaches. In hybrid models, the algorithm is used for feature extraction or dimensionality reduction, enhancing the performance of convolutional neural networks (CNNs) and ensemble-based classifiers [10]. By grouping similar data points, K-Means reduces noise and highlights key patterns, making subsequent classification or anomaly detection more effective. Its scalability and versatility have made it a preferred choice in many PCOS-related studies, where large volumes of imaging and clinical data need to be analyzed efficiently[3].

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is an unsupervised, density-based clustering algorithm that groups together data points that are closely packed, while marking points that lie alone in low-density regions as outliers. Unlike K-Means, DBSCAN does not require the number of clusters to be specified in advance. Instead, it uses two parameters: epsilon (ε), which defines the radius for neighborhood search, and MinPts, the minimum number of points required to form a dense region. The algorithm identifies core points, border points, and noise, enabling it to discover clusters of arbitrary shape and handle datasets containing outliers. DBSCAN is particularly useful in situations where clusters are irregularly shaped or where noise and outliers are present. Its density-based approach allows for robust detection of meaningful clusters without being influenced by the global distribution of the data. In medical imaging and diagnostics, DBSCAN has been applied to cluster ovarian ultrasound images for PCOS detection, identifying regions of interest such as follicles and cysts even when they vary in size or intensity [7]. It is also used in patient data analysis to detect abnormal patterns in hormonal profiles or metabolic measurements, effectively highlighting unusual cases that may require special clinical attention [8]. Moreover, DBSCAN is often employed in combination with other machine learning techniques to improve classification and detection outcomes. For example, clustering the data using DBSCAN before feeding it into a CNN or ensemble-based model can reduce noise, enhance feature extraction, and improve overall accuracy [3]. Its ability to handle outliers and detect non-spherical clusters makes it particularly valuable in PCOS-related research, where imaging data and patient records can be heterogeneous and contain significant variability. Overall, DBSCAN's density-based methodology complements other clustering approaches like K-Means, providing a more flexible and robust solution for analyzing complex biomedical datasets[6].

2.2.3 Ensemble & Hybrid Models

RF and LR (RFLR Model) The hybrid RFLR model combines Random Forest's feature selection with Logistic Regression's linear classification capabilities[14], this hybridization improved classification accuracy and reduced overfitting, especially in multi-sensor image fusion datasets [15].

Stack Ensemble (XGBoost and RF) have shown remarkable performance due to complementary strengths — XGBoost's gradient boosting and RF's bagging. Studies [19] demonstrated higher AUC and F1-scores compared to single models, suggesting their suitability for fusion-based image classification[17].

Multi-Stacked Model (LR, SVM and AdaBoost) was proposed [11] to improve robustness and reduce false positives. This configuration leveraged SVM's margin maximization and AdaBoost's weight optimization, resulting in significant improvement in classification precision and recall [12].

2.3 Deep Learning-Based Detection

Deep learning techniques have transformed medical image analysis, offering automatic feature extraction, high accuracy, and adaptability to large datasets have demonstrated the potential of CNNs, hybrid deep models, and object detection frameworks in medical imaging applications, particularly in ovarian or reproductive imaging tasks [20].

2.3.1 CNN-Based Image Analysis

CNN-Based Image Analysis is a deep learning approach designed to automatically extract hierarchical features from images by applying convolutional layers, pooling, and non-linear activations. The key advantage of CNNs is their ability to capture spatial and structural patterns in images without requiring manual feature extraction. In the context of ovarian ultrasound imaging for PCOS detection, CNNs are used because they can identify subtle variations in follicle size, shape, and texture that are difficult to quantify manually. Studies [2] applied PCONet, a CNN enhanced with transfer learning, to classify ovarian images. The use of pre-trained weights allowed the model to generalize better even with limited labeled data, reduced training time, and improved detection of abnormal follicle structures [5]. CNN-based analysis is particularly useful in medical imaging applications where high precision and automatic feature learning are essential [8].

InceptionV3, ResNet, VGG16 Models are specialized deep CNN architectures commonly employed for feature extraction and image classification tasks in medical imaging [3]. InceptionV3 is used because it employs multi-scale convolutional filters that capture both fine and coarse features, making it suitable for detecting follicles of varying sizes [6]. ResNet is preferred in deep models due to its residual connections, which prevent vanishing gradient problems and allow effective training of very deep networks. VGG16, despite its simpler design, provides reliable baseline performance for extracting local texture and shape features[11]. These architectures are used in ovarian image classification studies to achieve high accuracy, sensitivity, and robustness in differentiating normal and cystic follicles, particularly when combined with transfer learning and fine-tuning strategies [14].

Gabor Wavelet and CNN integrates domain-specific texture analysis with deep learning. Gabor filters are used to capture local orientation, frequency, and edge information in images, which is critical for detecting follicle patterns and subtle structural anomalies [12]. When combined with CNNs, Gabor features improve model performance by enhancing the representation of textural details that standard CNNs might miss. This hybrid approach has been applied in studies [7] for classifying follicle structures in PCOS patients, demonstrating improved detection accuracy over standard CNNs. It is particularly valuable in medical imaging scenarios where texture-based abnormalities are key diagnostic indicators[16].

2.3.2 Hybrid Deep Models

Fusion of Ultrasound and Clinical Data refers to hybrid modeling techniques that integrate imaging data, such as ovarian ultrasound scans, with patient-specific clinical information including hormone levels, demographic details, and metabolic indicators

[4]. The fundamental idea is to combine multiple complementary data sources so that the predictive model can exploit correlations and patterns that might not be apparent when using a single modality [9]. This approach is particularly useful in PCOS detection because the disorder manifests both in structural ovarian changes and in hormonal or metabolic irregularities [13] have demonstrated that models leveraging multimodal fusion achieve higher diagnostic accuracy and reduced false positives compared to imaging-only models. For instance, fusing ultrasound image features with clinical parameters allows deep learning architectures to capture both spatial abnormalities in ovarian follicles and biochemical patterns, producing more robust and clinically meaningful predictions. This technique is widely applied in medical imaging research where heterogeneous datasets are available and complementary information can improve classification, risk stratification, or prognosis [17].

CNN and ANN Fusion Models are hybrid architectures that combine convolutional neural networks (CNNs) for image-based feature extraction with artificial neural networks (ANNs) for classification, regression, or decision-making tasks [5]. In this framework, CNNs first learn spatial and structural patterns from medical images, such as follicle shapes or cystic formations, and the extracted features are then passed to ANNs, which provide flexible, non-linear mapping to the output label or score [10]. This hybrid approach is used because CNNs excel at learning complex hierarchical image features, while ANNs are effective at integrating heterogeneous features and performing higher-level reasoning. In PCOS research, CNN + ANN models have been applied to combine ultrasound-derived image features with other extracted parameters, improving classification accuracy and sensitivity [15]. These models outperform standalone CNNs or ANNs by capturing both low-level structural details and high-level decision patterns, making them suitable for clinical decision support systems in reproductive health diagnostics[18].

2.4 Lifestyle & Risk Management Module

This module focuses on identifying lifestyle-related risk factors and providing personalized recommendations to improve the overall health and well-being of users.

2.4.1 Personalized Recommendations

OvaSense constructs individualized care pathways by combining baseline demographics (age, height, weight, BMI), reproductive history (menstrual cycle patterns, parity), symptom logs (hirsutism, acne, hair thinning), and available biochemical parameters (LH/FSH, testosterone, fasting insulin, glucose, HbA1c) [1]. A user profile vector is produced and enriched with contextual features — activity level, sleep quality, stress scores, and medication history — to produce holistic recommendations tied to risk phenotypes. Hybrid recommender approaches (content-based for physiology + collaborative/filtering for behaviour patterns) ensure suggestions are both evidence-based and pragmatically adoptable by users [2]. The system's recommendation engine is grounded on prior work showing feasibility of AI-driven management advice and nutritional recommender systems for PCOS and related metabolic disorders. [3]

Practical outputs of this module include: prioritized lifestyle goals, individualized calorie and macronutrient targets, an exercise prescription matched to fitness level, stress-reduction micro-interventions, and an adaptive follow-up schedule. Recommendations are phrased in patient-centric language and include rationale (e.g., "lowering refined carbohydrate intake to reduce glycemic spikes that worsen insulin resistance") [2]. The module continuously refines suggestions using observed adherence and physiological responses (closed-loop personalisation). Evidence for the benefit of such AI-assisted lifestyle frameworks in PCOS and their acceptability among users is reported in systematic reviews and app-based studies.[14]

Diet Plans (Calorie & Glycemic Control) Dietary management in OvaSense targets two simultaneous goals: (a) caloric balance to achieve safe weight reduction where indicated, and (b) glycemic control to mitigate insulin resistance — a cardinal pathophysiologic driver in PCOS [8]. Daily energy needs are computed from BMR formulas (e.g., Mifflin–St Jeor) adjusted for activity level; when weight loss is desired, the app suggests a clinically safe deficit (commonly 300–700 kcal/day) and tracks progress longitudinally. Nutrient composition emphasizes moderate protein, healthy fats, and low–glycemic-index (GI) carbohydrate sources; clinical trials in PCOS show benefits from low-GI and hypocaloric high-protein diets for metabolic and reproductive outcomes. [16]

Features include a food database with GI scores, automatic calorie & macronutrient estimation, recipe suggestions, and meal clustering (e.g., pulses/legume-based meals shown beneficial in PCOS trials). Where image-based logging is used, deep-learning food classifiers can estimate portion size and macro content to reduce user burden[12]. The app also offers timed eating suggestions and postprandial activity nudges (e.g., a short walk after carbohydrate-rich meals) to blunt glucose excursions — a technique supported by metabolic studies. [9]

Fitness Tracking (Wearable Data Integration) Exercise prescriptions combine aerobic (endurance) and resistance training because both modalities improve insulin sensitivity and cardiovascular risk markers in PCOS. The app issues an initial fitness assessment and prescribes progressive weekly targets (e.g., 150 min of moderate aerobic activity plus two resistance sessions per week, with HIIT options where appropriate). Randomized and observational studies show aerobic training, resistance training, and combined regimes improve metabolic, hormonal and quality-of-life outcomes in PCOS. [8]

Wearable integration enables low-friction capture of steps, active minutes, heart-rate zones, sleep, and (where available) continuous glucose or BBT data. OvaSense consumes this stream to auto-update activity adherence, estimate energy expenditure (to refine calorie budgets), and detect reduced activity patterns that may trigger motivational interventions [4]. Device-agnostic connectors (Fitbit, Apple Health, Google Fit, Garmin, etc.) and secure OAuth based data flows ensure interoperability and privacy. Aggregated wearable metrics feed into the predictive models (Section 4.2) so the system can quantify how exercise modifies an individual's risk trajectory. [11]

Stress & Sleep Monitoring Psychological stress and disturbed sleep exacerbate endocrine dysregulation in PCOS (elevating cortisol, worsening insulin resistance and impacting ovulatory function). OvaSense uses daily stress self-ratings, brief validated questionnaires (e.g., PHQ-4/GAD-2-style items as screening), and wearable sleep metrics (duration, fragmentation, sleep stages if available) to estimate stress and sleep burden [13]. Correlational analytics identify temporal associations between stress/sleep disruptions and symptom flares (e.g., cycle irregularity, appetite dysregulation, mood). Clinical literature underlines the prevalence of mood disorders and sleep abnormality in PCOS and the value of behavioral interventions.[16]

Interventions include guided breathing, short CBT-informed modules, sleep-hygiene plans, and targeted nudges (e.g., wind-down reminders). The app continuously evaluates the effect of stress-reduction or sleep-improvement interventions on symptom trajectories and metabolic markers, closing the personalization loop [5]. Where salivary cortisol or continuous cortisol proxies are available (research cohorts or advanced wearables), time-series cortisol features can augment stress modeling.[6]

2.4.2 Predictive Analytics

The Risk Dashboard synthesizes multi-modal inputs (clinical questionnaire responses, biometric time series from wearables, dietary adherence, and lab results when available) into an interpretable risk score (e.g., Low / Moderate / High) for PCOS severity and for downstream metabolic risks (prediabetes, dyslipidaemia) [2]. The predictive backbone uses supervised classifiers validated in PCOS literature — Random Forest, XGBoost / gradient boosting families, and SVM — chosen for robustness on tabular clinical data and explainability (feature importance). Ensemble and stacking strategies frequently outperform single classifiers in published PCOS prediction studies [12]. Model training leverages feature selection, imbalanced-data handling (SMOTE), and nested cross-validation to avoid optimistic bias.[17]

The dashboard displays drivers of the current risk score (top contributing features) alongside counterfactual guidance ("reduce weekly sugary beverage intake by X and projected risk improves by Y%"), enabling actionable steps rather than opaque probabilities [6]. Calibration plots and confidence bounds are presented to convey predictive uncertainty — a best practice emphasized in health AI literature.[17]

Trend Visualization of Symptoms OvaSense uses time-series visualization to link user behaviour with health signals: weight trends, cycle length & regularity, symptom frequency (acne, hirsutism, mood change), sleep metrics, and activity. Interactive charts allow users to overlay inputs (e.g., stress scores vs. cycle regularity) and to apply smoothing windows (weekly/monthly) to detect meaningful patterns. Literature shows visualization supports self-insight and adherence; cycle prediction and fertile window visualization have been successfully implemented with wearables and statistical models. Trend visualization helps clinicians and users identify triggers for symptom exacerbation and evaluate the impact of interventions.[11] Time-aligned event markers (medication start, diet change, major life stressor) allow causal inspection. For researchers/clinicians, exportable anonymized trend reports can support teleconsultation and shared decision-making. [14]

2.4.3 Preventive Healthcare

Timely Alerts and Reminders Behavioral adherence is supported with context-aware reminders: meal logging prompts, activity nudges when sedentary time exceeds thresholds, medication/supplement reminders, and targeted prompts after high-risk behavior (e.g., late-night high-GI meal) [14]. Smart scheduling reduces alert fatigue: reminders are batched, prioritized, and modulated by user responsiveness [11]. Clinical studies and app evaluation research emphasize that personalized, evidence-based nudges improve engagement and metabolic outcomes in lifestyle interventions. Integration of wearable data enables real-time triggers (e.g., alert after prolonged inactivity) that align with glycemic-control strategies. [5]

For higher-risk patterns (progressive weight gain, rising fasting glucose, or sustained irregular cycles), the system escalates alerts recommending clinical review, diagnostic testing, or telemedicine consultation, providing printable summaries for clinicians. This escalation protocol follows guidance from PCOS management literature advocating early intervention to prevent long-term complications. [16]

Educational Support for Women's Health OvaSense embeds an evidence-based resource library: concise articles, explainer videos, recipe cards, exercise demos, FAQ, and links to guidelines. Content is curated from peer-reviewed literature and guideline sources and is presented at appropriate health-literacy levels. Recommender techniques surface the most relevant educational items based on the user's profile (e.g., fertility-focused content for users concerned about conception, metabolic content for those with insulin resistance). Prior work assessing app acceptability in PCOS demonstrates strong user interest in trustworthy, tailored educational resources. [14] The platform includes a "teach & test" microlearning pathway to reinforce behavior-change concepts and to measure knowledge gain. Community features (anonymous forums or moderated Q&A) can increase sustained engagement but must be implemented with moderation to avoid misinformation.[3]

The evaluation of machine learning and deep learning models for Polycystic Ovary Syndrome (PCOS) detection is a crucial aspect of verifying model reliability, clinical applicability, and generalization capability. Each of the twenty reviewed research papers utilized different evaluation metrics according to their dataset type, learning strategy, and model architecture [1]–[20]. These metrics were used to assess the efficiency of algorithms in classifying PCOS and non-PCOS cases, detecting cystic regions in ultrasound images, and predicting patient conditions using clinical and hormonal data. The most commonly reported measures include Accuracy, Precision, Recall (Sensitivity), F1-Score, Specificity, Dice Coefficient, Intersection over Union (IoU), and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

III. EVALUATION METRICS

Table 1. Evaluation Metrics Used

S.NO	Paper Title	Task / Model Used	Evaluation Metrics Reported
1	Detection of Polycystic Ovary Syndrome Using CNN	CNN on ovarian ultrasound images	Accuracy = 85%
2	Deep Learning for Ovarian Ultrasound Analysis	CNN-based classification (ultrasound)	F1-score = 100%; Accuracy = 76.36% (5-fold CV)
3	Gabor Feature Extraction and CNN for PCOS Detection	Gabor + CNN hybrid	Accuracy = 80.84%; Processing time ≈ 60.64 s
4	PCONet: Deep CNN Model for Polycystic Ovary Detection	CNN / Transfer learning (InceptionV3 fine-tuning)	Accuracy = 98.12%; InceptionV3 = 96.56%
5	DCCN + Inception Network for Ovary Image	Dual CNN (DCCN +	Accuracy = 84.81%

	Classification	Inception)	
6	Ultrasound & Clinical Feature Fusion using MobileNet	Fusion of image + clinical data	Accuracy = 82.46%
7	Transfer Learning–Based Hybrid Deep Model for PCOS	CNN-ANN fusion	Accuracy = 93%
8	ANN Model for PCOS Detection from Clinical Features	ANN vs. Bayesian classifier	ANN performed better; metrics not clearly reported
9	SNSSDA Feature Extraction + ANN for PCOS Prediction	Signal & statistical feature-based ANN	Qualitative evaluation; metrics not specified
10	Feature Selection with Naïve Bayes and ANN Classifiers	Hybrid ML model	Precision = 98.63%; Specificity = 100%; F1-measure = 68.76%; Accuracy ≈ 100%
11	ML Classification of PCOS Using Ensemble Boosting Models	XGBRF, CatBoost, RF	Accuracy = 96%; Precision, Recall, F1 reported
12	Feature Selection with Multiple Classifiers for PCOS Detection	RF, NB, DT, SVM	Accuracy = 93.12% (best)
13	Chi-Square Feature Selection with ML Algorithms	RF, SVM, LR, NB, KNN	Accuracy = 90.9% (RF best)
14	Follicle Detection and Classification Using SVM	Follicle segmentation + SVM	Accuracy = 82.55% (SVM RBF best)
15	SMOTE + ML Models for PCOS Risk Prediction	LR, RF, DT, SVM, KNN	LR performed best; metrics not shown
16	Comparative ML Models for PCOS Diagnosis	Decision tree, NB, RF, etc.	Accuracy = 93% (best for NB, RF)
17	Watershed-Based Ovary Segmentation and Bayesian Classification	Image segmentation + Bayesian classifier	Metrics not visible in PDF extract
18	I-HOPE Framework for PCOS Prediction Using ML	PCA + ensemble models	Accuracy, Precision, Recall, F1 compared (values in paper)
19	Ensemble RFLR Model for PCOS Prediction	Gradient Boosting, RF, LR ensemble	Accuracy = 91.01%; Recall = 90%; 40-fold CV
20	Follicle Counting and Classification Using SVM	SVM image-based classifier	Metrics not visible in PDF snippet

IV. Limitations

A comprehensive analysis reveals that, while machine learning and deep learning have achieved promising results in the detection and diagnosis of Polycystic Ovary Syndrome (PCOS), several significant limitations and research gaps remain. These challenges span across dataset quality, methodology, clinical applicability, and practical deployment. Addressing these limitations is crucial for improving diagnostic reliability, model interpretability, and real-world usability.

Dataset Limitations: Most studies were conducted using small-scale and private datasets collected from individual hospitals or laboratories [13]. Such limited datasets lead to overfitting and reduce the generalization capability of models on unseen patient populations. Moreover, data imbalance—where the number of PCOS and non-PCOS samples is unequal—was observed in many works [2] causing biased learning outcomes. Another major limitation is the lack of publicly available standardized datasets, which restricts reproducibility and comparative benchmarking. Only a few studies attempted multimodal fusion of ultrasound images with clinical or hormonal data [6] while others focused on a single data type, limiting diagnostic robustness.

Methodological Gaps: Many works relied on single-model architectures such as CNNs, SVMs, or Random Forests [1], [3] without leveraging ensemble or hybrid deep learning models that could capture complex clinical–image interactions. Additionally, most models lack explainability, as none of the reviewed studies incorporated model interpretation tools like Grad-CAM or SHAP to justify predictions [20]. Evaluation protocols also varied considerably—different data splits, cross-validation folds, and inconsistent metrics made results difficult to compare [18]. Moreover, computational aspects such as training efficiency, inference time, or hardware optimization were rarely discussed [19], limiting their deployment potential.

Clinical and Practical Gaps: Clinically, none of the proposed models have undergone real-world testing or physician-in-the-loop validation, which is essential for medical approval and clinical acceptance [15]. Most studies also ignored biochemical and hormonal parameters—such as LH/FSH ratio, testosterone levels, and insulin resistance—that are clinically significant indicators of PCOS [8]. Furthermore, almost all works focused solely on binary classification (PCOS vs. Non-PCOS) rather than assessing the severity or progression of the condition [5]. The absence of standardized benchmarks combining both clinical and imaging data continues to be a major research gap [2].

Research and Implementation Gaps: Few studies explored hybrid or multimodal architectures combining CNNs with ANNs or other deep models [7] leaving room for further innovation. Similarly, advanced feature selection and dimensionality reduction techniques such as PCA or Chi-square tests were applied inconsistently [18]. Emerging architectures like Vision Transformers, EfficientNet, or attention-based fusion models remain unexplored [1]. Another important limitation is the absence of uncertainty quantification, which helps measure the confidence of medical predictions [11]. Lastly, reproducibility remains low due to limited availability of open-source code, datasets, or pretrained weights, restricting further research and comparative validation [20].

Table 2: Limitations and Research Gaps Identified

Category	Identified Limitation / Gap	Impact on Research
Dataset Quality	Small and imbalanced datasets; private data sources	Causes overfitting and poor generalization
Data Accessibility	Lack of publicly available and standardized datasets	Reduces reproducibility and benchmarking
Modality Limitation	Use of only imaging or clinical data	Misses complementary diagnostic cues
Model Explainability	Absence of interpretability or feature visualization	Limits clinical trust and model transparency
Evaluation Inconsistency	Varying metrics, folds, and splits	Prevents fair performance comparison
Clinical Validation	No real-world or expert evaluation	Lacks medical reliability and acceptance
Limited Features	Exclusion of hormonal/genetic data	Partial representation of PCOS factors
Binary Diagnosis Focus	No severity-level or progression detection	Restricts medical insight and treatment support

V. Conclusion

This survey analyzed twenty recent studies on Polycystic Ovary Syndrome (PCOS) detection using machine learning, deep learning, and hybrid computational techniques. The review highlights that artificial intelligence significantly enhances automated PCOS diagnosis through the analysis of clinical, hormonal, and ultrasound data. Traditional algorithms like SVM, Random Forest, and Logistic Regression demonstrated effective classification of structured data, while deep learning models, particularly CNNs, achieved superior accuracy in image-based detection. Hybrid and ensemble approaches further improved diagnostic precision and robustness. However, current models are constrained by limited datasets, data imbalance, lack of multimodal integration, and minimal explainability. To address these limitations, the proposed OvaSense framework integrates ensemble and hybrid learning with clustering and explainable AI techniques to enhance reliability and interpretability. This approach aims to create a scalable, transparent, and clinically applicable diagnostic system that enables early PCOS detection and supports improved women's healthcare outcomes.

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