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Comprehensive Review of Polycystic Ovary Syndrome Detection Techniques

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ABSTRACT

Polycystic ovary syndrome is a serious hormonal disorder that affects women and significantly impacts their quality of life. In modern times, women are increasingly susceptible to this syndrome, which is a major cause of numerous health problems, most notably infertility. Early detection of PCOS significantly reduces complications, making an early and accurate diagnosis system crucial.

Among all diagnostic techniques, machine learning (ML) has demonstrated superior performance due to its ability to extract features and patterns from data. Therefore, this field has received widespread attention from researchers, and numerous studies have been conducted to detect PCOS using machine learning techniques. These methods have included convolutional neural networks (CNN), support vector machines (SVM), k-nearest neighbors (KNN), random forests, logistic regression, decision trees, and the Naive Bayes algorithm, among others.

This paper aims to shed light on all current techniques used in PCOS detection using machine learning algorithms, providing a comprehensive descriptive and contextual review. It also provides a detailed analysis of how various ML techniques have been used in this field over the past decades, with an in-depth discussion of these approaches. A comprehensive review of the various datasets used in PCOS diagnosis is also provided, comparing the performance of algorithms from both quantitative and qualitative perspectives. Finally, the paper discusses the most prominent challenges facing this field, in addition to exploring future research prospects.

ARTICLE INFO

Keywords:
Random forest (RF), Polycystic ovary syndrome (PCOS), Machine learning, CNN, SVM, PCOS detection, Ultrasound image, KNN.

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1. INTRODUCTION:

Polycystic ovary syndrome affects women of all ages, but is more severe in women of childbearing age, as it is considered a complex and multifaceted hormonal disorder that causes irregular menstrual cycles, high androgen levels, and infertility. Estimates indicate that 15-20% of women of childbearing age are most affected by this condition [1]. Various studies have also indicate that obesity, insulin resistance, high blood pressure, depression, and inflammation are lifestyle factors that promote this syndrome [2]. Symptoms of polycystic ovary syndrome include skin pigmentation and darkening, and are also linked to serious complications, including cardiovascular disease, type 2 diabetes, miscarriage in the first months of pregnancy, and sleep apnea [3]. Much research has been conducted on polycystic ovary syndrome in its various aspects, including clinical manifestations, treatment methods, and risk factors [4]. Current research focuses more on developing advanced diagnostic methods, especially those based on machine learning, rather than traditional diagnosis based on clinical assessment, hormonal tests, and pelvic ultrasound [5].

Ultrasound is commonly used to detect ovarian cysts and assess their shape, but its accuracy varies depending on the experience of the diagnosis and the quality of the equipment used [6]. Hormonal tests are used to detect disorders associated with polycystic ovary syndrome, such as hyperandrogenism. However, results may vary due to individual hormonal fluctuations [7]. The Rotterdam criteria are clinical criteria used as guidelines for diagnosing polycystic ovary syndrome, but they may lead to inappropriate diagnoses owing to the heterogeneous nature of the syndrome [8].

Machine learning-based techniques have shown promising results in accurately diagnosing polycystic ovary syndrome (PCOS) [9] Patterns and associations have been discovered that may be difficult for experts to identify, and machine learning techniques can help detect early signs of PCOS and effectively differentiate between affected and unaffected cases [10]. A widely used example of machine learning-based techniques for diagnosing PCOS is a computer-aided diagnostic systems that analyzes ultrasound images and hormonal profiles to support specialists in making accurate and reliable diagnostic decisions [11].

Computer-aided diagnostic systems use advanced algorithms to analyze ultrasound images and hormonal data to detect factors that may indicate polycystic ovary syndrome [12]. According to studies, in cases where cysts are difficult to identify visually or hormonal disturbances do not appear immediately, these systems are used, as they contribute to improving the accuracy and reliability of diagnosis [13]. Previous studies did not provide a systematic comparison of model performance; instead, they merely presented the results without offering an in-depth comparative analysis. Existing review papers also have notable limitations. First, they focused on a narrow range of studies and lacked a structured discussion on the shortcomings or differences in performance across these studies. Second, they failed to deliver quantitative or qualitative analyses of the applied techniques. Third, there was insufficient discussion regarding the datasets used, and no clear visualization of future research directions was provided.

This study conducted a comprehensive review of 34 scientific studies published between 2004 and 2024. The use of machine learning techniques in the detection of polycystic ovary syndrome (PCOS) has increased steadily over time. It can be noted that a maximum of eight research papers were selected from 2021 to 2023, a maximum of 8 papers are chosen followed by 2020.

Relevant research papers were identified using trusted tools, such as Google Scholar, IEEE Xplore, and ScienceDirect. A total of 60 articles were initially collected. After removing duplicates, 56 articles were retained for the preliminary screening. Following abstract screening, 17 articles were excluded owing to their lack of direct relevance to machine learning applications in PCOS detection. A total of 39 articles underwent a comprehensive evaluation, including five previous review papers. After completing all the screening phases, 34 studies were ultimately selected for inclusion in this review.

Figure 1: provides a clear visual representation of the study selection process, illustrating each stage from identification to screening to inclusion, offering a systematic overview that researchers can follow to identify relevant studies for their own work.

Following the identification of relevant articles, the next phase involved recognizing research gaps and categorizing studies based on the algorithms used, such as CNN and ANN. Studies that employed similar techniques were grouped into unified sections and linked accordingly. Subsequent steps included evaluating the algorithms using charts and tables and performing both quantitative and qualitative analyses. Finally, current research challenges are identified, and potential solutions are proposed.

detailed conceptual analysis of PCOS detection techniques using traditional methods.

- ◇ An exploration of current algorithms in the context of machine learning applications.
- ◇ A presentation of the various types of datasets used in this field.
- ◇ Assessment of the performance of each dataset when applied to various machine learning algorithms.
- ◇ A comprehensive comparison of the performance of currently available PCOS detection techniques is highlighted.
- ◇ Focus on the challenges associated with detecting PCOS using machine learning and provide research ideas for future work.

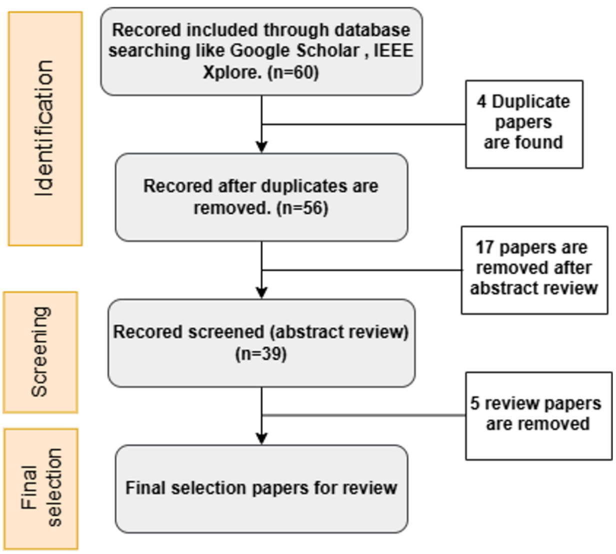

Figure 1. Mechanism of action of the traditional method for detecting polycystic ovary syndrome (PCOS)

The rest of the research is organized as follows. Section 2 discusses current approaches to detecting PCOS. Section 3 is organized by listing and describing the effective datasets. Section 4 addresses the challenges and potential solutions for implementing these algorithms and presents future directions for researchers. Section 5 concludes this study

2. EXISTING PCOS DETECTION TECHNIQUES

This section describes the different PCOS detection methods, along with their parameters and structures. There are two main categories of parent detection methods for PCOS. The conventional detection procedure is one, and ML-based detection methods are the other. Normal and PCOS hormonal ranges are crucial in conventional detection methods. For ease of comprehension, a thorough explanation of this hormonal range is provided in this section within a table. For a clear understanding, the structures of the machine learning algorithms are provided. A figure that explains each PCOS detection method in detail is included. Additionally, a thorough diagram of the conventional PCOS detection procedure and how physicians apply it is provided.

A. Traditional Methods

1. Hormone testing and symptom collection

In order to identify polycystic ovarian syndrome (PCOS), Certain hormone levels are thought to be essential markers:

i **Luteinizing Hormone (LH) And Follicle-Stimulating Hormone (FSH):** The physiology of female reproduction depends heavily on these hormones. Normally, 24 h before ovulation, LH levels increase to approximate 25–40 mIU/mL. While FSH levels are typically low (approximate 6 mIU/mL), LH levels are typically high (approximate 18 mIU/mL) in many women with PCOS. Previously, this hormonal imbalance was thought to be the main indicator of PCOS.

ii **Testosterone:**
The human body contains two types of testosterone: free and total testosterone. Free testosterone is the unbound and most physiologically active form, and its level normally ranges between 0.7 and 3.6 pg/ml, while total testosterone levels range between 6.0 and 86 ng/dL. Both free and total testosterone levels are often elevated in women with polycystic ovary syndrome (PCOS).

iii **Dehydroepiandrosterone sulfate:** Women with polycystic ovary syndrome (PCOS) tend to have elevated dehydroepiandrosterone sulfate levels, often exceeding 200 mcg/dL.

iv **Prolactin:** Polycystic ovary syndrome (PCOS) is often associated with elevated prolactin levels, which typically range between 25 and 40 ng/ml.

v **Estrogen:** In women with PCOS, estrogen levels typically remain within the normal range of 25–75 pg/mL, even in the presence of other hormonal abnormalities.

vi **Thyroid Stimulating Hormone:** TSH levels in PCOS patients usually range between 0.4 and 3.8 µIU/mL, which is the normal reference range [14]. When detecting polycystic ovary syndrome (PCOS),a combination of symptoms and hormone levels should be considered. These symptoms include obesity, irregular menstrual cycles, excessive hair loss, and elevated male hormones levels. Doctors test hormone levels and manually review the symptoms to diagnose PCOS. Hormonal testing is the costliest and most time-consuming method for the identification of PCOS. The traditional method of detecting PCOS symptoms relies on a set of questionnaires. These questionnaires can be used to identify clinically apparent PCOS cases in the relatives of the affected women. Studies indicate that approximately 50% of sisters with PCOS have not been reported, although most affected mothers can be identified through interviews using written questionnaires [15].

2. Manual Ultrasound Doctors diagnose polycystic ovary syndrome manually by counting the number of follicles (cysts)visible on ultrasound images. The presence of more than 12 follicles, each measuring 29 mm in diameter, in one ovary is considered an indicator of PCOS [16]. This procedure requires doctors to manually count cysts, which is time-consuming and prone to errors, such as missing some cysts or mistaking other masses for cysts. In addition to transabdominal ultrasound, another type of ultrasound is transvaginal ultrasound. In this type, the doctor inserts a lubricated probe into the woman's vagina and displays the internal organs on a screen to show the uterus and cervix. The doctor then counts the follicles in the ovaries and measures the size of the ovaries to determine the likelihood of PCOS. However, this procedure is not foolproof, as the doctor may miscount the follicles or misestimate the size of the ovaries. More importantly, the procedure is not painless, and many women do not opt for it due to social and cultural barriers.

B. Machine Learning

Machine learning is an advanced processing technology that aims to replicate human intelligence by learning from its environment and can be divided into two main categories: classification and categorization. [16].

1) Classification

Classification is a data mining technique that focuses on supervised learning and is used to determine which category or group a new observation belongs to, based on its characteristics; the model learns patterns from previously classified data and can make predictions about the distribution of unknown data.

i **Support Vector Machine (SVM):**
SVM is one of the most popular classification and regression algorithms and relies on machine learning principles to achieve predictive accuracy while minimizing the possibility of overfitting. The algorithm works by constructing a hyperplane that divides the data into multiple points and is capable of solving both linear and nonlinear problems, making it suitable for practical applications.
One of the advantages of SVM is that it is easy to train and does not suffer from local optimality problems, such as neural networks. However, one of its biggest drawbacks is that one must choose the correct kernel function to be successful.
Algorithms are used to classify PCOS patients and are sometimes combined with other algorithms in mixed models to improve their performance.
Nandipati et al. study [17] show that the application of SVM with SMOTE achieves better results in terms of accuracy, recall and F1 scores. Nsugbe [18] also used advanced versions of the SVM, demonstrating the versatility and power of this algorithm in handling classification problems.

ii **Naïve Bayes (NB):** Nave is a supervised learning algorithm that is based on Bayesian principles. This technique optimizes the learning process by assuming that the data attributes within each classification class are independen. This means that any two attributes are considered independent of each other during classification. Although this assumption is theoretically simple and convenient, the Naive Bayes algorithm generally outperforms dense algorithms. Despite some limitations, nine studies applied this algorithm to PCOS. NB has also been combined with neural networks NNs and other classification algorithms to improve performance. Prabhati and Chitu [19] achieved 93% accuracy using this algorithm, making it the second highest accuracy rate after the Random Forest algorithm.

iii **K-Nearest Neighbors (KNN) Algorithm:** The KNN algorithm is the simplest and the most efficient classification method. It is involved in the reserved learning process and ensures similarity between sources for class identification. The algorithm classifies a point according to the number of neighbors by calculating the distance between a new point in the dataset and all other points. KNN is a non-parametric algorithm, meaning that it does not consider the distribution of a particular data set, making it useful for many applications. For a data record "t", its k nearest neighbors are identified, and the result of a majority vote among these neighbors is used to classify it. It is important to choose an appropriate value for the variable "k," as this value has a significant impact on the performance of the algorithm. Denny et al. [20] also used an internal set algorithm and obtained relatively good results.

iv **Decision Tree (DT):** A decision tree is a simple but effective classification algorithm for performing classification tasks. One of its main advantages is that it provides clear and human- understandable classification criteria, making it easier to interpret the model's results trees within their models. One of the major drawbacks of the DT algorithm is the need to rank all quantitative (numerical) features when deciding whether to split a node. This is a cumbersome process that consumes time and memory, particularly when dealing with large datasets.
Despite some shortcomings, decision trees are still widely used in research owing totheir powerful capabilities. They were used in seven studies related to the detection of polycystic ovary syndrome. Aggarwal and Pandey [21] combined it with other classification algorithms, and most recent studies have sought to enhance the performance of decision tree-understandable classification criteria, making it easier to interpret the model's results.
Despite some shortcomings, decision trees are still widely used in research owing to their powerful capabilities. They were used in seven studies to diagnose polycystic ovary syndrome. Aggarwal and Pandey [22] combined this with other classification schemes, and recent studies have tried to improve the performance of classification trees.

v **Random Forest (RF):** This technique was developed by Leo Breiman in 2001 and has since gained popularity as an effective tool for classification and rotation. It relies on aggregating predictions from multiple random decision trees, which makes it highly efficient, particular in cases where the number of variables is larger than the number of samples. Random forests are also characterized by their ability to handle divergent value measurements, making them suitable for large-scale problems [23]. This model has been used as a classification tool in 12 studies related to the diagnosis of polycystic ovary syndrome (PCOS). Bharati et al [24] achieved high detection accuracy using a random forest model, combined with logistic regression (LR) in a hybrid model, which showed excellent performance in their study.

vi **Logistic Regression (LR):** Logistic regression is a statistical technique used to estimate the probability of yes/no or yes/no binary outcomes, and is commonly used to estimate binary outcomes [25].
Logistic regression is widely used in PCOS diagnosis and is often combined with random forest RF models to form hybrid models. These models showed better performance than the other segmentation models in diagnosing PCOS.

2) CLUSTERING

Clustering is a machine learning technique that aims to sort data into groups based on similarities and is used in anomaly detection because of its ability to identify unique data; clustering is also used in unsupervised data mining [26].

i. **K-means Algorithm:** The K-means algorithm is one of the most popular clustering methods; It divides the unlabeled dataset into several groups based on the similarity of features, and the number of groups is determined by the "K" value [27]. K-means was the only clustering method used to investigate polycystic ovarian syndrome (PCOS), and it was used in only two cases. Agrawal and Pandey [28] used a basic version of the K-means algorithm, and Thara [29] used an advanced version called "adaptive K-means" for detection.

3) Artificial Neural Network (ANN)

Artificial neural networks (ANNs) mimic neural networks in the human brain in terms of information processing, creating a simple structure in which multiple networks are connected according to different patterns. A neural network is a computing system consisting of a group of nodes (or neurons) that are connected to each other. Each node represents a processing function that is generated by a specific output from the input signals.

The nodes are connected to each other through links represented by weights, that represent the "memory" of the neural network. The interaction structure of the nodes, sum of the weights, and reward function significantly affect the network [30].

i. **Convolutional Neural Network (CNN):**

A convolutional neural network is a type of deep neural network based on linear mathematical operations between matrices. CNNs consist of several layers, including convolutional, nonlinear, convolutional, and fully connected layers. It is important to note that convolutional and nonlinear layers do not have learnable parameters.

CNNs are popular in the field of machine learning due to their versatility and efficiency. They have proven to be very sensitive in detecting cysts on ultrasound images. Models trained using CNNs can accurately predict whether an ovary is normal or is affected by PCOS. This paper reviews six studies that used convolutional neural network (CNN) architectures for polycystic ovary syndrome (PCOS) detection, each based on different datasets and hidden structures. Most of the models have demonstrated accurate and useful results. For example, Kahiono et al. [31] achieved a perfect performance rate of 100% using a convolutional neural network (CNN) for polycystic ovary syndrome (PCOS) detection. Multi-layer perceptual processor (MLP):

An MLP is a type of neural network characterized by nonlinear relationships between inputs and outputs. This model consists of an input layer, an output layer, and one or more hidden layers with a large number of interconnected neurons.

Unlike the neurons in the traditional perceptron model that rely on specific activation functions that determine the threshold, the neurons in the MLP network use any suitable activation function, such as ReLU or Sigmoid. MLP is one of the least used neural network techniques for the detection of PCOS.

Meher and Polat [32] and Bhatt and Gupta [33] used MLP networks to detect polycystic ovary syndrome (PCOS).

Figure 2 shows the general structure of the traditional PCOS detection methods. This diagram allows researchers to easily understand the steps of traditional research and compare them with those of other AI methods. The process begins with the collection of symptoms from the patient. Based on the recorded symptoms, hormonal tests or ultrasound examination are performed and a diagnosis is made.This diagram provides a comprehensive overview of various research methods, which will help researchers develop future research in a more accurate and systematic manner. To provide a clear overview of previous research in the field of PCOS detection, Table 1 summarizes the main objectives, algorithms employed, notable limitations, and key observations reported in the literature. This summary offers an integrated perspective on the applied machine learning techniques and highlights existing challenges, paving the way for identifying research gaps and potential future improvements.

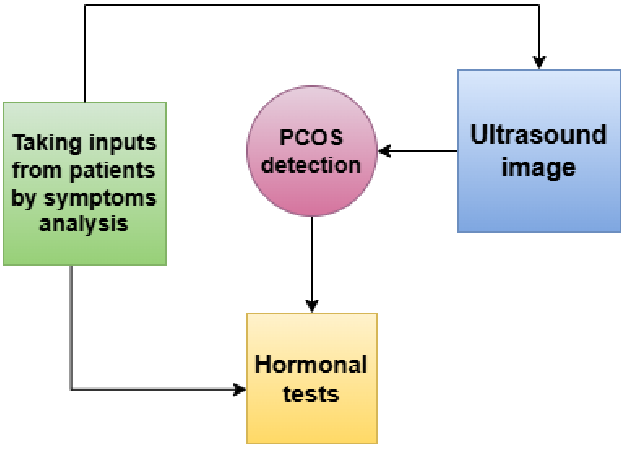

Figure 2. Mechanism of action of the traditional method for detecting PCOS.

3. DATASET

This section provides a detailed overview of the datasets used for PCOS detection techniques reviewed in Section 2. As training and testing datasets are essential for

Table 1. This table summarizes the objectives, algorithms used, weaknesses, and important observations in previous research related to the detection of polycystic ovary syndrome (PCOS).

Reference	objectives	Algorithms used	Weaknesses	important observations
[10]	Follicle detection of PCOS using YOLO	YOLO (You Only Look Once)	Limited dataset; potential for false positives	Focuses on image-based follicle detection with promising accuracy
[11]	Classification of ovarian ultrasound images for PCOS diagnosis	CNN, LSTM, hybrid CNN-LSTM	Requires large labeled dataset; black-box nature	Improved detection accuracy, potential for clinical use
[12]	Predict response to ovulation induction in PCOS	LSTM, XGBoost	Treatment-specific;requires detailed clinical data	Supports personalized therapy planning
[13]	Predict PCOS using clinical and laboratory variables	BorutaShap, Random Forest	Limited features, dataset size, and population diversity	Achieved 86% accuracy with feature importance ranking
[14]	Early detection of PCOS among fertile women	Multi-stackingML, Explainable AI	Potential overfitting, dataset-specific results	Achieved highest accuracy of 98%
[15]	Early detection in women with menstrual irregularities	LSTM	Sensitive to data quality; longitudinal data needed	Aids early intervention, high accuracy
[16]	diagnosis with feature selection	Feature Selection, LR, RF, Gradient Boosting	Limited dataset, feature correlation issues	Achieved 91.01% accuracy
[17]	Self-diagnosis of PCOS via machine learning	CatBoost	Limited interpretability, dataset constraints	Highest non-invasive accuracy of 90.1%
[18]	Diagnosis combining ultrasound and clinical data	Ensemble models (Logistic Regression, SVM, RF)	Complex data processing; ensemble computational load	Robust multimodal diagnosis approach
[19]	PCOS detection with MRI and ultrasound images	CNN (PCONet)	Large dataset requirement; computational resources	Achieved high accuracy (98.12%)
[20]	Automated PCOS diagnosis using hybrid feature selection	SVM	Limited features, generalizability concerns	Achieved 91.6% accuracy
[21]	PCOS identification with multiple classifiers	Logistic Regression, RF, SVM, Naïve Bayes	Model overfitting risks, small dataset	Random Forest achieved 96% accuracy
[22]	Basic PCO classification via CNN	Simple CNN	Lower accuracy; limited in complex scenarios	Quick, easy implementation but less precise
[23]	Explainable AI for PCOS diagnosis	Explainable AI frameworks	Additional resources needed; interpretability considerations	Enhances trust and understanding of models
[24]	Classify polycystic ovary based on ultrasound images	Competitive Neural Network	Limited accuracy ($\sim$80.84%), lack of extensive clinical validation	Early approach; needs improvement for practical use
[25]	Diagnose PCOS through machine learning and feature selection	Various ML techniques	Accuracy around 82-90%; models may lack interpretability; limited clinical validation	Promising but needs real-world testing
[26]	Privacy-preserving diagnosis using federated learning	Federated Learning	Collaboration complexity; communication overhead	Maintains data privacy across institutions
[27]	Deep learning-based PCOS detection from ultrasound	CNN models	Limiteddata; hardwaredependence	Demonstrates high accuracy in limited data settings

abdominal wall analysis, this section focuses on the type, components, and dimensions of the data.

PCOS is a globally important gynecological disease; however, limited data are available. This section contains the tables used to analyze the data. Table 2 describes the datasets used, allowing researchers to compare the performance of different models depending on the type and effectiveness of the classification algorithm and a set of performance metrics, including the accuracy, precision, recall, specificity, and F1 score, as reported in various

Table 2. Dataset details, description, and performance analysis of the clusters used in the current work.

Structure	Reference	Dataset Description	Implementation Method	Top Performance and Comments
Traditional Neural Network	[10]	Ultrasoundimageswith extractable features	MATLAB, standalone	∼80.84%accuracy;limited clinical validation; foundational approach
Classical ML (SVM,NB, KNN, RF)	[11]	Ultrasoundfeatures+ demographic	dataPython (scikit-learn)	Up to 93.9% accuracy with SVM; requireslargerdatasetsandvalidation
DenseNet CNN	[12]	Ultrasound images	Python (Tensor-Flow/Keras)	∼62.92% accuracy; performance limited, needs improved models or data q
CNN + Follicle Detection	[13]	Ultrasound images with follicle annotations	Deep learning frameworks	∼77.81% accuracy; combines detection with classification, still needs validat
Deep Learning (Inception V3, MobileNet, ResNet)	[14]	Ultrasoundimages; potentially combined with other features	TensorFlow/Keras	Up to 84.81% (Inception V3); fusion models improve accuracy, validation ongoin
Custom CNN (F-Net) (Proposed Work)	[15]	Ultrasound images for follicle detection and classification	Python (TensorFlow, Keras)	97.5% accuracy; AUC 0.99; promising but needs clinical validati
Random Forest (RF)	[16]	145 samples, 58 features, healthy and PCOS patients	Python (scikit-learn)	86%Limited details; may require improvements for better accuracy
Random Forest + Shrinkage	[17]	541 patients from India	Python	91.01%Uses a large dataset with diverse
Multi-Stacking ML	[18]	541 patients from India	Python	98%High performance; computationally intensiv
Random Forest (RF)	[19]	541 patients	Python	96%Excellent results with minor architectural enhancements needed
LSTM (Long Short-Term Memory)	[21]	equential clinical and ultrasound data	Sequential data processing; moderate to high hardware needs	When combined with CNN, accuracy up to 96.07%
CNN Architectures (Simple CNN, PCONet)	[22]	Ultrasound images of ovaries, labeled for PCOS presence	Deep learning; GPU recommended	Up to 98.12% with PCONet
Deep Hybrid Systems	[23]	Ultrasound images	Deep learning with data augmentation	89.7% accuracy
CNN (Convolutional Neural Network)	[24]	Ultrasound images with labels for PCOS	Deep learning; requires GPU support	High accuracy (exact value not specified)
Gradient Boosting	[25]	541 patients	python	98.89%Among the top performing models, needs careful
Transfer Learning Models	[26]	Ultrasound images; dataset size varies, pre-trained source	Deep learning; leverages pre-trained models	High accuracy depending on model cho
CNN Architectures (Simple CNN, PCONet)	[27]	Ultrasound images of ovaries, labeled for PCOS presence	Deep learning; GPU recommended	Up to 98.12% with PCONetDemonstrates high accuracy, simpler models yield lo

studies. This analysis helps researchers to evaluate past studies based on quantitative performance metrics, paving the way for more accurate and objective future studies. In addition to quantitative analysis, qualitative analysis is equally important and provides insights into the effectiveness of models that may not be numerically quantifiable. This analysis allowed researchers to gain a deeper understanding of the nature and real-world impact of the study. Table 3 shows a qualitative analysis of the performance of the models in the current literature using the Delphi method. This analysis was based mainly on the following three questions:

1. Can this model determine whether the ovaries are affected by PCOS?
2. Does this model include a data preprocessing step?
3. Is this model language-dependent?

Based on the answers to these questions, analytical comments were provided to help researchers understand the effectiveness of various models and their potential for future development.

4. CHALLENGES AND FUTURE TRENDS

This section addresses the most prominent obstacles and difficulties associated with detecting polycystic ovary syndrome (PCOS) in previous studies, with the intention of providing a roadmap for researchers to identify areas of focus. Future directions in this field are also addressed.

A. Poor Quality of Standard Datasets

Although effective datasets are available, they have several limitations. For example, the available methods for detecting polycystic ovary syndrome (PCOS) are very few, small, and lack diversity. Most of these are custom-built and are typically few small. Dataset available on Kaggle are very limited.

Machine learning techniques perform better when large and diverse datasets are available, allowing the model to effectively learn and extract features. Therefore, it is essential that the database is large-scale, geographically neutral, and includes women from various of age groups to ensure diversity. If the database is not large and uniform, the model results may lack accuracy and reliability. By implementing one or more machine learning algorithms (e.g., CNN, YOLO, Random Forest) on real-world PCOS datasets, researchers can provide practical insights into their performance. Open-access datasets, such as Kaggle or hospital-based ultrasound image datasets, can be utilized to conduct pilot studies and test the feasibility of these algorithms.

B. Database Imbalance

A database is considered balanced if it it contains an equal number of samples in each class. Some existing are considered efficient, but some are unbalanced, with too many samples in one class and too few in another. This problem significantly affect the accuracy of the model results and inhibits clear and effective effects.To address this issue, advanced preprocessing techniques, such as data augmentation, synthetic oversampling (SMOTE), and transfer learning can be applied. Collaborations with hospitals and research institutions could help gather larger and more diverse datasets to train robust models.

C. Noise in Ultrasound Images

For a convolutional neural network (CNN) model to function effectively, the image must be clear. However, ultrasound images are often affected by various noises, such as speckle noise, salt and pepper noise, etc. These noises adversely affects the accuracy of the model and reduces the accuracy of cyst recognition results. Many previous studies have not removed this noise, which reduces the effectiveness of the model. Therefore, dilation, grayscale conversion, and other image improvement techniques must be utilized to improve the quality of the results.

D. Detection Rate

To achieve reliable adoption of automated PCOS detection techniques using AI, the detection rate must be 100%. However, in previous studies, the detection rate was not ideal, as most models did not exceed 98% accuracy. Therefore, efforts must be made to improve the performance of the models through further training and tuning to achieve Higher accuracy.A meta-analysis of the performance metrics in the included studies (accuracy, sensitivity, specificity, F1 score, and area under the curve) also revealed a high degree of accuracy. This could help identify the most appropriate algorithms and correct the shortcomings of the current training.

E. Lack of Use of Object Detection Techniques

Object detection algorithms have revolutionized the field of computer vision. They are characterized by their ability to simultaneously locate and classify objects, making them faster and more efficient than the traditional methods. However, most current studies focus solely on classification algorithms, without taking advantage of techniques such as YOLO or Fast RCNN, which can be effectively used to detect cysts from ultrasound images. Incorporating these algorithms into this field can enhance detection accuracy and speed.

F. Underuse of Clustering Methods

Most current studies on PCOS detection rely on only one clustering algorithm, K-means, but there are several other clustering algorithms that have not yet been exploited, such as DBSCAN, Gaussian Mixture Model (GMM), Birch, and OptiCS. Using these algorithms may improve the performance and provide a deeper understanding of the performance of clustering-based models in PCOS detection. Therefore, we encourage you to test these algorithms to obtain improved results.

Future studies should investigate how clustering can group patients with similar PCOS features and how object detection can enhance follicle recognition in ultrasound images.

G. Overlapping Symptoms

Symptoms of polycystic ovary syndrome (PCOS) often overlaps with the symptoms of other diseases, such as hypothyroidism and adrenal hyperplasia, making diagnosis difficult and reducing the accuracy of differentiation between these diseases. To address this issue, ensemble learning techniques can be used to. Additionally, feature selection algorithms can be used to identify the features that most clearly distinguish PCOS from similar diseases, and combine the results of multiple

Table 3. A qualitative assessment of the reviewed studies was conducted utilizing the Delphi method

Reference	Round 1 Question	Round 2 Question	Round 3 Question	Comments
	Detection Type	**Is the model has prepro-cessing step?**	**Does the model have any language dependency?**	
[10]	Simple cyst or PCOS	Yes	Yes	No comment.
[11]	PCO or non PCO	No	No	Incorporating preprocessing step and eliminating language dependency would be great.
[12]	PCO or non-PCO ovary	Yes	No	Making language independent would be great.
[17]	Patients having PCOS of low risk, moderate risk, and high risk.	No	No	It would be better if the preprocessing step is included, and language dependency is removed.
[18]	Ovary as normal or PCOS	Yes	No	Language independence would be better.
[19]	Affected by PCOS or not	Yes	Yes	No comment.
[20]	Affected by PCOS or not	Yes	Yes	No comment.
[21]	Affected by PCOS or not	Yes	Yes	No comment.
[25]	Affected by PCOS or not	Yes	No	Language independency is appreciated.
[26]	Affected by PCOS or not	No	No	A model with preprocessing step and language independency would be better.
[27]	Affected by PCOS or not	Yes	Yes	No comment.
[28]	Data-driven diagnosis of PCOS infected or not	Yes	Yes	No comment.
[29]	Affected by PCOS or not	Yes	No	Removing language dependency would be great.
[34]	Affected by PCOS or not	Yes	Yes	No comment.

models to identify symptom overlap. For example, SVM performs well on small datasets but struggles with high-dimensional data, whereas CNN excels in image-based classification but requires large training data, or proposes a hybrid framework that combines multiple algorithms, such as an ensemble of CNN and Random Forest, to leverage the strengths of different models. Such innovation would provide a more robust diagnostic tool for PCOS detection implement federated learning to ensure patient data privacy while training models across different healthcare institutions, or adopt explainable AI frameworks to improve model interpretability in clinical practice.

5. CONCLUSION

This study descriptively and conceptually evaluated all known detection methods for Polycystic Ovary Syndrome (PCOS), focusing on machine learning (ML) techniques. We review the methods of current algorithms', their features, effectiveness, analytical techniques, and outputs result. In addition, we briefly discuss the used in these algorithms. This study also highlights the shortcomings of current algorithms and the potential problems associated with them. Despite significant research efforts towards developing effective models for PCOS detection, several open challenges remain. This study focused on the most significant shortcomings, including the small number of , imbalance between, low detection rates, and limited utilization of various clustering techniques. In future studies, we aim to use a larger, more balanced and improved performance of Convolutional Neural Networks (CNNs) by applying several optimizations. We also plan to use other clustering algorithms such as DBSCAN and OPTICS, rather than relying solely on the K-means algorithm, to understand the effectiveness of K-means in this field. This study provides a new perspective to the research community to understand the current algorithms based on machine learning techniques for the detection of Polycystic Ovary Syndrome. Analyzing the shortcomings and future potential of these algorithms will enable researchers to develop new and more effective ways to address this issue. In future work, the researchers plan to study state of the art PCOS detection algorithms and apply them to a benchmark database to analyze their performance, as well as test different clustering algorithms to assess their success rate.

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