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Review Article

Intelligent detection for Polycystic Ovary Syndrome (PCOS): Taxonomy, datasets and detection tools

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ABSTRACT

Recent research on Polycystic Ovary Syndrome (PCOS) detection increasingly employs intelligent algorithms to assist gynecologists in more accurate and efficient diagnoses. However, intelligent PCOS detection faces notable challenges: absence of standardized feature taxonomies, limited research on available datasets, and insufficient understanding of existing detection tools' capabilities. This paper addresses these gaps by introducing a novel analytical framework for PCOS diagnostic research and developing a comprehensive taxonomy comprising 108 features across 8 categories. Furthermore, we analyzed available datasets and assessed current intelligent detection tools. Our findings reveal that 12 publicly accessible datasets cover only 54% of the 108 features identified in our taxonomy. These datasets frequently lack multimodal integration, regular updates, and clear license information—constraints that potentially limit detection tool development. Additionally, our analysis of 42 detection tools identifies several limitations: high computational resource requirements, inadequate multimodal data processing, insufficient longitudinal analysis capabilities, and limited clinical validation. Based on these observations, we highlight critical challenges and future research directions for advancing intelligent PCOS detection tools.

Contents

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1. Introduction

Polycystic Ovary Syndrome (PCOS) is one of the most common gynecological endocrine disorders affecting reproductive aged women. Its clinical characteristics primarily include clinical or biochemical hyperandrogenism, chronic anovulation, and polycystic ovarian morphology, often accompanied by insulin resistance and obesity [1,2]. In recent years, the prevalence of PCOS has been increasing. Globally, the prevalence of PCOS is estimated to be between 10% and 13% based on the Rotterdam criteria. This high prevalence significantly impacts women's quality of life and has emerged as a major public health issue worldwide [3]. Moreover, PCOS is associated with significant long-term health implications, including metabolic syndrome, type 2 diabetes, cardiovascular disease, psychological disorders, and various other metabolic disturbances. Compounding these risks, PCOS symptoms and severity often fluctuate throughout a woman's reproductive lifespan, with different manifestations emerging at various life stages. The dynamic nature of this condition, combined with its serious comorbidities, necessitates longitudinal monitoring and adaptive management strategies throughout a woman's life. These interconnected challenges highlight the critical need for both early diagnosis and comprehensive long-term management of PCOS [4–7].

The Rotterdam criteria represent the most widely adopted diagnostic framework for PCOS internationally. According to these criteria, PCOS is diagnosed when two of the following three conditions are present (after excluding other causes of hyperandrogenism): oligo- or anovulation, clinical or biochemical signs of hyperandrogenism, and polycystic ovarian morphology [1,2,8]. However, traditional medical approaches to PCOS diagnosis continue to face significant challenges. These approaches are frequently subjective, heavily dependent on individual clinician expertise, and may involve invasive and uncomfortable procedures for patients. Additionally, the heterogeneity and individual variability of symptoms may result in misdiagnosis or delayed diagnosis [9].

To address these diagnostic challenges, researchers have increasingly explored the use of intelligent technologies, particularly machine learning and deep learning algorithms, to enhance the accuracy and efficiency of PCOS diagnosis. In recent years, numerous studies implementing intelligent algorithms for PCOS detection have emerged in the literature. For instance, in 2011, Mehrotra et al. [10] proposed an automated PCOS detection method based on a Bayesian classifier utilizing clinical and metabolic parameters. In 2019, Denny et al. [11] developed a system using Random Forest (RF) with minimal yet promising clinical and metabolic parameters for early detection and prediction of PCOS. Similarly, in 2020, Bharati et al. [12] presented a tool based on hybrid Random Forest and Logistic Regression (RFLR) for reliable classification of PCOS patients. Most recently, in 2023, Alamoudi et al. [13] proposed

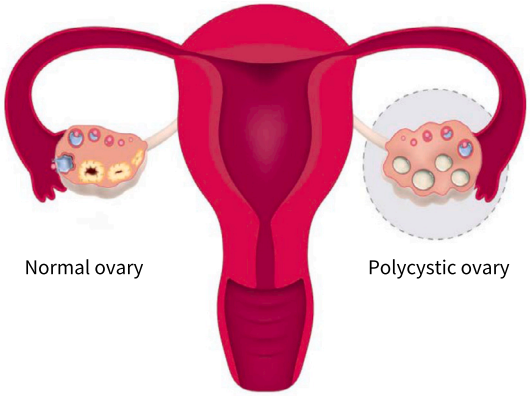


Fig. 1. Polycystic Ovary and Normal Ovary Illustration.

a fusion model incorporating ultrasound images and clinical data to diagnose PCOS, along with a basic categorization of the features used in their study. Despite these advances, current research exhibits several significant barriers: lack of comprehensive investigations into PCOS detection features and their interrelationships; insufficient exploration of available datasets used for detection; and limited in-depth analysis of existing intelligent PCOS detection tools and their capabilities.

In this paper, we propose a novel multi-module analytical framework for evaluating the current status of PCOS diagnostic research, specifically designed to address the aforementioned barriers. In the systematic literature review module, we conducted a rigorous literature analysis to identify the most relevant studies related to PCOS intelligent detection. In the taxonomy construction module, we developed a comprehensive taxonomy of PCOS detection features based on both the selected studies and diagnostic guidelines provided by gynecologists (physicians specializing in diagnosing and treating gynecological diseases). Additionally, we provided detailed annotations for each feature, including the acquisition methods and difficulty levels. In datasets status analysis module and tools capability analysis module, based on the taxonomy, we analyzed the current status of datasets used for PCOS detection and conducted an in-depth evaluation of the capabilities of existing intelligent detection tools. Based on this research framework, we answer three key research questions (RQs):

- **RQ1:** What are the features used for PCOS detection and their relationships?
  Through the systematic literature review, we identified 93 of the most relevant studies. By analyzing these studies, we constructed a comprehensive taxonomy of PCOS detection features, encompassing 108 features across 8 categories.
- **RQ2:** What is the current status of datasets used for PCOS detection?
  We analyzed 12 publicly available datasets. These datasets collectively cover 58 features, with an overall coverage rate of 54% compared to the 108 features included in our taxonomy. Additionally, we observed that none of the publicly available datasets are multimodal, some have not been updated for years, and most lack clear license information.
- **RQ3:** What are the capabilities of current intelligent PCOS detection tools?
  Our analysis of 42 intelligent detection tools filtered from relevant studies and open-source projects revealed that, while many perform well on their test datasets, they still exhibit significant limitations: high training costs, limited multimodal processing capabilities, lack longitudinal analysis capabilities, and inadequate clinical validation.

In light of these findings, our research deepens the understanding of PCOS feature taxonomy, datasets, and intelligent detection tools, offering valuable insights for future studies.

2. Background and related work

This section introduces the background of PCOS detection and related work in three aspects: machine learning-based detection tools, deep learning-based detection tools and existing reviews of PCOS detection.

2.1. Background of PCOS detection

PCOS is a complex endocrine disorder with an unclear etiology, but it is widely believed to be associated with genetic factors, insulin resistance, and elevated levels of androgens in the body. Fig. 1 illustrates the morphological differences between normal ovaries and polycystic ovaries. The symptoms of PCOS are varied and may include irregular menstruation, infertility, hirsutism, acne, and weight gain. Additionally, many patients with PCOS also exhibit characteristics of metabolic syndrome, such as hypertension and dyslipidemia [2]. The detection of PCOS typically relies on the Rotterdam criteria, which require the presence of at least two of the following three conditions: oligo-ovulation or anovulation, clinical or biochemical signs of hyperandrogenism, and ultrasound findings of polycystic ovaries [8]. Given the complexity and variability of PCOS presentation, numerous studies have explored applying intelligent algorithms to enhance PCOS detection accuracy and efficiency [11–13].

Fig. 2 shows the stakeholders and overall process related to the use of intelligent algorithms in PCOS detection. The stakeholders include patients seeking treatment, researchers employing artificial intelligence for diagnosis, and physicians making comprehensive diagnostic decisions. The diagnostic process begins when patients initially visit healthcare facilities, where health care professionals conduct preliminary assessments through comprehensive medical history collection and targeted physical examinations. The collected physical information is then processed using artificial intelligence, which grades features such as the severity of hair loss, acne, and hirsutism. Based on these preliminary findings, health care professionals may request further examinations, including ultrasound and biochemical tests. All data obtained during the examinations are recorded in electronic medical records, and researchers utilize this data through AI-assisted diagnostic tools for intelligent diagnosis. Gynecologists integrate all information to make comprehensive diagnostic decisions. Finally, the results of the diagnosis are communicated back to the patients. Importantly, despite their potential, current PCOS intelligent detection tools have not yet been implemented in routine clinical practice—a significant limitation discussed in detail in Section 4.3.3.

Our focus in this process is particularly on the stage of intelligent detection, where feature information is input into AI for assisted detection, as highlighted in the light green part of the diagram. This paper provides a systematic literature review of the PCOS intelligent detection field and establishes a taxonomy of PCOS features involved in the detection process.

2.2. Machine learning-based detection tools

Within the domain of PCOS intelligent detection, machine learning techniques have been primarily applied in two key areas: classification algorithms and feature selection methodologies.

The main machine learning classification techniques used for PCOS detection include support vector machines (SVM), decision trees, and ensemble methods. Specifically, Deshpandei et al. [14] employed the SVM algorithm to classify clinical, biochemical, and imaging data for PCOS diagnosis. Chauhan et al. [15] compared several machine learning algorithms and found that decision tree classifiers (DT) were among the most accurate models for predicting PCOS. Based on this, they developed a mobile app to help users predict PCOS in its early stages. Denny et al. [11] proposed a method with a minimal yet effective set of clinical and metabolic parameters. Zhang et al. [16] used a stacking classifier

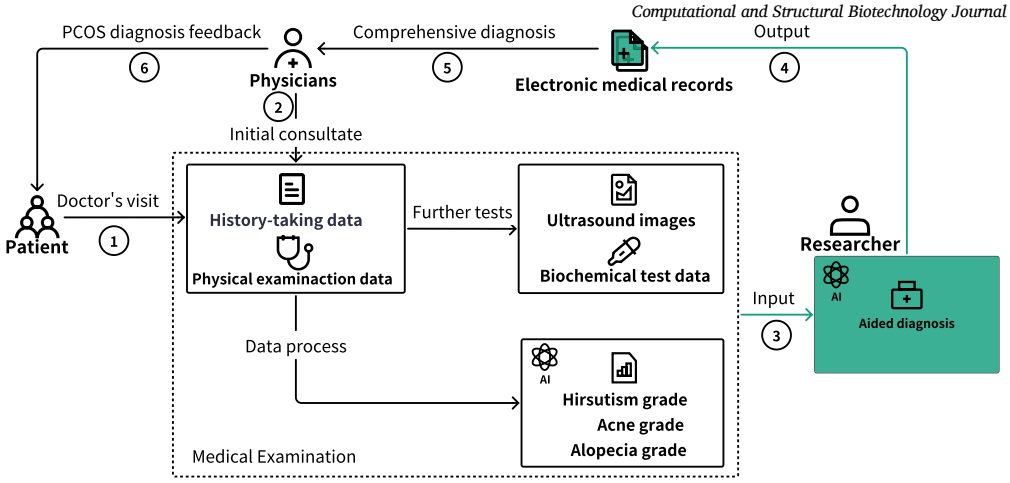


Fig. 2. Stakeholders and Processes Related to PCOS Intelligent Detection.

model based on k-nearest neighbors, RF, and extreme gradient boosting to analyze Raman spectra of follicular fluid and plasma for PCOS screening.

In addition to classification algorithms, researchers have also delved into feature selection in PCOS detection to optimize performance. For instance, Zigarelli et al. [17] used principal component analysis (PCA) to extract features from highly correlated variables, achieving dimensionality reduction. Subha et al. [18] employed three traditional methods (correlation ranking, chi-square test, and recursive feature elimination) along with two swarm intelligence methods (particle swarm optimization and firefly algorithm) for feature selection to identify significant PCOS features. Syed et al. [19] combined RF feature importance and highest correlation (HC) methods to select 10 features and used AdaBoost to achieve the highest detection accuracy for PCOS.

In summary, machine learning techniques in PCOS detection primarily focus on classification and feature selection. Through strategic combinations of specialized classification algorithms and optimal feature selection methods, these approaches have demonstrated substantial improvements in both diagnostic accuracy and computational efficiency. In contrast, this paper reviews and compiles the features used by various tools, constructs a taxonomy comprising 108 detection features, and provides a deeper analysis of the capabilities and limitations of existing machine learning-based detection tools.

2.3. Deep learning-based detection tools

Deep learning techniques have demonstrated remarkable potential in PCOS detection, particularly in two critical domains: medical image analysis and data processing. Convolutional neural networks (CNN) have been widely applied to PCOS ultrasound image feature extraction and automatic detection due to their outstanding performance in handling image data. Specifically, Srivastav et al. [20] used a pre-trained VGG16 model to extract key features with CNN for PCOS detection. CNNs have also been applied to scleral image processing, where Lv et al. [21] proposed a deep learning-based method for screening PCOS through scleral image analysis.

Beyond image processing applications, deep learning architectures have proven equally effective for analyzing clinical, biochemical, and other forms of structured one-dimensional data, enabling more comprehensive automatic PCOS diagnostic systems. For example, Abouhawwash et al. [22] processed a dataset containing 39 features using deep learning models, including CNN, multilayer perceptron (MLP), recurrent neural networks (RNN), and bidirectional long short-term memory networks (Bi-LSTM). Additionally, Kumar [23] introduced a novel chaotic red deer optimization algorithm (CRDODL-BDADC) combined with big data analysis techniques based on deep learning, applying it to detection. Thomas et al. [24] proposed a deep learning method using CNN and the Adam optimization algorithm to classify PCOS-related terms in ultrasound text reports, enabling PCOS prediction and diagnosis. By analyzing textual data, this study highlights the versatility of deep learning applications in PCOS detection.

In summary, deep learning techniques in PCOS detection primarily concentrate on processing and analyzing medical images and structured one-dimensional data, substantially enhancing both the accuracy and efficiency of detection processes. Building upon this understanding, our paper provides a systematic review of deep learning-based PCOS detection tools and presents a comprehensive evaluation of their technical capabilities, clinical applicability, and inherent limitations.

2.4. Existing reviews of PCOS detection

Complementing the individual studies on intelligent algorithm-based PCOS detection described above, several comprehensive reviews have systematically evaluated the broader landscape of PCOS detection methodologies. Specifically, Modi [25] conducted a comprehensive analysis of AI applications in predicting lifestyle diseases, including PCOS, highlighting models, symptoms and risk factors, dataset selection, and research challenges that contribute significantly to healthcare research. In comparison, Suha [26] focused on computer-aided approaches for PCOS detection, achieving five main objectives: analyzing research aims and history, evaluating data sources and algorithms, summarizing research gaps, and proposing future directions. Barrera et al. [27] systematically reviewed studies applying machine learning and artificial intelligence techniques for diagnosing and classifying PCOS, showcasing high detection accuracy, and recommending future efforts to enhance standardization and methodological improvements for better clinical applications.

While previous reviews have primarily focused on evaluating algorithmic models used in PCOS detection, our paper takes a fundamentally different approach. For the first time, we systematically review the relevant literature to construct a comprehensive taxonomy of PCOS detection features. This taxonomy then serves as a structured framework through which we critically analyze both the capabilities and limitations of current diagnostic tools and methodically assess the current state of available datasets.

3. Research design

In this section, we begin by presenting three research questions along with the motivations behind them. Subsequently, we introduce the overall framework of the empirical study and provide a detailed description of each module.

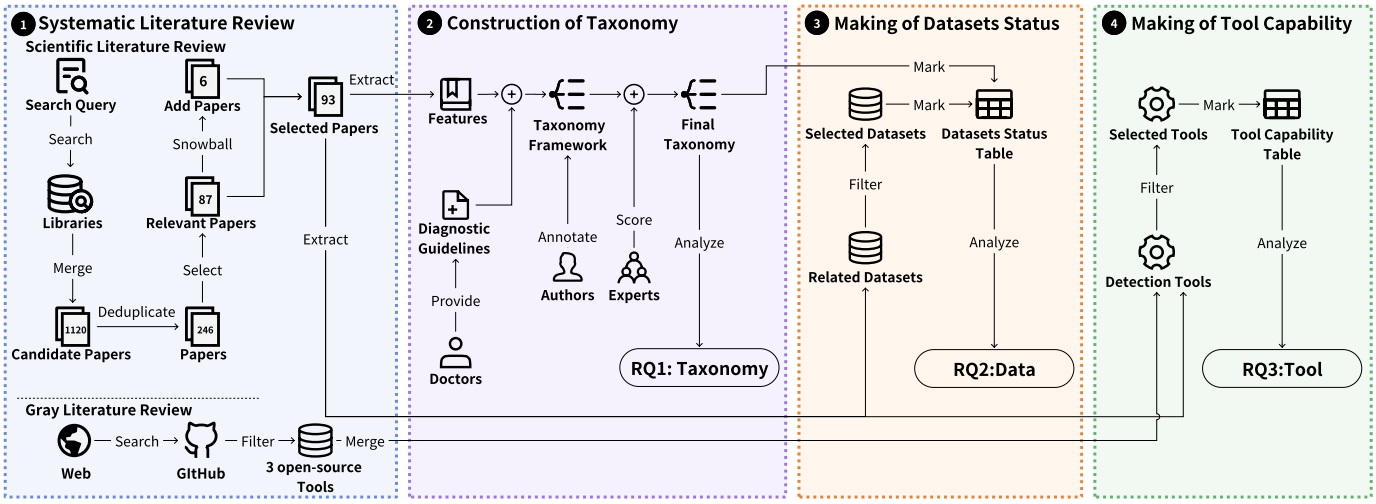


Fig. 3. The Framework of Our Study.

3.1. Research questions (RQs)

- RQ1: What are the features used for PCOS detection and their relationships? PCOS detection research is currently fragmented, lacking a comprehensive understanding of the features used. A taxonomy of PCOS detection features would help us better understand the existing features and their relationships. The motivation behind establishing such a taxonomy is to provide a unified framework, facilitating clearer communication between researchers and clinicians and identifying the most relevant features for effective diagnosis. Currently, no such taxonomy exists, making this a critical gap in the field.
- RQ2: What is the current status of datasets used for PCOS detection? A major obstacle in PCOS detection research is the unclear status of the datasets. There is a lack of in-depth analysis regarding the current datasets, particularly concerning their openness, scale, license, and maintenance status. The purpose of conducting a comprehensive analysis of the current datasets is to identify their limitations, assess their availability, and guide future data collection efforts to improve the quality and accessibility of datasets for detection research.
- RQ3: What are the capabilities of current intelligent PCOS detection tools? While PCOS intelligent detection tools have demonstrated certain detection performance in their respective datasets, their capabilities are not fully investigated. The aim of understanding these tools' capabilities is to evaluate their strengths and weaknesses, thus enabling the selection of the most appropriate tools and guiding the development of more accurate and efficient detection methods.

3.2. Research framework

To address the three research questions outlined above, we propose an analytical framework for the current status of PCOS detection research, based on the taxonomy construction method employed by Ladisa et al. [28]. As illustrated in Fig. 3, the framework consists of four modules.

First, in the systematic literature review module, we obtained candidate literature through our constructed search query, then filtered it and conducted snowballing to identify the final selection of literature most relevant to intelligent PCOS detection. From these selected papers, we extracted relevant information and explored gray literature. Second, in the taxonomy construction module, based on the features we collected and the diagnostic guideline provided by gynecologist, we constructed a taxonomy framework for PCOS detection features. We then conducted a survey inviting experts to evaluate and provide feedback on the taxonomy's rationality, completeness, and practical utility. Feedback indicated a high level of endorsement for the taxonomy's rationality, completeness, and practical utility. Consequently, based on this feedback, we finalized the taxonomy framework and formed the final taxonomy for PCOS detection features, thereby addressing RQ1. Third, in the dataset status analysis module, we leveraged our established feature taxonomy as an analytical framework to systematically identify and filter eligible datasets used in PCOS detection research. We then conducted a multi-dimensional assessment of these datasets, effectively addressing RQ2. Fourth, in the tool capability evaluation module, similarly, using our feature taxonomy as a baseline reference, we identified representative PCOS detection tools from the literature. We then performed a systematic capability assessment, thereby thoroughly addressing RQ3.

By implementing this four-module research framework, we provide a holistic analysis of the current state of PCOS detection research, encompassing features, datasets, and tools—the three fundamental components necessary for advancing this critical clinical domain.

3.3. Systematic literature review

This section presents a comprehensive systematic review of both scientific literature and gray literature pertaining to intelligent PCOS detection ❶, as outlined in the first module of our research framework (Fig. 3). We implemented a rigorously structured approach to literature identification and analysis, following established systematic review methodologies [29,30] to ensure thoroughness and reproducibility.

3.3.1. Scientific literature review

The scientific literature review component of our methodology was executed in two sequential stages: comprehensive candidate literature searching, and systematic literature filtering.

Candidate Literature Searching: The systematic literature review on PCOS detection research began by designing effective search queries [31,32]. First, to ensure a comprehensive search, we conducted an exploratory search on Google Scholar using the keyword "PCOS detection". This preliminary search found four relevant studies [18,33–35], providing initial information on the topic and helping us identify relevant keywords. Subsequently, based on these initial studies, we carefully analyzed their keywords and created a search query string to retrieve articles most relevant to PCOS intelligent detection. Let the keyword sets be $K_1, K_2, K_3, \ldots, K_n$, the keywords within each set are synonymous or closely related terms, representing similar concepts or phrases used in the context of PCOS detection, where:

$$K_1 = \{\text{PCOS}, \text{polycystic ovary syndrome}\}$$
$$K_2 = \{\text{detection}, \text{screening}, \text{diagnosis}, \text{identification}, \text{predicting}, \text{classification}\} \quad (1)$$
$$K_3 = \{\text{deep learning}, \text{machine learning}, \text{AI}, \text{artificial intelligence}, \text{algorithm}\}$$

The search query string Q can be expressed as:

$$Q = (K_1) \text{ AND } (K_2) \text{ AND } (K_3) \quad (2)$$

Using this carefully designed search query Q, we conducted extensive literature searches across six authoritative databases: IEEE Xplore, Scopus, Google Scholar, ACM Digital Library, PubMed and Web of Science. The search was limited to titles, abstracts, and author keywords, including only English publications, covering journals, conference proceedings, and book chapters. For each database $D \in \{\text{Google Scholar}, \text{Scopus}, \text{IEEE Xplore}, \dots\}$, we define the number of papers retrieved from each database as $n(D)$. The total number of papers retrieved is:

$$\text{Total Papers} = \sum_{D \in \text{Databases}} n(D) \quad (3)$$

The specific numbers are:

$$n(\text{Web of Science}) = 231, n(\text{Scopus}) = 500, n(\text{ACM Digital Library}) = 2$$
$$n(\text{IEEE Xplore}) = 200, n(\text{PubMed}) = 0, n(\text{Google Scholar}) = 187 \quad (4)$$

Therefore:

$$\text{Total Papers} = 187 + 500 + 200 + 2 + 231 = 1120 \quad (5)$$

It should be noted that results from the PubMed medical database were excluded because they were not highly relevant to intelligent PCOS detection. This search process was completed by April 7, 2024.

Literature Filtering: The literature filtering process was conducted in four steps to identify the most relevant papers on PCOS intelligent detection.

First, since there are duplicate entries, we carefully removed duplicate entries from the initial 1,120 candidate papers. After this step, 386 papers proceeded to the next round of screening. Second, to ensure that the selected literature was directly related to PCOS intelligent detection, we filtered the papers further. We examined the metadata of each paper, such as the type of publication, title, and abstract, to filter out papers unrelated to the topic. After this step, 246 papers remained. Third, to ensure sufficient information for our review, we obtained the full texts of all articles and focused on the introduction, methods, and results sections. To be included, articles had to meet the following criteria: they must describe a PCOS detection tool and dataset; be at least four pages in length, and be written in English. Articles not meeting these criteria were excluded from the review. To ensure accuracy and reliability, each articles were independently reviewed by at least two authors, with final inclusion based on consensus, resulting in 87 relevant articles. Finally, to ensure comprehensive coverage, we applied a bidirectional snowball strategy, tracing forward and backward references from the 87 selected articles. Only references directly cited by or citing the selected papers were included, with a one-layer depth to maintain focus. This process added 6 papers, resulting in a final selection of 93 relevant papers for our study on PCOS intelligent detection.

Fig. 4 shows the annual publication trend of the 93 selected papers. As depicted by the blue trend line, the number of publications has been steadily increasing. This trend indicates that research in the field of intelligent PCOS detection has been growing, reflecting the growing attention from both academic and the research community. This growth can likely be attributed to technological advancements and the increasing demand for early diagnosis and precise treatment of PCOS. It is worth noting that the number of selected papers for 2024 has decreased, as our paper collection cutoff date was April 7, 2024, and only papers published before that date were included.

3.3.2. Grey literature exploration

In addition to scientific literature, we explored gray literature sources, such as blog posts, technical forums, and GitHub, the largest open source software website [28]. This stage aimed to comprehensively cover intelligent PCOS detection tools, enhancing the depth of our research. We regularly reviewed various repositories and blogs, using the same search query in Google as for scientific literature. The preliminary query revealed that gray literature related to PCOS detection was mainly concentrated on the open-source platform GitHub. We applied the same criteria used for scientific literature to filter these sources and used a snowball sampling strategy to expand the literature pool, ensuring thorough coverage. From the initial gray literature search, we identified 24 relevant entries. After further screening, projects that were not starred or forked were excluded. Ultimately, we identified 3 valuable open-source projects.

3.4. Taxonomy construction

This section describes our approach to developing a comprehensive taxonomy for PCOS detection features ❷, corresponding to the second module in Fig. 3. While previous studies have employed feature selection methods to identify PCOS-relevant features [33,35,36], a systematic feature taxonomy has not yet been established. We constructed this taxonomy through three consecutive steps: taxonomy framework construction, feature annotation, and expert survey validation.

3.4.1. Taxonomy framework construction

The taxonomy framework construction step involved three processes: extracting features from the reviewed literature, removing redundant features, and systematically classifying the features according to diagnostic guidelines.

From the 93 previously identified studies, we extracted features using an inclusive approach to ensure comprehensiveness. We carefully reviewed each paper and incorporated all features used for PCOS detection, including those derived from feature extraction techniques (e.g., Principal Component Analysis). For example, we documented all the features presented in Table 4 of Kumari's study [35], which were selected for PCOS detection using backward feature elimination.

Subsequently, to eliminate redundancy, we refined the data on PCOS detection features by merging similar features. Two types of similarity were considered: textual similarity, where features had identical definitions, synonymous terms, or referred to the same characteristic (e.g., "Sex hormone binding globulin" and "SHBG" representing the identical laboratory parameter with different textual representations); and conceptual similarity, where features used different terminology but shared clinical or pathological significance (e.g., varied descriptions like "Hair growth(y/n)" and "Excess facial or body hair" merged into the clinical concept "Hirsutism"). For merged features, we recorded both the original features and the unified name as shown in the Table 1, with detailed information available on our website [37]. Each feature underwent manual verification, with two authors independently reviewing categories based on textual descriptions, examples, and attributions. A third author arbitrated any disagreements. This rigorous process identified 108 distinct PCOS features, all validated by a gynecologist to confirm their clinical relevance and practical application in real-world PCOS diagnostic settings.

Following the identification of 108 distinct features, we proceeded to establish a systematic taxonomy framework. We consulted with gynecologists, including our third author, to obtain comprehensive insights into international PCOS diagnostic guideline. The established diagnostic modules and sub-modules from these clinical guideline served as the

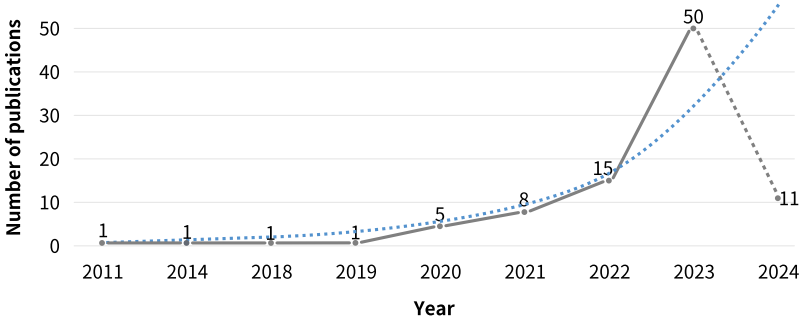


Fig. 4. Annual Trends in PCOS Intelligent Detection Research Publications.

Table 1
Merged Features.

Merged to	Features	Criterion
Cycle(R/I)	Cycle(R/I); Regularity of menses; Cycle regularity; Missed/irregular periods	Similar description and instances
Age	Age; Age group	Similar description
BMI	BMI; Nomal BMI	Similar description and instances
Restbps	Restbps; Resting blood pressure	Similar description and instances
High BP (Y/N)	High BP (Y/N); Hypertension	Similar description
Menstrual cycle	Cycle length (days); Period length; Cycle length; Duration of the cycle	Similar description and influence
FSH (mlU/mL)	FSH (mlU/mL); Basal FSH Level (IU/L)	Similar description
LH (mlU/mL)	LH (mlU/mL); Basal LH Level (IU/ L)	Similar description
Sex hormone binding globulin	Sex hormone binding globulin; SHBG	Similar instances
Hair loss(Y/N)	Hair loss(Y/N); Hair thinning/loss; Loss of hair	Similar concepts
Skin darkening(Y/N)	Skin darkening(Y/N); Dark patches; Dark areas on skin	Similar concepts
Weight gain(Y/N)	Weight gain(Y/N); Weight gain/loss; Recent weight gain	Similar concepts
Hirsutism	Hair growth(Y/N); Unwanted Hair growth(Y/N); Excess facial or body hair	Similar concepts
Anxieties(Y/N)	Anxieties(Y/N); Anxiety	Similar description and instances
Reg.Exercise (Y/N)	Exercise(Y/N); Reg.Exercise (Y/N); Regular exercise	Similar description
Negative emotions	Low mood; Negative emotions	Similar description and concepts
Hemoglobin (Hgb) (cbc)	Hb (g/dl); Hemoglobin (Hgb) (cbc)	Similar description and instances
Fasting blood glucose (mg/dL)	Fasting glucose; Fasting sugar	Similar description

foundation for our hierarchical classification system, providing both primary categories and subcategories [3]. We methodically mapped each of our collected features to the appropriate classification category based on its clinical relevance and diagnostic purpose. First, we analyzed each feature's primary diagnostic function (e.g., hormonal assessment, morphological evaluation, or metabolic indication) by reviewing its clinical application in the original literature. Then, we assessed which diagnostic module in the PCOS guidelines most closely aligned with the feature's function. For features with potential relevance to multiple categories, we consulted with our gynecologist collaborators to determine the most appropriate classification based on the feature's primary clinical utility in PCOS diagnosis. This mapping process ensured that features were systematically organized according to established diagnostic criteria while maintaining clinical relevance.

Additionally, leveraging the extensive clinical expertise of our collaborating gynecologists, we enriched our taxonomy with features routinely employed in clinical practice but not previously documented in the literature. These clinically-derived features were distinctly marked with asterisks to differentiate them from literature-sourced features, ensuring transparency regarding the origin of each element.

This classification process involved collaboration between two authors and two gynecologists, ensuring both academic rigor and clinical relevance. The resulting taxonomy framework accurately reflects both evidence-based literature and real-world clinical diagnostic practices for PCOS.

3.4.2. *Feature annotation*

In this step, we annotated each feature with its acquisition method and difficulty level. Working with our gynecologist co-author, we identified how each feature is typically obtained in clinical settings. Based on acquisition methods, resource requirements, and detection complexity, we categorized all features into three difficulty levels:

- Level 1 (Easily Acquirable): These features are acquired through non-invasive and routine methods without requiring complex detection techniques or equipment. They typically involve self-reported information, simple physical measurements, or standard physical examinations.
- Level 2 (Moderately Acquirable): These features require specialized tests or equipment, often involving complex measurements or lab tests. While not highly invasive, the acquisition process may be time-consuming or require trained medical personnel to perform.
- Level 3 (Difficult to Acquire): These features necessitate highly complex detection methods or specialized equipment, potentially involving invasive procedures or advanced laboratory techniques, and are not part of routine testing. The acquisition process may be technically challenging and costly. In addition, some characteristics involve subjective assessments, and the accuracy of the assessment may be affected by individual self-reporting bias or different assessment criteria.

3.4.3. *Expert survey*

To validate our taxonomy framework, we conducted an expert evaluation involving healthcare professionals and researchers through two complementary approaches: a structured online survey and in-depth expert interviews.

The online survey evaluated (a) the taxonomy's rationality, completeness, and practical utility; and (b) the appropriateness of our feature acquisition annotations. It included thirteen questions with specific evaluation objectives. Six questions used a Likert scale from 1 (low) to 5 (high) to assess various dimensions of the taxonomy [38]. Two questions

Table 2
Demographic Information of Experts.

Demographic Information	Measure	Number	Percentage
Age	18-25	6	7%
	26-30	15	17%
	31-40	30	34%
	41-50	26	30%
	51-60	10	12%
Years of work experience	0-2	8	9%
	3-5	9	10%
	6-10	21	24%
	11-15	18	21%
	Over 16	31	36%
Occupation	Medical professionals	83	95%
	Researcher	1	1%
	Other	3	4%
Familiarity with PCOS	5 (Familiar)	30	35%
	4	41	47%
	3	11	13%
	2	3	3%
	1 (Unfamiliar)	2	2%

were binary (yes/no), evaluating the use of the taxonomy and AI tools in PCOS detection. Additionally, four questions were used to collect demographic information such as age, work experience, and professional background of the participants. One question verified whether participants had read the taxonomy documents and background materials before rating, ensuring data quality. The online survey was conducted on the Wjx.cn platform from August 7 to August 21, 2024, and collected 87 responses. Anonymity was ensured through privacy measures, with no personal identification information collected. Detailed information about the survey can be found on our website [37].

Table 2 presents demographic information of the 87 participating experts. This information includes age, years of professional experience, occupational background, familiarity with the concept and implications of PCOS. Results showed that 80% of the experts had over six years of experience, with 31 having more than 16 years. More than 95% of the experts are senior physicians and nurses, and 81% of the experts rated their understanding of PCOS as 4 or 5 points, whose expertise in disease diagnosis provides a solid guarantee for the validity of the taxonomy.

The expert interviews aimed to assess the practical utility, relevance, and applicability of the taxonomy in real-world clinical and research settings. One open-ended question aims to gather experts' thoughts on the taxonomy and their insights on how it could improve clinical workflows and integrate with existing detection tools. The question posed was: "In your clinical practice or research, how do you view integrating our taxonomy into existing diagnostic workflows or AI tools? Do you have any suggestions for adapting the taxonomy to different healthcare settings or detection tools?" The interviews, held between November 10 and 30, 2024, involved four experts. All data was anonymized, and privacy measures ensured confidentiality. Insights from these interviews were qualitatively analyzed to assess the taxonomy's potential for clinical adoption.

Overall feedback confirmed the taxonomy's rationality, completeness, and practical utility, validating our taxonomy framework.

3.5. Analysis of datasets

As shown in Fig. 3, in order to comprehensively understand the current status of PCOS detection datasets, we conducted a filtering and analysis of datasets relevant to PCOS detection ❸.

3.5.1. Filtering

We systematically evaluated all datasets reported in the 93 PCOS detection-related articles identified in our literature review to determine which met the fundamental requirements for PCOS detection research. To ensure rigor and relevance in our selection process, we established two essential criteria:

- **Criterion #1 (Presence of PCOS Detection Instances):** The dataset must clearly include feature data for PCOS detection, ensuring researchers can extract instances for analysis and modeling.
- **Criterion #2 (Accessibility of the Dataset):** The dataset must be documented in the relevant publications and clearly indicate its availability to ensure practical support for research.

Through the application of these rigorous selection criteria, we identified 36 distinctive datasets specifically suitable for PCOS detection research. These datasets were systematically cataloged with the prefix "D" followed by a numerical identifier based on the sequence of review, creating a standardized reference system for subsequent analysis and comparison.

3.5.2. Analysis

We conducted a systematic analysis of the 36 identified datasets across seven key dimensions: openness, instance types, scale, usage frequency, license, maintenance status, and feature coverage.

First, to assess openness, we examined each dataset's availability, categorizing them as open access, restricted access, or not publicly available, while documenting access links and conditions for accessible datasets. Second, we reviewed "Methods" sections in relevant literature to classify data types (image, numerical, or other formats) within each dataset. For license assessment, we examined both literature descriptions and dataset websites to identify license types and usage restrictions for research or commercial purposes. We evaluated dataset scale by counting the number of instances, and for datasets with the same scale, we further examined their similarities and differences by comparing the features contained in them. Usage frequency was determined by counting dataset citations across academic publications. To assess maintenance status, we recorded the last update date for each dataset, providing insight into their current research relevance. Finally, we analyzed how comprehensively the open-source datasets covered the 108 features identified in our taxonomy. Column 6 of Table 3 specifies which datasets include each feature, indicating the dataset's coverage of that particular characteristic.

This comprehensive analytical approach provides a detailed understanding of the current state of PCOS datasets, highlighting areas for improving data availability and research applicability.

3.6. Analysis of intelligent detection tools

Following our methodology in Fig. 3, we identified and analyzed representative intelligent PCOS detection tools ❹ from the 93 selected articles, applying rigorous filtering criteria to ensure comprehensive evaluation.

3.6.1. Filtering

To ensure a focused and meaningful analysis of PCOS detection technologies, we established a comprehensive set of filtering criteria. Only intelligent detection tools satisfying all of the following rigorous requirements were included in our analysis:

- **Criterion #1 (Applicability to PCOS Detection):** The tool must directly address PCOS detection, with descriptions containing terms like "identification," "detection," or "classification" and producing binary outcomes (PCOS or non-PCOS).
- **Criterion #2 (Automation):** The tool must feature automated functionality to overcome limitations of manual detection (inconsistent standards, inefficiency, etc.).
- **Criterion #3 (Industry Validation):** For reliability assessment, the tool must either be referenced in comparative studies or have its associated research indexed in SCIE.

- **Criterion #4 (Performance Metrics):** The tool must report transparent performance metrics (accuracy, precision, recall, etc.) to enable valid cross-tool comparisons.

Applying these criteria to the 93 articles yielded 39 eligible intelligent detection tools. We supplemented this selection with three additional open-source tools identified from gray literature, creating a final collection of 42 representative PCOS detection technologies. As the majority of these tools lacked formal nomenclature in their original publications, we assigned standardized identifiers using the prefix "T" followed by a numerical designation based on the sequence of review.

3.6.2. Analysis

We conducted a comprehensive analysis of these tools across five key dimensions: technical approaches, input data types, performance metrics, temporal analysis capabilities, and tool comparison/availability status. Our analysis relies on the reported capabilities of the tools rather than directly executing them.

First, we reviewed the techniques employed by each tool by examining the "Methods" sections of relevant papers. We extracted details about classification and feature selection algorithms, prioritizing combinations that achieved the highest accuracy as noted in the "Results" sections. These techniques were recorded using abbreviations, and we counted their usage frequency to identify the most commonly used techniques across the tools. Second, we identified the types of input data processed by each tool by documenting information from the "Methods" section of each paper. This allowed us to categorize tools based on the data types they handle, such as image, numerical, or text data. Third, we thoroughly assessed the performance metrics of each tool, focusing on the indicators reported in the "Results" sections. We recorded the performance achieved by the representative techniques of each tool and compiled the types of performance metrics reported. From this, we selected the four most commonly used metrics—accuracy, precision, F1 score, and recall—as the evaluation criteria. Tools were then categorized based on the data types they processed, and their performance metrics were analyzed to identify which tools demonstrated the best performance across different data types. Given the urgent need for long-term PCOS management in clinical settings, we also evaluated whether each tool underwent clinical validation and had capabilities for longitudinal monitoring. Lastly, we reviewed the comparisons of representative tools documented in the selected papers, counting the number of times each tool was compared with others. We also documented their availability status, providing access links for open-source tools.

This systematic analysis provides a comprehensive evaluation framework for understanding the relative strengths and limitations, establishing a foundation for both clinical implementation and future research development.

4. Results

Building on the methodology framework detailed in Section 3.2, this section presents our findings addressing the three research questions concerning PCOS detection features, datasets, and intelligent tools.

4.1. Taxonomy

For RQ1, we constructed a comprehensive taxonomy of PCOS detection features from the 93 selected studies using the methodology outlined in Section 3.4.

As shown in Table 3, our taxonomy comprises 8 categories, 31 subcategories, and 108 distinct features relevant to PCOS detection. Each entry includes the feature name, acquisition method, difficulty level, and literature references. For brevity, the seventh column of Table 3 lists only the three most recent papers citing each feature, with the complete reference list available on our website [37]. Fig. 5 provides a visual representation of this taxonomy. Our analysis covers three key aspects: feature categories, acquisition methods and acquisition difficulty, and validation through expert survey results.

4.1.1. Categories

Fig. 6 illustrates the distribution of features across categories. The "Demographic and Basic Health Data" category contains 12 features across 3 subcategories, primarily collected through questionnaires. Body Mass Index (BMI) emerges as the most frequently utilized feature in this category, appearing in 32 studies as a PCOS detection parameter. The "Vital Signs" category encompasses 7 features in 2 subcategories, obtained through standard medical measurements, with systolic blood pressure (SBP) referenced in 10 studies, reflecting the correlation between blood pressure and PCOS. "Menstrual and Reproductive Health" includes 13 features in 2 subcategories, mostly gathered via patient questionnaires. Menstrual cycle regularity (Cycle R/I) appears in 35 studies, reflecting its diagnostic importance. The "Biochemical Indicators" category is the most extensive, comprising 34 features across 8 subcategories derived from laboratory testing. Anti-Müllerian Hormone (AMH) is particularly significant, utilized in 30 studies for PCOS detection algorithms.

The "Imaging Indicators" category contains 13 features across 3 subcategories, derived from medical imaging techniques. Follicle count in the right ovary (Follicle No.(R)) appears in 40 studies, underscoring its critical role in ovarian morphology assessment for PCOS diagnosis. The "Physical Characteristics" category encompasses 15 features obtained through physical examination or standardized measurements. Hirsutism and weight gain are particularly prominent, cited in 43 studies, reflecting their status as cardinal PCOS manifestations. This category notably includes visible surface features such as acne, hair loss, and hirsutism which, according to the *2023 international evidence-based guideline for the assessment and management of polycystic ovary syndrome* [3], are crucial diagnostic indicators. Interestingly, our analysis reveals that current intelligent detection tools have not yet effectively incorporated these visible physical characteristics as direct inputs, despite their clinical significance. The "Lifestyle" category comprises 5 features collected through patient questionnaires. Fast food consumption (Fast food Y/N) appears in 26 studies. Though lifestyle features are less frequently incorporated into detection algorithms, they provide valuable contextual information about modifiable risk factors and patient behaviors that influence PCOS manifestation. The "Psychological and Emotional Health" category contains 9 features across 2 subcategories, predominantly assessed through standardized psychological questionnaires, reflecting the increasing recognition of the psychological dimensions of PCOS.

Comparative analysis reveals that "Biochemical Indicators" contains the highest number of features (34), while "Lifestyle" contains the fewest (5). Across all 108 features, hirsutism was the most frequently referenced in the literature (43 studies), highlighting its primacy in PCOS detection research.

4.1.2. Features acquisition methods and difficulty levels

Beyond categorizing features by clinical domain, our taxonomy also classifies acquisition methodologies to support implementation considerations. We identified six distinct acquisition methods: questionnaires, calculations, laboratory tests, medical measurements, physical examination, and Imaging Examination. Questionnaires represent the predominant data collection approach, yielding 38 features through patient self-reporting. Calculations (generating derived metrics like BMI) are the least frequently employed methods, contributing a single feature to the taxonomy.

To enhance practical utility, we further stratified features according to their acquisition difficulty using a three-tier classification system: easy, moderate, and difficult to obtain. Our analysis revealed that the majority of features (73/108, 68%) are classified as easily accessible. A smaller proportion (23/108, 21%) present moderate acquisition challenges. Only 12 features (11%) are categorized as difficult to obtain, generally involving complex imaging. This difficulty stratification pro-

Table 3
Taxonomy of Features for PCOS Detection.

Categories	Sub-categories	Feature	Acquisition methods	Acquisition difficulty levels	Datasets	Papers using this feature
Demographic and Basic Health Data	Standard items	Age	Questionnaires	1	D1,D2,D4,D6,D7	[33,39,40]
		Height	Questionnaires	1	D1,D2,D4,D7	[41–43]
		Weight	Questionnaires	1	D1,D2,D4,D7	[23,40,44]
		BMI	Calculation	1	D1,D2,D4,D6,D7	[33,39,45]
		Blood Group	Laboratory testing	2	D1,D2,D4,D7	[42,45,40]
		Marriage Status	Questionnaires	1	D1,D2,D4,D7	[39,45,23]
		Age of menarche	Questionnaires	1		[34]
		Family history of diabetes and hypertension	Questionnaires	1	D9	[46]
	Education Level	Postgraduate	Questionnaires	2		[34]
		Some College/Technical/Vocational School	Questionnaires	2		[33]
	Race	Hispanic/Latina	Questionnaires	1		[33]
		Black/African American	Questionnaires	1		[33]
Vital Signs	-	RR (breaths/min)	Measurement	2	D1,D2,D4,D7	[39,23,40]
	Cardiovascular Parameters	Pulse rate (bpm)	Measurement	2	D1,D2,D4,D7	[41,47,42]
		BP_Systolic (mmHg)	Measurement	1	D1,D2,D4,D7	[23,40,48]
		BP_Diastolic (mmHg)	Measurement	1	D1,D2,D4,D7	[23,48,43]
		Restbps	Measurement	1	D10	[49,50]
		High BP (Y/N)	Measurement	1		[33,51]
		Normal BP	Measurement	1		[33]
Menstrual and Reproductive Health	Menstrual Characteristics	Menstrual cycle	Questionnaires	1	D1,D2,D4,D7	[41,42,19]
		Cycle (R/I)	Questionnaires	1	D1,D2,D4,D7,D9	[41,47,18]
		Intermenstrual bleeding*	Questionnaires	1		
		Dysmenorrhea	Questionnaires	1		[34]
		Menstrual period time*	Questionnaires	1		
		Menorrhagia*	Questionnaires	1		
		Hypomenorrhea*	Questionnaires	1		
		Amenorrhea*	Questionnaires	1		
	Pregnancy History	Pregnant (Y/N)	Questionnaires	1	D1,D2,D4,D7	[39,41,42]
		Presence of children	Questionnaires	1		[47]
		No. of abortions	Questionnaires	1	D1,D2,D4,D7	[41,47,42]
		Gravidity	Questionnaires	1		[33]
		Months of conception tried	Questionnaires	2		[47]
Biochemical Indicators	Hormonal Levels	FSH (mlU/mL)	Laboratory testing	1	D1,D2,D4,D7	[41,42,33]
		LH (mlU/mL)	Laboratory testing	1	D1,D2,D4,D7	[41,42,33]
		FSH/LH	Laboratory testing	1	D1,D2,D4,D7	[41,23,40]
		TSH (mlU/L)	Laboratory testing	1	D1,D2,D4,D7	[41,42,23]
		AMH (ng/mL)	Laboratory testing	1	D1,D2,D4,D7	[47,45,23]
		PRL (ng/mL)	Laboratory testing	1	D1,D2,D4,D7	[41,19,52]
		Vit D3 (ng/mL)	Laboratory testing	2	D1,D2,D4,D7	[41,42,45]
		PRG (ng/mL)	Laboratory testing	1	D1,D2,D4,D7	[41,42,45]
		Beta-HCG (mlU/mL)	Laboratory testing	2	D1,D2	[40,33,43]
		Testosterone	Laboratory testing	1		[13]
		Estradiol levels	Laboratory testing	1		[33]
		Sex hormone binding globulin	Laboratory testing	1		[33]
		free testosterone*	Laboratory testing	1		
		17{α}-OHP*	Laboratory testing	2		
		dehydroepiandrosterone sulfate*	Laboratory testing	1		
		free testosterone index*	Laboratory testing	1		
		HOMA-IR*	Laboratory testing	2		
	Hemoglobin Levels	Hemoglobin (Hgb) (cbc)	Laboratory testing	1	D1,D2,D4,D7	[39,41,23]
	-	Ferritin	Laboratory testing	3		[13]
	Cholesterol and Lipid Levels	Cholesterol	Laboratory testing	1	D10	[13,50]
		Triglycerides (TG)	Laboratory testing	1		[13]
		High-density lipoprotein (HDL)	Laboratory testing	1		[33,13]
		Low-density lipoprotein (LDL)	Laboratory testing	1		[13]

Table 3 (*continued*)

Categories	Sub-categories	Feature	Acquisition methods	Acquisition difficulty levels	Datasets	Papers using this feature
Biochemical Indicators	Glucose Levels	Glucose	Laboratory testing	1	D6	[49,50]
		Fasting glucose	Laboratory testing	1	D10	[48,49,13]
		RBS (Random blood sugar)	Laboratory testing	3	D1,D2,D4,D7	[39,23,40]
		Insulin level	Laboratory testing	1	D4	[45]
		Hemoglobin (Hgb) A1c	Laboratory testing	1		[13]
	-	Uric acid*	Laboratory testing	1		
	Renal function	Creatinine*	Laboratory testing	1		
		Blood Urea Nitrogen*	Laboratory testing	1		
	Liver function	Liver function*	Laboratory testing	1		
		Aspartate transaminase*	Laboratory testing	1		
		Alanine transaminase*	Laboratory testing	1		
Imaging Indicators	Ultrasound features	Polycystic Ovary Morphology	Imaging Examination	1		[13]
		Follicle No. (L)	Imaging Examination	1	D1,D2,D4,D7	[42,45,23]
		Follicle No. (R)	Imaging Examination	1	D1,D2,D4,D7	[45,23,18]
		No. of ovarian follicles	Imaging Examination	1		[14]
		Avg. F size (L) (mm)	Imaging Examination	2	D1,D2,D4,D7	[45,23,40]
		Avg. F size (R) (mm)	Imaging Examination	2	D1,D2,D4,D7	[45,23,40]
		Size of follicles (La and Ro.) (mm)	Imaging Examination	2		[11]
		Right ovarian volume*	Imaging Examination	2		
		Left ovarian volume*	Imaging Examination	2		
		Endometrial (mm)	Imaging Examination	1	D1,D2,D4,D7	[39,45,40]
		Uterine size*	Imaging Examination	2		
	-	Ovarian ultrasound image	Imaging Examination	2	D3,D8,D11	[53,54,20]
	-	The number of major vessels colored by fluoroscopy	Imaging Examination	3	D10	[50]
Physical Characteristics	Anthropometric Measurements	Waist (inch)	Measurement	1	D1,D2,D4,D7	[23,40,43]
		Hip (inch)	Measurement	1	D1,D2,D4,D7	[41,42,45]
		Waist:Hip Ratio	Measurement	1	D1,D2,D4,D7	[41,45,23]
	-	Acne or Skin tags	Physical examination	1	D1,D2,D4,D7,D9	[39,45,40]
	-	Hair loss (Y/N)	Physical examination	1	D1,D2,D4,D7,D9	[39,45,40]
	Associated with mFG scores	Hirsutism	Physical examination	1	D1,D2,D4,D7,D9	[45,23,18]
	Physical Symptoms	Weight gain (Y/N)	Measurement	1	D1,D2,D4,D7,D9	[45,23,18]
		BODY Weight Maintainence	Measurement	1		[55]
		Skin darkening (Y/N)	Physical examination	1	D1,D2,D4,D7,D9	[39,45,23]
		Oily skin	Physical examination	3	D9	[55]
		Obesity	Measurement	1		[33,15]
		Breast distension	Questionnaires	2	D10	[15,50,34]
	Body Surface Images	Acne Symptoms Images	Physical examination	2	D36	[56–58]
		Hair Loss Symptoms Images	Physical examination	2	D5	[59–61]
		Hirsutism Symptoms Images	Physical examination	3		
Lifestyle	-	Fast food (Y/N)	Questionnaires	3	D1,D2,D4,D7,D9	[42,19,36]
	-	Reg.Exercise (Y/N)	Questionnaires	2	D1,D2,D4,D7,D9	[42,43,62]
	-	Eating and sleeping habits	Questionnaires	2		[46]
	-	Sleep Disorders	Questionnaires	2		[34]
	-	Smoker	Questionnaires	1		[33]
Psychological and Emotional Health	Psychological Symptoms	Anxieties (Y/N)	Questionnaires	1	D9	[46,51,55]
		Depression	Questionnaires	1	D9	[46,55]
		Negative emotions	Questionnaires	1	D9	[15,34,55]
		Social Phobia	Questionnaires	3		[46]
		Body image dissatisfaction	Questionnaires	3		[46]
	Mental Stress	Mental stress due to new admission in hostel (Y/N)	Questionnaires	3	D9	[55]
		Mental stress due to personal problems (Y/N)	Questionnaires	3	D9	[55]
		Mental stress due to peer pressure (Y/N)	Questionnaires	3	D9	[55]
		Mental stress due to change in dietary habits (Y/N)	Questionnaires	3	D9	[55]

*Clinically used features added by gynecologists.

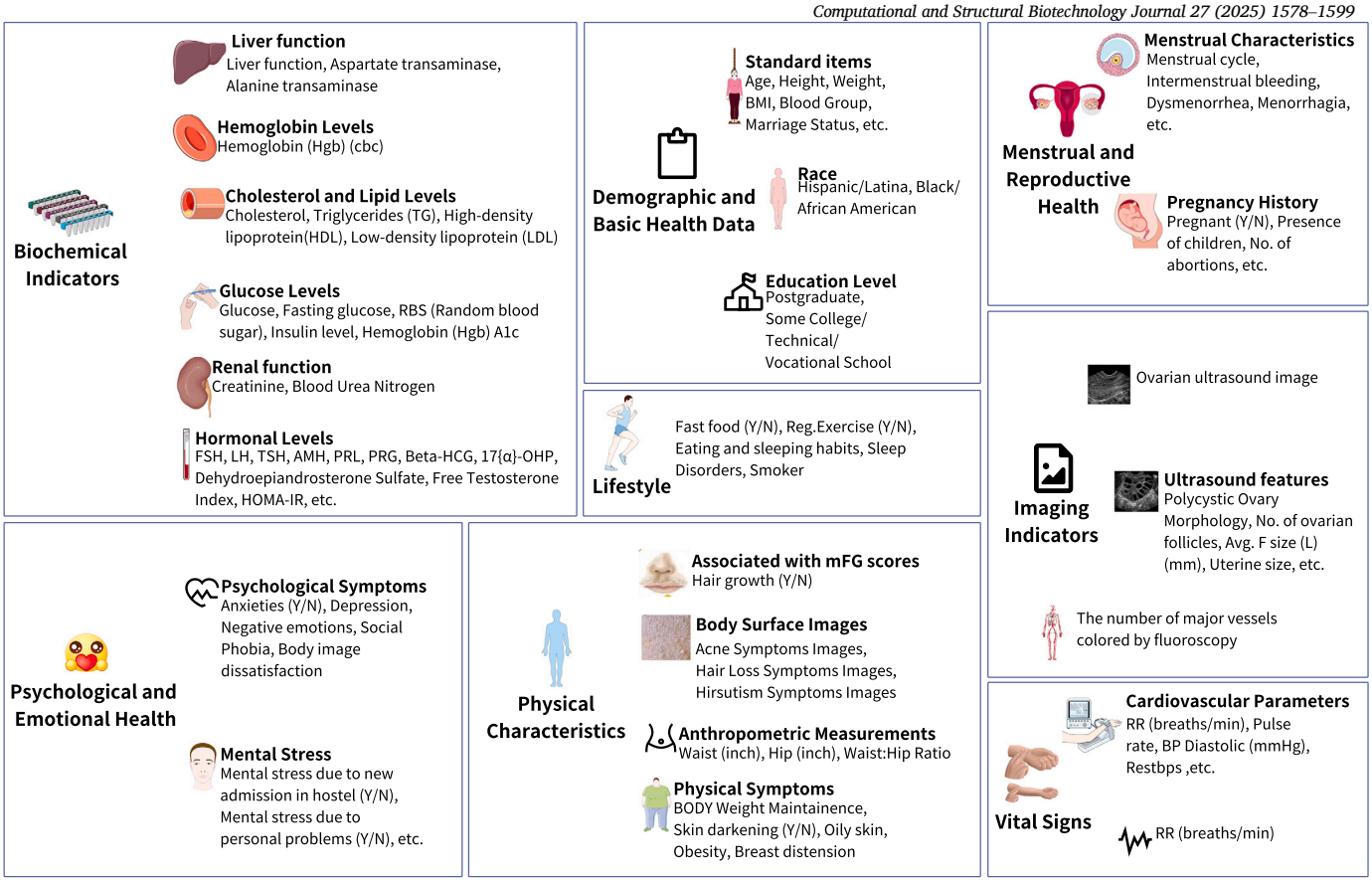


Fig. 5. Features Illustrated in PCOS Detection Taxonomy.

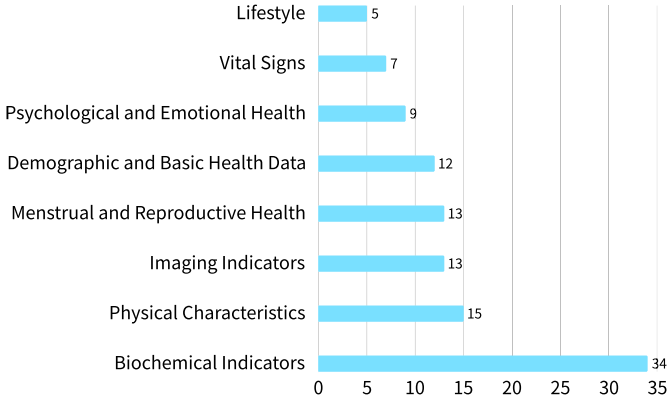


Fig. 6. The Distribution of Features Across Each Categories.

vides critical implementation guidance for researchers and clinicians developing PCOS detection tools. By understanding acquisition difficulty, researchers can optimize diagnostic tools that reduce resource expenditure, minimize diagnostic time, and decrease patient discomfort by prioritizing non-invasive methods when they can deliver comparable results. The outcome is a more efficient, cost-effective, and patient-centered diagnostic approach.

4.1.3. Survey results

To validate our taxonomy's clinical relevance and practical utility, we conducted both quantitative evaluation through an online practitioner survey (results in Table 4) and qualitative assessment through expert interviews (findings summarized in Table 5). Both evaluation methods yielded strong endorsement from clinical and research professionals in reproductive endocrinology and gynecology.

Survey results demonstrated robust support for our taxonomy framework. Among the 82 valid survey respondents, 91% assigned high ratings (4 or 5 on a 5-point scale) across all evaluation dimensions: structural rationality, classification validity, completeness, and practical utility. Notably, 94% of participants specifically endorsed our methodological innovations regarding feature acquisition pathways and implementation difficulty annotations. The survey also revealed significant gaps in current clinical practice: only 48% of respondents reported using any form of standardized PCOS classification system in their practice, while merely 22% had experience implementing AI-based detection tools. This substantial disconnect between the technical possibilities and clinical implementation highlights an important opportunity for knowledge translation and technology adoption in PCOS management.

Qualitative assessment through expert interviews (n = 4) further validated our taxonomy, with experts strongly supporting its potential to standardize PCOS diagnosis across clinical, endocrinological, gynecological, and research perspectives. They highlighted its role in improving clinical practice and advancing the development of intelligent diagnostic tools.

Answer to RQ1: Based on our systematic review of 93 scientific publications, we developed a comprehensive taxonomy of PCOS detection features. This taxonomy organizes 108 detection features into 8 distinct categories and provides annotations regarding acquisition methods and difficulty levels in clinical settings. The taxonomy received positive validation from 82 domain experts and researchers, including senior physicians and nurses.

Table 4
Feedback Results of Online Survey.

# Feedback	# Valid Feedback	Structural Rationality	Classification Validity
87	82	91%	94%

Completeness	Practical Utility	Acquisition Methods Annotation	Difficulty Levels Annotation
96%	92%	95%	94%

Table 5
Responses of Expert Interview.

Expert 1: "As a clinician, I am very interested in your taxonomy. The diagnosis of PCOS in clinical practice often relies on a comprehensive analysis of multiple symptoms and signs, but existing classification systems often lack standardization, leading to inconsistencies and misdiagnoses in clinical work. I believe your taxonomy can help clarify and unify the characteristics of different types of PCOS, providing doctors with a clearer framework for diagnosis."
Expert 2: "From an endocrinological perspective, the diagnosis of PCOS not only depends on ultrasound and clinical manifestations, but also involves hormone level testing. Your taxonomy covers multiple dimensions and takes into account the diversity of different features from a clinical perspective, which is highly commendable."
Expert 3: "From a gynecological perspective, the taxonomy you have developed helps bridge the gap between clinical practice and research. The multidimensional approach helps us better understand the different manifestations of PCOS, especially the differences across various patient groups."
Expert 4: "As a researcher in intelligent detection, I believe your taxonomy holds great potential, especially in advancing the development of intelligent diagnostic tools. The standardization of the taxonomy can provide a unified input framework for machine learning models, which is crucial for improving the accuracy and consistency of PCOS detection tools. Additionally, the system can facilitate interdisciplinary collaboration by offering a common framework for experts across fields like endocrinology, gynecology, and AI."

Table 6
Datasets List for PCOS Detection.

Dataset	Type	Scale	Usages	Openness	License	Year
D36	image	1457	3	Yes [64]	-	2019
D5	image	4492	2	Yes [65]	-	2021
D11	image	1639	1	Yes [66]	-	2022
D3	image	3856	16	Yes [67]	-	2022
D8	image	-	1	No [63](Restricted)	-	-
D6	numerical	768	2	Yes [68]	CC0: Public Domain	2016
D9	numerical	119	1	Yes [69]	-	2017
D10	numerical	1273	2	Yes [70]	-	2019
D12	numerical	100	1	Yes [16]	-	2020
D2	numerical	541	40	Yes [71]	CC BY-NC-SA 4.0	2020
D4	numerical	541	1	Yes [72]	-	2020
D7	numerical	541	2	Yes [73]	Data files © Original Authors	2021
D1	numerical	541	3	Yes [74]	-	2022

4.2. Dataset status

In addressing RQ2, we evaluated the current status of PCOS datasets across seven dimensions: openness, instance types, scale, usage frequency, license information, maintenance status, and feature coverage. Following our methodology (Section 3.5), we identified 36 datasets containing PCOS feature instances.

Table 6 presents the publicly accessible and restricted datasets, while the complete list of all 36 datasets is available on our website [37]. The following sections detail our analysis results for each dimension.

4.2.1. Openness

Dataset openness analysis (Fig. 7a) revealed that among the 36 PCOS datasets, 23 (64%) are not publicly available, 12 (33%) offer open access, and 1 (3%) requires restricted access. Most datasets used in PCOS research remain inaccessible to the broader scientific community. The restricted dataset D8 [63] requires membership for access, and the specific number of instances it contains is unclear. Therefore, in subsequent statistics, any data involving instance counts will exclude this dataset. This quasi-open status effectively restricts researchers' direct access to the data and impacts the usability and broad application of the datasets.

Insight: The predominance of closed-access datasets (67%) creates significant barriers to research reproducibility and collaborative innovation in PCOS studies.

4.2.2. Instance type

Instance type analysis (Fig. 7b) shows the 36 datasets comprise three data modalities: images, numerical data, and text. The distribution includes 14 image datasets (39%), 18 numerical datasets (50%), 3 hybrid datasets combining images and numerical data (8%), and 1 text dataset (3%). Notably, among all open-source datasets, none are multimodal. The lack of multimodal datasets (combining two or more instance types) hinders support for diverse diagnostic needs, limiting the generalization ability of existing tools.

Insight: The dominance of single-type datasets limits diagnostic versatility and tool adaptability in complex clinical scenarios.

4.2.3. Scale

Dataset scale analysis revealed considerable size variations across collections. The largest image dataset, D5 [56] contains 4,492 instances, substantially exceeding other image collections. Among numerical datasets, D10 [70] with 1273 instances, is the largest. Notably, D1 [74], D2 [71], D4 [72], and D7 [73] share identical instance counts, and further examination indicates a high degree of overlap in features, suggesting these datasets may originate from the same primary dataset. D4 [72] differs slightly by including an additional insulin level measurement feature.

4.2.4. Usage frequency

Usage frequency analysis identified D2 [71] and D3 [67] as the most frequently cited datasets, appearing in 40 and 16 publications re-

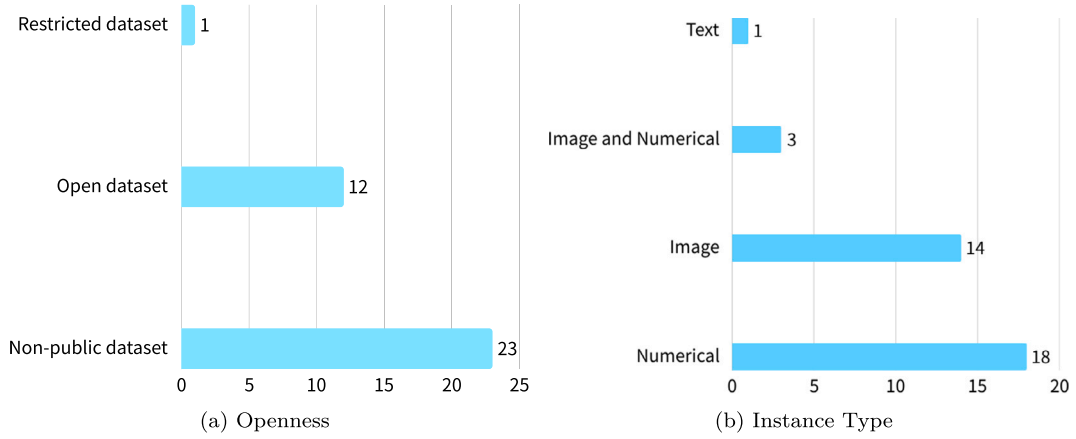


Fig. 7. The Openness and Instance Type of the 36 Datasets.

spectively. These datasets contain 541 and 3,856 instances, reflecting their established value in PCOS research. D2 [71] has gained particular prominence despite its moderate size, due to its comprehensive numerical features that facilitate algorithm training and evaluation.

4.2.5. License

License analysis of the 12 open-source datasets revealed that only three explicitly state their license terms. D6 [68] utilizes the CC0: Public Domain license, enabling unrestricted use without permission for both research and commercial applications. D2 [71] utilizes the CC BY-NC-SA 4.0 license, permitting researchers to share and modify the data for non-commercial purposes, provided they adhere to attribution, non-commercial use, and share-alike requirements [75]. This has contributed to the prominence of D2 [71] in academic citations. Additionally, D7 [73] only states that the data file copyrights belong to the original authors, lacking further usage terms, which may impose limitations on public use.

Insight: Only three datasets have clear usage licenses, while most lack explicit license information, leading to uncertainty in their use and potentially preventing researchers from using them due to legal issues.

4.2.6. Maintenance status

Maintenance status analysis of the 12 open-source datasets revealed varying update frequencies. The most recently maintained include D1 [74], D3 [67] and D11 [66] all last updated in 2022. However, several datasets show significant maintenance gaps. D6 [68] has not been updated since 2016, and D9 [69] last update was in 2017. Without sustained maintenance, affecting the applicability of models built on them, which is particularly problematic in fast-evolving fields like PCOS detection.

Insight: The lack of regular updates in datasets poses the risk of obsolescence, which can undermine the accuracy and reliability of models in PCOS detection research.

4.2.7. Coverage

Feature coverage analysis, as shown in the sixth column of Table 3, reveals that publicly available datasets collectively encompass 58 of the 108 PCOS features identified in our taxonomy, representing a 54% overall coverage rate. Individual datasets vary substantially in feature representation, ranging from 39 features (maximum) to just 1 feature (minimum). Some datasets exhibit limited feature coverage, hindering comprehensive support for future developments and applications of PCOS detection tools. Notably, our correlation analysis with performance metrics (Section 4.3) revealed no significant relationship between feature coverage and tool performance, suggesting that quality and relevance of features may outweigh quantity.

Answer to RQ2: Our analysis identified 36 PCOS datasets, of which 12 are publicly accessible. These datasets collectively cover 58 features, representing 54% of the 108 features in our taxonomy. However, several concerns exist with current datasets: absence of multimodal data integration, lack of recent updates, and insufficient license information.

4.3. Capabilities of intelligent detection tools

To address RQ3, we systematically evaluated the capabilities of PCOS detection tools from both scientific publications and gray literature. Applying the methodology described in Section 3.6, we identified and analyzed 42 representative PCOS intelligent detection tools.

Table 7 summarizes the key characteristics of these tools, including their implementation approaches, data requirements, and performance metrics. We present our analysis across five dimensions: technological approaches, input data types, performance evaluation metrics, temporal analysis capabilities, and tool comparison/availability status.

4.3.1. Technology

Our technology analysis (Fig. 8a) reveals that traditional machine learning approaches dominate the PCOS detection landscape, with 36 tools (86%) implementing these techniques compared to only 6 tools (14%) utilizing deep learning methods. Among classification techniques (Fig. 8b), Stacking Models (SM) show the highest adoption rate, implemented in eight tools. For feature selection approaches (Fig. 8c), PCA leads with implementation in four tools. Deep learning implementations primarily utilize CNN and MobileNet architectures, particularly for ultrasound image analysis or multimodal classification combining imaging with numerical data.

Model training and implementation require considerable computational resources across both ML and DL approaches. For example, T37 [40], which employs XGBoost for numerical data analysis, explicitly reports in its publication that “a computer system with an i7 2.50 GHz processor and 16 GB of primary memory” is the minimum hardware configuration for effective implementation. The substantial computational demands of more advanced tools may lead to higher implementation costs and extend the model development cycle, creating barriers to widespread adoption.

Insight: The computational requirements of complex models may limit their popularization in resource-limited medical institutions, further hindering the widespread application of advanced detection technologies.

Table 7
Tools List for PCOS Detection.

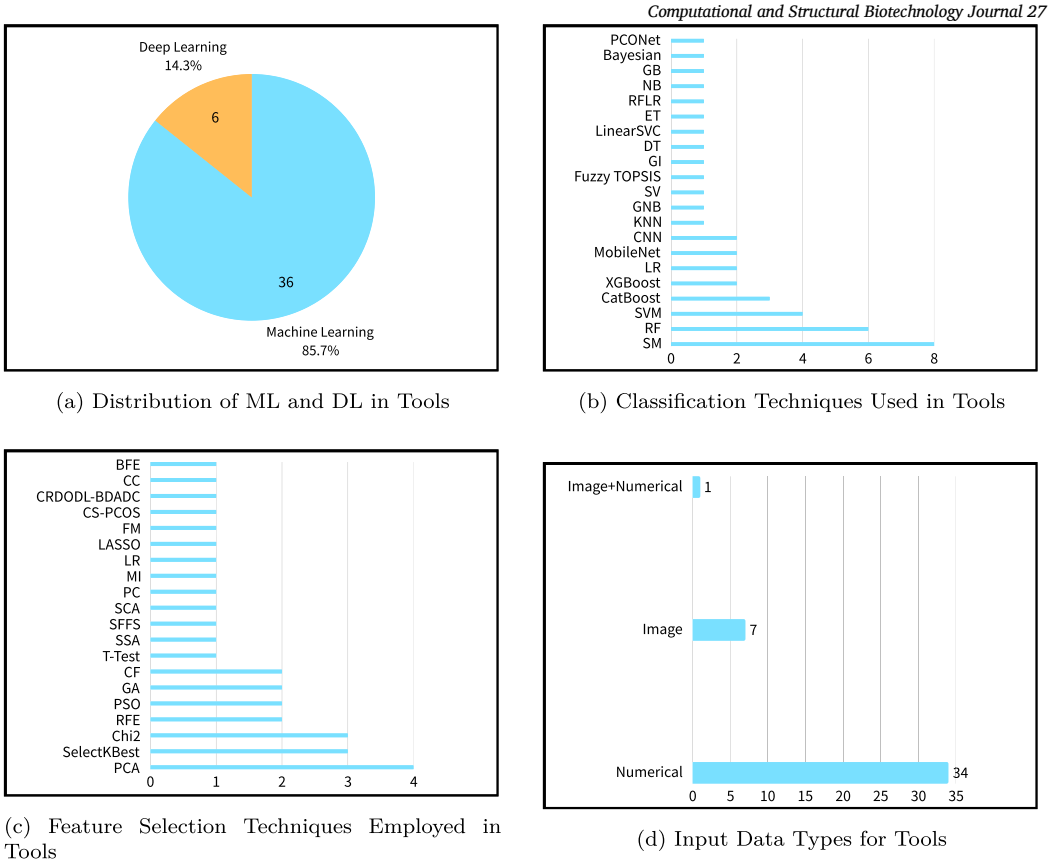
Tools	Year	Venue	Technique	Input Type	Accuracy	Precision	F1-Score	Recall	Clinical Validation	Compared by	Count	Availability
T4 [76]	2021	Frontiers in Public Health	KNN	image	97.00%	-	-	-	No	[53]	1	No
T1 [77]	2022	ICEET	PCONet	image	98.12%	96.00%	97.00%	97.00%	No	[78], [79], [80]	3	No
T20 [81]	2022	Scientific Reports	SM	image	99.89%	99.00%	99.00%	100.00%	No	[48]	1	No
T17 [82]	2023	ICEARS	CNN	image	95.00%	91.00%	95.00%	91.12%	No	[79], [80]	2	No
T18 [83]	2023	INDIACom	CNN	image	97.01%	97.06%	96.52%	97.31%	No	[79], [80]	2	No
T32 [84]	2023	GitHub	MobileNet	image	100.00%	-	-	-	No	-	0	Yes [84]
T36 [54]	2024	Expert Systems	SM	image	98.12%	97.88%	96.89%	97.16%	No	-	0	No
T5 [13]	2023	Appl. Comput. Intell. Soft Comput.	MobileNet	image+numerical	82.46%	84.62%	81.00%	78.57%	No	[23], [79], [80]	3	No
T19 [10]	2011	INDICON	Bayesian and T-Test	numerical	93.93%	82.50%	-	92.85%	No	[48], [85], [86], [51]	4	No
T27 [14]	2014	ICACCCT	SVM	numerical	95.00%	-	-	-	No	[46]	1	No
T26 [55]	2018	Int J Comput Eng Manag	NB	numerical	97.65%	95.00%	-	95.00%	No	[46,85]	2	No
T2 [11]	2019	TENCON	RF and PCA	numerical	89.02%	95.83%	42.00%	-	No	[36,18,48,87,52,22, 88,89,46,85,86,51]	12	No
T34 [90]	2019	GitHub	LR and CF	numerical	88.30%	88.90%	84.20%	80.00%	No	-	0	Yes [90]
T7 [91]	2020	IJMTES	LR and FM	numerical	92.00%	93.00%	92.00%	93.00%	No	[40,88,89,51]	4	No
T11 [12]	2020	TENSYMP	RFLR and SelectKBest	numerical	90.01%	89.90%	-	90.00%	No	[18,48,92,87,52,93, 88,62,89,86]	10	No
T12 [94]	2020	AMCI	RF	numerical	90.83%	91.33%	-	90.82%	No	[18,46,35]	3	No
T28 [95]	2020	IJSR	ET and GA	numerical	88.00%	88.00%	80.00%	73.00%	No	[35]	1	No
T3 [96]	2021	Biosci Biotechnol Res Commun	RF and Chi2	numerical	90.90%	89.10%	86.40%	80.00%	No	[97,40,52,88,89, 51]	6	No
T6 [85]	2021	ICABME	LinearSVC and SFFS	numerical	91.60%	93.66%	-	80.66%	No	[40,43,52,22,93]	5	No
T13 [86]	2021	CCWC	XGBoost and PCA	numerical	95.83%	97.50%	95.12%	92.86%	No	[18], [92]	2	No
T14 [16]	2021	Molecular and Cellular Endocrinol-ogy	SM and GA	numerical	89.32%	-	-	88.89%	No	[18]	1	No
T22 [15]	2021	ICCICT	DT and GI	numerical	81.00%	70.00%	52.00%	41.00%	No	[52]	1	No
T45 [46]	2021	Frontiers in Public Health	Fuzzy TOPSIS	numerical	98.20%	-	-	-	No	-	0	No
T33 [98]	2021	GitHub	CatBoost and CF	numerical	87.73%	82.93%	77.27%	72.34%	No	-	0	Yes [98]
T9 [99]	2022	TENSYMP	CatBoost and SelectKBest	numerical	96.34%	88.88%	94.11%	100.00%	No	[40]	1	No
T10 [100]	2022	Expert Systems with Applications	RF and CC	numerical	92.40%	-	-	-	No	[40,20,48,52,101]	5	No
T21 [102]	2022	AICDS	SVM and PC	numerical	93.00%	96.00%	-	-	No	[52], [101]	2	No
T24 [17]	2022	JMIR Formative Research	CatBoost and PCA	numerical	90.10%	95.00%	92.80%	90.90%	No	[101], [93]	2	No
T25 [103]	2022	ISDA	SV and SelectKBest, Chi2	numerical	91.12%	90.00%	90.00%	91.00%	No	[101]	1	No
T44 [62]	2022	IEEE Access	GNB and CS-PCOS	numerical	100.00%	100.00%	-	100.00%	No	-	0	No
T15 [101]	2023	Applied System Innovation	SM and SSA	numerical	98.00%	97.00%	98.00%	98.00%	No	[18]	1	No

(continued on next page)

Table 7 (*continued*)

Tools	Year	Venue	Technique	Input Type	Accuracy	Precision	F1-Score	Recall	Clinical Validation	Compared by	Count	Availability
T16 [52]	2023	Diagnostics	SM and RFE	numerical	98.87%	98.00%	98.89%	98.87%	No	[18]	1	No
T23 [101]	2023	Applied System Innovation	SM and MI	numerical	98.00%	97.00%	98.00%	98.00%	No	[52]	1	No
T39 [35]	2023	Expert Systems with Applications	SM and BFE	numerical	90.24%	90.00%	89.82%	89.93%	No	-	0	No
T40 [104]	2023	Heliyon	SM and PCA	numerical	95.70%	95.20%	95.00%	95.20%	No	-	0	No
T41 [105]	2023	Digital health	SVM and LASSO	numerical	94.40%	-	-	97.10%	No	-	0	No
T42 [34]	2023	EuJIM	SVM and RFECV	numerical	83.70%	-	87.80%	-	No	-	0	No
T43 [49]	2023	Expert Systems with Applications	GB and Chi2	numerical	98.90%	-	-	-	No	-	0	No
T8 [106]	2023	Research Square	RF and PSO	numerical	93.87%	92.31%	90.57%	88.89%	No	[40,20]	2	No
T35 [18]	2024	EAAI	RF and PSO	numerical	92.64%	95.24%	86.96%	80.00%	No	-	0	No
T37 [40]	2024	Multimedia Tools and Applications	XGBoost and SCA	numerical	98.78%	95.56%	96.69%	93.56%	No	-	0	No
T38 [23]	2024	Multimedia Tools and Applications	CRDODL-BDADC	numerical	96.93%	96.64%	96.37%	96.12%	No	-	0	No

Abbreviation of technology: KNN, K-Nearest-Neighbours; SFFS, Sequential Forward Floating Selection wrapper; PSO, Particle Swarm; RFLR, Optimization Hybrid Random Forest Logistic Regression; RFE, Recursive Feature Elimination; KNN, K-NearestNeighbor; SCA, Sine Cosine Algorithm; BFE, Backward Feature Elimination; LASSO, Least Absolute Shrinkage and Selection Operator Regression; RFECV, Recursive Feature Elimination with Cross-Validation; LR, Logistic Regression, GA:Genetic Algorithm; SSA, Salp Swarm Optimization; MI, Mutual Information; CF:, Correlation Factor; FM, Filter Method; CC, Correlation coefficient; SM, Stacking Model; GI, Gini Importance; SV, Soft Voting; PC, Pearson Correlation; GB, Gradient Boosting; ET, Extra Trees; NB, Naïve Bayes; GNB, Gaussian Naive Bayes.



(a) Distribution of ML and DL in Tools

(b) Classification Techniques Used in Tools

(c) Feature Selection Techniques Employed in Tools

(d) Input Data Types for Tools

Fig. 8. Analysis of Technological Components in PCOS Intelligent Detection Tools.

4.3.2. *Input data types*

Input data analysis (Fig. 8d) demonstrates a strong preference for single-modality approaches. Among the 42 detection tools, 34 (81%) process exclusively numerical data, while 7 (17%) rely solely on image analysis. Only T5 [13] implements a multimodal approach by integrating both image and numerical data. This overwhelming predominance of unimodal tools (98%) contrasts sharply with the multifaceted nature of PCOS diagnosis in clinical practice, which typically requires synthesis of diverse data types. Notably, even tool developers acknowledge this limitation—the authors of T10 [100] explicitly state that "This study's future scope could include the use of multi-modality data sets for PCOS diagnosis, such as ultrasound scans, as well as the use of different or larger data sets for diagnosis." This recognition of multimodal data's importance, without actual implementation in current tools, further highlights the gap between clinical diagnostic processes and computational approaches.

Insight: The critical shortage of multimodal detection tools (only 2%) prevents the full utilization of multimodal data to enhance diagnostic accuracy.

4.3.3. *Performance metrics*

Performance metrics analysis revealed significant variations across PCOS detection tools. Image-based tools demonstrated particularly strong results, with T32 [84] achieving 100% accuracy and T20 [81] reporting 99% precision and F1 scores with 100% recall. These findings highlight the diagnostic potential of properly analyzed imaging data. These findings highlight the diagnostic potential of properly analyzed imaging data. Numerical data-based tools showed comparable capabilities, with T29 [107] and T44 [62] both achieving 100% accuracy and precision through effective feature selection and classification algorithms. T9 [99] demonstrated perfect recall (100%), indicating exceptional sensitivity. T2 [11], despite high accuracy (89%) and precision (96%), reported a substantially lower F1 score (42%), revealing a critical imbalance between precision and recall that could result in missed diagnoses. Importantly, as shown in the tenth column of Table 7, none of the 42 tools have undergone formal clinical validation. Most remain in preliminary research phases without real-world clinical testing. For instance, T10 [100] is explicitly described in its publication as "an experimental method based on machine learning," clearly indicating its pre-clinical status.

Insight: The gap between laboratory performance and clinical validation represents a critical limitation, as algorithmic success in controlled environments may not translate to diverse real-world patient populations and clinical scenarios.

4.3.4. *Temporal analysis capabilities*

Temporal analysis capabilities assessment revealed a universal limitation: 100% of examined tools (N = 42) exclusively utilize single time-point data for binary diagnostic outputs, with none offering longitudinal progression analysis or predictive risk assessment. This limitation is evident even in tools that claim predictive capabilities. For instance, T2 [11] explicitly states in its publication that it "proposes a system for the early detection and prediction of PCOS from optimal and minimal but promising clinical and metabolic parameters, which act as an early marker for this disease." However, closer examination reveals that T2 [11] relies solely on single time-point data analyzed through a Random Forest Classifier—an algorithm designed for static classification rather than temporal progression modeling. Similarly, most tools, such as T10 [100], simply state their ability to "detect and diagnose PCOS" without any mention of temporal analysis capabilities. This cross-sectional approach is fundamentally misaligned with the dynamic clinical nature of PCOS, in which manifestations evolve throughout a patient's lifespan. The absence of longitudinal analysis capabilities may stem primarily from two factors: the complete absence of longitudinal datasets tracking PCOS progression over time, and the prevalent implementation of

feature selection and classification algorithms inherently designed for static rather than sequential data analysis.

Insight: The gap in temporal analysis capabilities presents a critical opportunity for PCOS detection tools to evolve from one-time diagnostics to longitudinal monitoring systems that enable proactive risk prediction and personalized treatment aligned with the syndrome's dynamic nature.

4.3.5. Tool comparison and availability status

Tool comparison and availability analysis identified T2 [11] and T11 [12] as benchmark standards, serving as comparison references in 12 and 10 other studies respectively—indicating their substantial academic influence. A notable dichotomy emerged between academic and practical implementation: the most academically influential tools remain closed-source, while open-source implementations derive exclusively from gray literature. These open-source tools, despite enabling broader implementation, have not been included in comparative evaluations within the scientific literature, creating a disconnect between academic validation and practical accessibility.

Insight: The dominance of closed-source tools in academic comparisons limits transparency and broader adoption, while open-source tools, though underrepresented, offer key benefits for scalability and collaboration.

Answer to RQ3: We evaluated 42 representative PCOS detection tools, all utilizing machine learning and deep learning technologies. These tools demonstrate strong performance on their respective test datasets, with some achieving 100% detection accuracy. Despite these promising results, several limitations persist: high computational resource requirements, limited multimodal data processing capabilities, insufficient clinical validation, and inadequate longitudinal analysis capabilities.

5. Discussion

In this section, we critically examine our research findings through three key perspectives: takeaways, methodological limitations, and emerging challenges that warrant future investigation.

5.1. Takeaway

Our comprehensive taxonomy of PCOS detection features provides valuable insights for diverse stakeholders across academia, healthcare, and industry.

- *Standardization*: As Expert 1 mentioned in Table 5. Researchers and medical professionals will benefit from the taxonomy, which offers a standardized framework for PCOS detection features. The taxonomy eliminates ambiguities and facilitates clear communication between researchers and industry experts, ultimately enhancing their understanding of detection features.
- *Data Evaluation*: Data scientists will find valuable insights for future data collection and usage strategies. We conducted a detailed analysis of the datasets used for PCOS detection, evaluating aspects such as openness, size, maintenance status, and coverage. This process uncovered deficiencies in feature coverage and the availability of multimodal data, providing a clear direction for future dataset improvements.
- *Tool Evaluation*: Researchers in the field can utilize the results of the tool evaluation to refine existing tools or develop new methodologies that enhance diagnostic accuracy. By assessing the capabilities of existing PCOS detection tools, we identified their limitations, guiding the development of more efficient detection algorithms.
- *Interdisciplinary Collaboration*: As Expert 4 mentioned in Table 5. The taxonomy offers a common language and toolset for researchers across different fields, promoting interdisciplinary collaboration and supporting the integration of various diagnostic methods to enhance the comprehensiveness of PCOS detection. This fosters teamwork among medical researchers, data scientists, and healthcare practitioners, ultimately improving patient outcomes.
- *Clinical Impact*: Our taxonomy serves as a comprehensive reference for clinicians, mapping both utilized and underrepresented diagnostic indicators in current detection systems. By exposing the disconnects between established clinical knowledge and technological implementation, our findings enable more informed clinical decision-making regarding AI tool adoption. Ultimately, this framework supports the development of more holistic detection systems that could facilitate earlier diagnosis and personalized treatment planning.

5.2. Limitations

This study has several limitations that may affect the generalizability and accuracy of the findings.

First, our taxonomy relies exclusively on features extracted from accessible literature and publicly available datasets. Access limitations, language barriers, and database restrictions may have excluded relevant sources, potentially introducing selection bias that affects taxonomy completeness. Additionally, our gray literature inclusion criterion (requiring at least one star and fork) may have introduced selection bias, as these metrics can be influenced by the authors themselves.

Second, despite incorporating expert feedback during feature labeling, the inherently subjective nature of manual annotation may have introduced inconsistencies in feature classification. Resource constraints prevented us from independently validating the performance of each PCOS detection algorithm, potentially allowing discrepancies between reported and actual tool effectiveness to persist in our analysis.

Third, our study relies on currently available public datasets, which may not fully represent the diversity and complexity of PCOS patients, especially in the absence of multimodal data, limiting the generalizability and applicability of our conclusions in different clinical settings.

Finally, the rapid evolution of PCOS detection technologies presents inherent challenges to the longevity of our findings. As emerging algorithms, feature extraction methods, and diagnostic approaches develop, our taxonomy will require regular updates to maintain clinical relevance and technological currency.

5.3. Challenges

Our research identifies three critical challenges impeding PCOS detection advancement: taxonomy timeliness constraints, dataset limitations, and detection tool deficiencies. Strategic solutions to these challenges are essential for meaningful progress in both research and clinical applications.

5.3.1. Taxonomy deficiencies

The taxonomy lacks mechanisms for real-time updates, hindering its adaptability to emerging diagnostic trends, novel biomarkers, and technological innovations in this rapidly evolving field. As PCOS research increasingly incorporates multi-omics data, the existing framework struggles to integrate these complex dimensions and their interactions with traditional clinical manifestations. Additionally, the marked heterogeneity of PCOS across diverse populations challenges the establishment of a universally applicable yet clinically specific classification system.

To address this challenge, future research should develop a dynamic, self-updating taxonomy with automated learning capabilities. Such a system would continuously extract and integrate new features from emerging literature and clinical datasets, intelligently adjusting

feature weights and relationships based on evolving evidence. Implementation of cross-disciplinary validation protocols would ensure clinical relevance while maintaining scientific rigor. This evolution from static framework to adaptive tool would significantly enhance the taxonomy's utility in AI-driven diagnostics and enable more personalized approaches to PCOS management.

5.3.2. Dataset inadequacies

Existing PCOS datasets present significant limitations that impede research progress. These constraints include restricted accessibility, infrequent updates, insufficient sample sizes, and a notable absence of multimodal dataset. While some datasets are widely utilized in research, most fail to combine multiple data types—a deficiency that compromises diagnostic accuracy and restricts the generalizability of detection algorithms. Even publicly available datasets often lack relevance to contemporary clinical practices, further diminishing their research value.

Addressing these dataset challenges requires coordinated action across the research ecosystem. Strategic institutional collaborations between academic centers, healthcare providers, and technology developers offer promising pathways for developing more comprehensive resources. Additionally, implementing standardized data sharing frameworks with robust privacy protections, consent mechanisms, and maintenance protocols would substantially enhance data quality and availability.

To directly address these identified gaps, we have established partnerships with Shenzhen People's Hospital and gynecological specialists across African institutions. These collaborations focus on developing new datasets that incorporate patients from diverse ethnic backgrounds, geographic regions, and clinical presentations—better reflecting real-world diagnostic challenges and improving detection accuracy across heterogeneous patient populations.

5.3.3. Detection tool constraints

Existing intelligent detection tools exhibit critical limitations that compromise their clinical utility. These tools frequently suffer from high computational resource requirements, limited multimodal processing capabilities, insufficient clinical validation, and—perhaps most significantly—an absence of longitudinal analysis capabilities. Most current approaches are restricted to single data types and isolated timepoint assessments, failing to capture the dynamic nature of PCOS progression throughout a patient's life. Moreover, their development using region-specific datasets undermines their applicability across diverse healthcare settings with varying patient demographics.

Future research should prioritize developing computationally efficient, multimodal detection models with robust temporal analysis capabilities. Such advanced tools could transform PCOS management by enabling pre-symptomatic identification of high-risk individuals, facilitating personalized treatment pathways based on disease progression patterns, and supporting proactive rather than reactive care approaches. Incorporating large-scale pre-trained models with few-shot and zero-shot learning techniques could enhance model adaptability while maintaining sensitivity to patient-specific temporal variations, even with limited training data. These technological advances would effectively transform PCOS detection from an isolated diagnostic event into a continuous monitoring system, significantly improving health outcomes for affected individuals.

In conclusion, addressing these challenges will lay a robust foundation for advancing PCOS detection. Research priorities should focus on developing dynamic taxonomical frameworks, constructing comprehensive multimodal datasets with diverse representation, and creating clinically validated detection tools with longitudinal monitoring capabilities. These coordinated efforts will significantly enhance diagnostic accuracy, system scalability, and ultimately, improve patient outcomes across diverse healthcare settings.

6. Conclusion

This study addresses critical barriers in PCOS detection research, specifically concerning the taxonomy of detection features, intelligent detection tools, and available datasets. We constructed a comprehensive taxonomy of PCOS detection features based on 93 relevant papers. This taxonomy comprises 8 categories encompassing 108 features, with annotations for each feature's acquisition method and difficulty level. Using this taxonomy as a foundation, we analyzed PCOS datasets, evaluating their current status and limitations for detection research. We also reviewed existing intelligent detection tools, revealing their capabilities and limitations. Our future work will focus on developing a unified dataset to enable systematic comparison of detection tools, ultimately leading to more efficient PCOS detection algorithms.

CRediT authorship contribution statement

Meng Li: Writing – review & editing, Writing – original draft, Resources, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Zanxiang He:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Liyun Shi:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Mengyuan Lin:** Validation, Methodology, Investigation, Conceptualization. **Minge Li:** Validation, Methodology, Investigation. **Yanjun Cheng:** Validation, Investigation, Data curation. **Hongwei Liu:** Visualization, Project administration, Methodology. **Lei Xue:** Writing – review & editing, Project administration, Methodology. **Kabir Sulaiman Said:** Writing – review & editing, Methodology, Investigation. **Murtala Yusuf:** Writing – review & editing, Investigation. **Hadiza Shehu Galadanci:** Writing – review & editing, Formal analysis. **Liming Nie:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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