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A Literature Review on Machine Learning Approaches for Polycystic Ovarian Syndrome

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Abstract. Polycystic ovarian syndrome (PCOS) is a condition found in women of reproductive age and has been shown to have a major impact on the cause of infertility. PCOS displays symptoms such as obesity, irregular periods, excessive male hormone secretion, acne, and hirsutism. It's not just ovarian dysfunction, but also the primary cause of female infertility worldwide. As a result, treating PCOS has become increasingly important. In terms of medical diagnostics by human specialist, it is very limited due to its mildness, complexity and the variety of the disease. Machine learning is a type of artificial intelligence that enables systems to learn and improve on their own without the need for explicit programming. Machine learning performed better than traditional statistical analysis. Machine learning provides highly accurate solutions to medical diagnosis and potential alternative to future application in healthcare industry. By using the right keywords, it is necessary to collect articles in line with the discussed research topics. Generated content is used by Harxing's Publish or Perish application to search for Scopus-indexed research books. The paper provides a review of the research done on diagnosis of disease using different machine learning algorithms of PCOS. Based on the review, there are several algorithms used: Naive bayes, Logistic, K-Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient, Artificial Neural Network (ANN), Lasso, Principal Component Analysis (PCA), Natural Language, Decision Tree, K-Means. KNN, SVM and ANN are commonly used in disease identification research.

Keywords: K-Nearest Neighbor, Machine Learning, Polycystic Ovarian Syndrome, Systematic Literature Review

1. Introduction

Polycystic Ovary Syndrome (PCOS) is a condition that affects women who have high levels of androgens, which can manifest as excess testosterone or androgenic disorders such as hirsutism or hyperandrogenemia. Women with PCOS may also experience ovulatory failure, irregular menstruation, and polycystic ovarian morphology, which is an excess of preantral follicles in the ovary(Azziz et al., 2016) . PCOS affects between 5 to 20% of women of childbearing age worldwide, and in 2004, it had an economic impact of over $4 billion in the United States alone. Additionally, PCOS is associated with an increased risk of breast cancer, type 2 diabetes (T2DM), and other conditions.

PCOS is a significant contributor to ovulatory infertility and impacts between 5 to 20% of women of reproductive age (Azziz et al., 2016) (Zhang et al., 2021). At present, the world's female population is affected by premature birth, infertility, and anovulation. Polycystic ovarian syndrome (PCOS) is a condition found in women of reproductive age and has been shown to have a major impact on the cause of infertility. The condition is challenging to diagnose due to the diversity of associated symptoms and the presence of multiple gynecological disorders linked to it. (Denny et al., 2019). Certain genetic markers for PCOS can serve as predictive and diagnostic tools, but their effectiveness may be limited by the condition's intricate genetic nature. Combining several markers in a diagnostic panel can significantly improve the success rate (Xie et al., 2020). PCOS is the primary cause of female infertility worldwide and has garnered attention not only for its ovarian dysfunction but also for other related characteristics. As a result, the treatment of PCOS has become increasingly vital (Wang et al., 2022).

Although symptoms of PCOS are more common among women of reproductive age, the condition can also present risks and symptoms in prepubertal and postmenopausal women, which are only now beginning to be recognized. Around 50-80% of women with PCOS are obese, and the risk of developing related conditions is affected by factors such as age, obesity, and a family history of diabetes (McCartney & Marshall, 2016). From many articles and books, PCOS will target women who are still of childbearing age or still have an active level of ovarian function. Many are conducting research related to this disease because there are still many who do not know about PCOS disease, but this disease can also be considered a dangerous disease. PCOS symptoms encompass a range of manifestations such as excessive hair growth, menstrual irregularities, acne, hormonal imbalances, obesity, diabetes, and difficulties with fertility, often associated with high levels of insulin or insulin resistance (Maheswari et al., 2021). Moreover, women with polycystic ovary syndrome often experience insulin resistance. This leads to increased production of androgens in the ovaries (and adrenal glands) and higher levels of androgens available in the body due to decreased sex hormone-binding globulin levels (McCartney & Marshall, 2016).

Nowadays, technology has been developed to significant progress. One of the results of technology is artificial intelligence (AI). Machine learning (ML) has emerged as a powerful tool in various fields to develop intelligent predictive algorithms in the domain of artificial intelligence. With machine learning, it's possible to analyze high-dimensional and multivariate data, and uncover complex and dynamic relationships within the data, even in industrial environments (Wuest et al., 2016). However, the performance of these applications depends on the right choice of machine learning techniques. Machine Learning applications are revolutionizing healthcare, including sensing, data prediction, and image recognition. Its primary objective is to create algorithms that can utilize datasets provided to them and use the information for the purpose of network learning (Denny et al., 2019).

Machine learning performed better than traditional statistical analysis. Therefore, these studies supported the feasibility of machine-learning approaches to problem- solving (Wang et al., 2022). AI can also identify patterns in medical data, such as hormone levels, to differentiate PCOS patients from those who do not have it (Ndefo et al., 2013). This increased accuracy can diagnose PCOS patients earlier and more accurately for overall accuracy results (Ndefo et al., 2013).

Treatment options for PCOS involve a combination of medication and lifestyle changes. In addition, scanning procedures like ultrasound scans may be performed to monitor the condition. It is important to note that treatment for PCOS aims to control the symptoms and improve overall health, but it may not completely cure the condition. The early detection and diagnosis of PCOS with minimal tests and imaging procedures is of utmost importance and of great significance as the condition directly leads to ovarian dysfunction with an increased risk of miscarriage, infertility or even gynaecological cancer and mental agony for the patients due to wastage of time and money (Denny et al., 2019). The objective of conducting this systematic literature review is to review the recent literature to determine what has been studied and what can be concluded about machine learning to identify PCOS. Thus, the present study aimed to explore the effects of diagnose in patients with PCOS and predict using a machine- learning approach. The limitations arise from variations in the materials and methods used by different researchers, resulting in differing focuses of each study despite their common identification of PCOS disease.

2. Methodology

2.1. Research Question

The first stage for identifying problems in a study is making research questions. This is useful for facilitating research and providing boundaries to focus research. The following is a research question compiled for special research from the review as follows:

- RQ1: What keywords are in the research of machine learning for identifying PCOS?
- RQ2: What machine learning algorithm is used to identify PCOS?
- RQ3: What journals have published a Machine Learning for Identification PCOS?
- RQ4: What is the most algorithm used for analysed PCOS?
- RQ5: How many studies about analysed PCOS with machine learning?

2.2. Record Identification and Screening

2.2.1 Keywords Decision

By using the right keywords, it is necessary to collect articles in line with the discussed research topics. In this research, the keywords are collected by defining the terms in the research questions and using keywords and suffixes according to the research subject and if needed from the “AND” and “OR” operators.

This research reviews articles indexed by Scopus, so the keywords used are in English. The search strings are obtained as follows:

1. ((“Polycystic Ovarian Syndrome” OR “PCOS”) AND “Machine Learning”)
2. ((“PCOS” OR "Polycystic Ovary Syndrome”) AND “Identification”)
3. ((“PCOS” OR "Polycystic Ovary Syndrome”) AND “Deep Learning”)
4. (“SVM” AND (“PCOS” OR "Polycystic Ovary Syndrome”))
5. (“PCOS” AND “KNN”)
6. (“PCOS” AND “CLASSIFICATION”)

The search strings above are used as search keywords in this study. Search for articles Harzing Publish or Perish (PoP) App only articles indexed by Scopus were filtered. For each keyword obtained fewer than 100 articles that related to the research topic, so it is equal to 200-400 articles but only 35 articles are eligible for this research.

2.2.2 Quality Evaluation

- **Inclusion and Exclusion Criteria**

In order to obtain articles relevant to a research topic, specific criteria such as inclusion and exclusion criteria must be chosen. Entry criteria are used as criteria for document selection, and exit criteria are not used in document selection (Table 1).

Table 1: Inclusion Criteria and Exclusion Criteria

No	Inclusion Criteria	Exclusion Criteria
1	Research journal published between 2013-2023	Research journals not published in general or for a fee
2	English language research journals	Non-English language research journals
3	Research journals have a quartile value and an SJR value with a minimum of 0.15	Research journals don't have quartile values or SJR values
4	Research journals use machine learning methods to identify PCOS	Research journals not use machine learning for PCOS identification

- **Prisma Protocol**

Once the inclusion criteria were set, the study commenced with the search for relevant articles using the PRISMA (Preferred Reporting Items for Systematic Review and Meta-analysis) protocol. With PRISMA there are 3 steps to remove research reviews to make them appropriate and aligned with the research topic. These steps are described in the following flowchart (Figure 1).

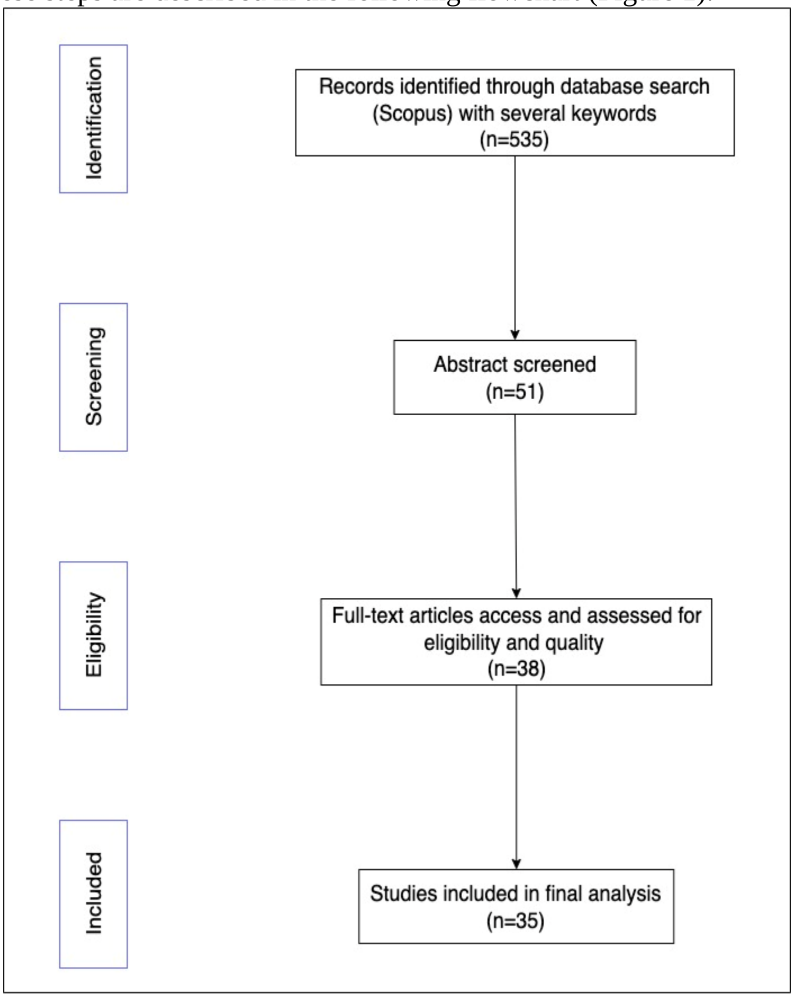

Fig.1: PRISMA flow diagram for the systematic review of articles included in this review

3. Result & Discussion

3.1. Keywords

Generated content is used by Harxing's Publish or Perish application to search for Scopus-indexed research books. The following are the search results for each generated keyword (Figure 2).

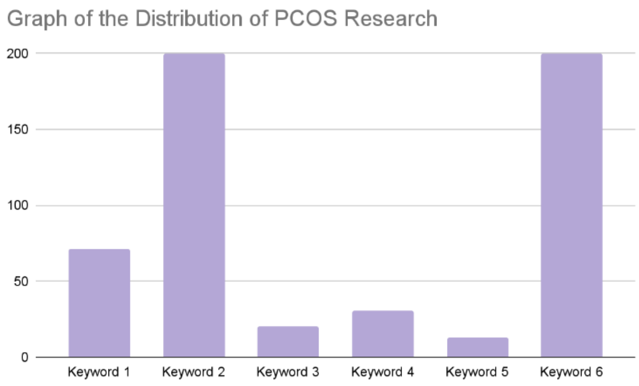

Fig.2: Graph of Distribution of PCOS Research

After obtaining research papers by keyword search through Harzing's Publish or Perish application, there is an option to determine the quality of the research papers obtained. Research papers will be reviewed using the SCImago Journal & Country Rank website. The criterion for the research articles has an SJR value greater than 0.15. The screening was performed using the PRISMA protocol using predefined inclusion and exclusion criteria using criteria to ensure the quality of the research articles. Then 35 research articles that met the Scopus Quartile Rating qualification obtained as follows below is a graph of the distribution of SJR values from research articles that meet the requirements (Figure 3).

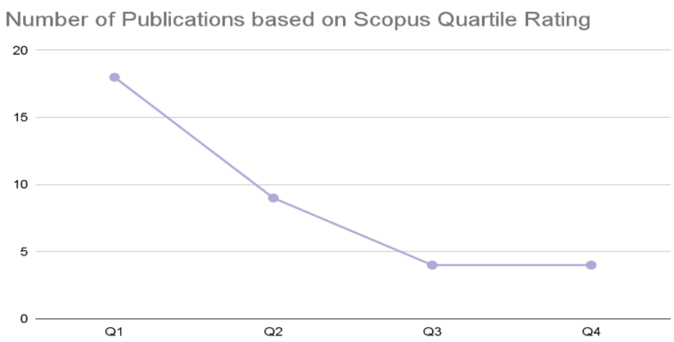

Fig.3: Graph of Distribution of Number of Publications based on Scopus Quartile Rating

The graph shows that the quartile value of the journals evaluated by the SJR value is proportional to the obtained Scopus quartile score.

3.2. Machine Learning Algorithms

Related to conducting a search for the identification of PCOS, there are still not many articles discussing the identification of PCOS disease. So, as support for the search, other research articles were obtained based on several algorithms or methods used to be able to identify PCOS disease. Each of the methods used can be run based on data in the form of images, but there is also data in the form of numeric data based on the examination results of each patient. there are several algorithms used: Naive bayes, Logistic, K-Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient, Artificial Neural Network (ANN), Lasso, Principal Component Analysis (PCA), Natural Language, Decision Tree, K-Means. KNN, SVM and ANN are commonly used in disease identification research (Figure 4).

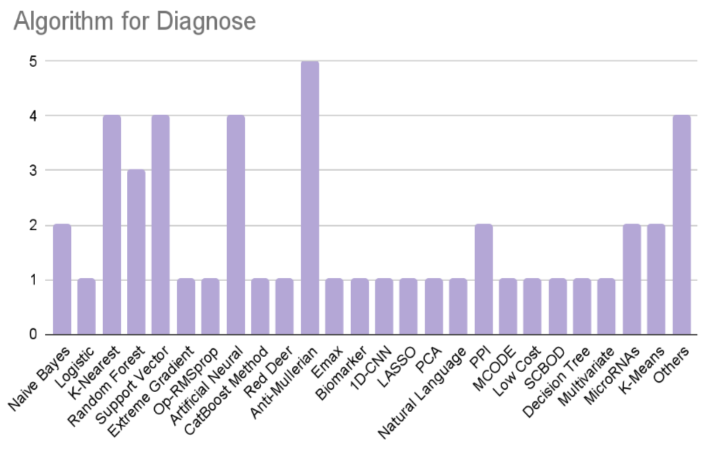

Fig.4: Graph of Algorithm for Identify

3.3. Journal Research

Of the 35 research articles that passed the qualification, 32 journals published those articles. Journal Human Reproduction is the publisher with the most publications of 3 qualifying research papers (Figure 5).

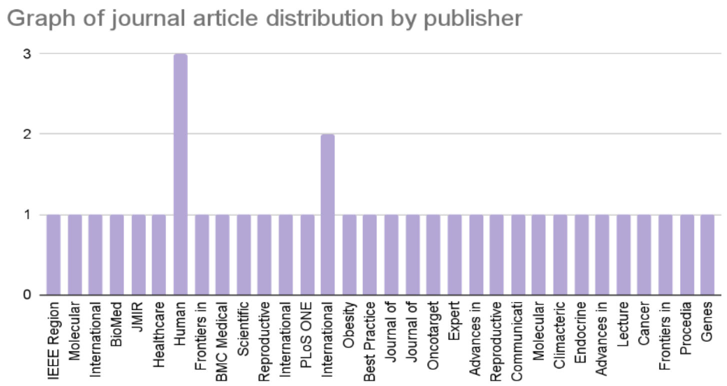

Fig.5: Graph of distribution of number of research article based on journal publisher

3.4. **Research** Article for PCOS

From 35 selected research articles on PCOS disease. Most of the surveys conducted are identified with a total of 10, and other studies with a total of 11. The following is a distribution graph (Figure 6).

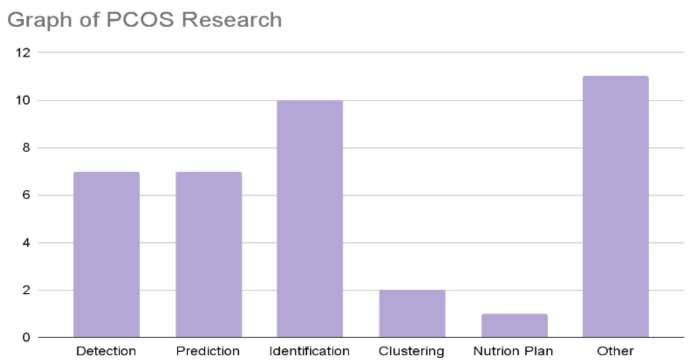

Fig.6: Graph of PCOS Research

This shows that little research has been conducted to identify PCOS disease using machine learning methods. Where the PCOS identification system using machine learning will help health experts in checking PCOS disease. Because PCOS disease has a diagnosis that is fairly easy to see, but it has a more examination process to find out whether you have PCOS disease or not. Due to the different perspectives and research methods employed, which involve varying methods and symptoms, it can be challenging to achieve a comprehensive diagnosis of PCOS using machine learning.

3.5. Research Article Summary

Based on the 36 research articles included in carrying out the PRISMA protocol. The research articles have been analyzed to obtain the objectives, methods, and results that have been achieved. The following table shows the results of research articles (Table 2). Various machine learning algorithms were employed. KNN, SVM and ANN are commonly used in disease identification research. KNN classifier had the best result in terms of sensitivity (Hdaib et al., 2022), the SVM was chosen as the best performer in terms of precision, accuracy and recall (Abu Adla et al., 2021), and incorporation of ANN and Naïve Bayes produced the best result in accuracy (Thomas & Kavitha, 2020).

Table 2: Research Articles Results

Author	Method	Result
(Denny et al., 2019)	Naïve Bayes classifier method, logistic regression, K-Nearest neighbor (KNN), Classification and Regression Trees (CART), Random Forest Classifier, Support Vector Machine (SVM) in Spyder Python IDE	Best method with Random Forest Classifier with accuracy 89%
(Zhang et al., 2021)	The algorithms used were k-nearest neighbor, random forests, and extreme gradient boosting.	Models for classification, An accuracy rate of 89.32% was achieved by utilizing follicular fluid and employing k-nearest neighbor, random forest, and extreme gradient algorithms. This rate was notably higher than the accuracy achieved with follicular fluid samples, which had a rate of 74.78%.
(P & C, 2022)	- the optimized-hybrid - Op-RMSprop (Optimized-Root Mean Square Propagation)	got exhibited89.03% accuracy with optimized hybrid method for tested over the PCOS datasets
(Xie et al., 2020)	-Random Forest - Artificial Neural Network	The microarray dataset showed an Area Under Curve (AUC) of 0.7273, while the RNA-seq dataset had an AUC of 0.6488.
(Zigarelli et al., 2022)	- CatBoost method for classification - K-fold cross-validation for estimating the performance of models - SHAP (Shapley Additive Explanations) values to explain the importance of each variable.	In patient models, the accuracy rate of predicting PCOS status without invasive measures ranged from 81% to 82.5%, while The accuracy rates obtained by using both noninvasive and invasive predictor variables ranged from 87.5% to 90.1%.

(Sreejith et al., 2022)	- red deer algorithm - random forest classifier	The proposed approach, which used a set of 20 optimized functions, the model achieved an accuracy rate of 89.81%, with a specificity of 90.43% and a sensitivity of 89.73%.
(Fraissinet et al., 2017)	- anti-Mülleran hormone (AMH) - Ultrasound	In this population, inconsistencies were found between ultrasound (U/S) and serum AMH measurements were taken to evaluate the polycystic ovarian morphology (PCOM) in 103 patients, which accounted for 16.1% of the sample. However, the study still found that the diagnosis of PCOM using serum AMH levels and pelvic U/S results had good agreement (83.9%), which is consistent with previous studies.
(Wang et al., 2022)	- Emax of carnitine	To obtain the best therapeutic outcome, patients with PCOS were administered 250 mg/day of carnitine supplementation for a minimum of 14.4 weeks to determine the effect of this supplementation on body weight.
(Yu et al., 2021)	- Biomarkers	- Proteomic biomarkers help to understand PCOS bette - There was no significant statistical difference observed in terms of age and BMI between the two groups (with a p-value > 0.05).
(Mohammed et al., 2021)	- deep learning model - one-dimensional convolutional neural network (1D-CNN) - SVM models were used with different types of kernels, including radial basis function, linear, and polynomial kernels. - artificial neural networks (ANN) - K-nearest neighbors (kNN) - bagging trees. - LASSO regression.	Compared to other classifiers, LASSO exhibits superior performance.

(Sun et al., 2019)	- SWATH mass spectrometry - PCA (Principal Component Analysis)	- The SWATH technique identified 5408 composite features, while the DDA technique identified 3942 composite features in follicular fluid. - SWATH mass spectrometry has revealed 9 probable metabolic biomarkers.
(Castro et al., 2015)	- electronic health records - Natural language processing	To identify positive/probable PCOS, the study used a cutoff value that classified 6,295 patients (48.6%) in the data store as true PCOS, This means that the test has a 91% accuracy rate in predicting positive or probable PCOS cases, with a confidence interval of 95% ranging from 0.84 to 0.96.
(Ramly et al., 2019)	- PPI - MCODE - Pathway - network - Subnetwork	- The PCOS PPI network was constructed using 8185 proteins that were related to PCOSrps. - The MCODE algorithm was used to identify 17 diseases within 12 disease subnetworks of PCOS.
(Branavan et al., 2018)	low cost genotyping techniques	Cases and controls did not show any significant difference in terms of the demographic characteristics of the two groups were similar, suggesting comparability. However, women with PCOS had significantly higher BMI and MFG scores.
(Jeevitha & Priya, 2022)	- SCBOD (Size and Count-Based Ovarian Detection) Algorithm - in Ultrasound Image - SVM Classifier	Accuracy gives 94% yield with good yield.
(Skubleny et al., 2015)	- Bariatric surgery - Systematic review	The association between obesity and PCOS and its clinical implications are complex and may be linked.

(Dewailly, 2016)	-Androgens - anovulation - ultrasound - anti-mullerian	
(Sahmay et al., 2014)	- anti-Müllerian hor- mone (AMH) - clinical features of polycystic ovary syn- drome (PCOS), - polycystic ovarian morphology (PCOM), - oligo/amenorrhea (OA) - hyperandrogenism (HA)	According to the Rotterdam criteria, the combination of OA and/or HA with AMH has a specificity of 100% and a sensitivity of 83%. The National Laboratory health standards (NIH) show a sensitivity of 83% and specificity of 89%, whereas the Androgen Excess Society (AES) criteria exhibit a sensitivity of 82% and specificity of 93.5%.
(Maheswari et al., 2021)	- Naive Bayesian classifier - artificial neural networks.	The suggested model achieved an accuracy rate of 98.63%, precision and specificity of 100%, an F-score of 68.76%, and a recall rate of 55%.
(Huang et al., 2016)	- protein-protein interaction network - pathobiological similarity	Potential targets for medication in polycystic ovary syndrome (PCOS) can effectively indicate The potential drug targets for PCOS have the ability to effectively indicate drug response, classify samples as either normal or diseased, distinguish between disease and post-treatment states, and provide a precise representation of the treatment's effect on PCOS.
(Alenzi, 2021)	- GDM cost-effectiveness - Decision tree	Using metformin is the most cost-effective approach for treating polycystic ovary syndrome (PCOS) during pregnancy. It leads to an average savings of $7,593,372.97 in pregnant women with PCOS and significantly improves normal glycemic control without gestational diabetes by an average of 2271%.
(Wisesty et al., 2017)	- Neural network - Backpropagation	The Levenberg-Marquardt method achieved the highest accuracy of 93.925% using 33 neurons and 16 vector features, the Conjugate Gradient-Fletcher Reeves method achieved an accuracy of 87.85% by utilizing 13 neurons and 16 vector features, whereas the other methods did not perform as well.

(Guzman et al., 2013)	Using multivariate regression analysis	AMH and AFC appear to be the only independent predictors of COC performance in IVM treatment in PCOS patients.
(Aydos et al., 2016)	the Venny Venn’s diagrams drawing tool	The validation using qRT-PCR confirms that there is a disturbance in the molecular signaling by MGC and CC in PCOS, which is crucial for the maturation of follicles and oocytes and could potentially contribute to the development of the syndrome.
(Eliyani et al., 2019)	segmentation	
(Hou et al., 2019)	- microRNAs - bioinformatic analysis	The miRNAs associated with PCoS can provide new insights into diagnosis, prognosis, treatment and prognosis. - The presented data offers a comprehensive analysis of miRNAs (microRNAs) that potentially play a role additional research is needed to elucidate the biological roles and underlying mechanisms of these factors in the onset of PCOS.
(Minooee et al., 2018)	Anti-M€ullerian hormone (AMH)	-significantly higher than in the controls -ovulating women may have up to two years longer reproductive life expectancy than naturally ovulating women, as evidenced by significantly higher than average AMH levels.
(Matsuzaki et al., 2017)	Anti-Mullerian hormone (AMH), Transvaginal ultrasound	The PCOS group had a considerably higher serum level of AMH compared to the control group. Measuring AMH levels can aid in evaluating ovarian conditions without the need for A transvaginal ultrasound is used as a diagnostic tool for PCOS.
(Mandal et al., 2021)	K-means clustering	The accuracy rate is 90.90%, and the hit rate is 84.61%. The rate of incorrect acceptance, also known as type I error, is 7.69%, while the rate of incorrect rejection, also known as type II error, is 23.07%.

(Nilofer & Ramkumar, 2021)	Adaptive K-means clustering	Maintained segmentation accuracy of 93% and 94%.
(HUANG et al., 2018)	Support Vector Machine	The SVM model achieved a prediction accuracy of around 73% for a separate external validation dataset consisting of 40 compounds.
(Palomba et al., 2015)	Non Algo	While metformin seems to be well-tolerated, there is a scarcity of data from prospective, randomized controlled trials to provide sufficient evidence for its use during pregnancy.
(Naz, 2014)	Non Algo	With advances in genetic analysis, the controversial association between PCOS and male relatives may be better understood.
(Cherif, 2018)	- K-Nearest Neighbor - SVM	The proposed algorithm outperforms K Nearest Neighbor, NB, and SVM in the analyzed dataset, achieving an f-score slightly above 94%.
(Sørensen et al., 2014)	microRNAs	Detecting various miRNAs in the bloodstream could serve as a valuable diagnostic tool and potentially aid in the treatment of PCOS.

4. Conclusion

This literature review finds out what research can be done to determine whether people are infected with PCOS or not and also to assist medical experts in identifying PCOS disease using machine learning. Our study concluded that KNN, SVM and ANN are commonly used in disease identification research. It requires a significant amount of time to display multiple pieces of research. Also, there is still a need to address the challenges of machine learning approaches for diagnose PCOS.

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