



Gynecology Diseases Aided AI: Subject Review

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Articles Information	Abstract
Received: 25.01.2025 Accepted: 01.09.2025 Published: 15.09.2026	Artificial intelligence (AI) has made tremendous progress in the application to healthcare, including gynecological diagnosis, because AI has the ability to analyze complex data and assist in making, prognosis and diagnosis more accurately. This paper discusses the main AI techniques that have been employed to this determine, namely expert systems, semantics networks, genetic algorithms, machine learning, deep learning and transformers. It offers an in-depth analysis of the problems and the limitations of each approach, concerns about data quality, bias, and the Lack of transparency of each one. The objective of this study is to provide researchers with a broad knowledge map about the current technologies, to point out the issues that have not been hitherto studied, and to propose the future direction, such as improving data quality, adapting models to the gynecological context, combining text analysis with medical images, and considering privacy need.
Keywords: Artificial Intelligence, Gynecology, Machine Learning, Ovarian Cancer, Women's Health, Natural Language Processing.	

<http://doi.org/10.22401/ANJS.29.3.14>

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1. Introduction

Artificial Intelligence (AI) is the scientific and software development to enable electronic devices to perform or carry out intelligent tasks that may sometimes exceed human capabilities. The study is still ongoing in the field of artificial intelligence to develop technologies that enable computers to understand complex contexts and make decisions based on the study, analysis and comprehensive understanding of data, which has enable it to provide advanced solutions to challenges that were difficult to overcome in the past [1]. Artificial intelligence is a specialized field that includes logic, information, perception, systems, and reasoning, and is used in knowledge processing, machine learning, pattern recognition, and natural language processing [2]. Recently, people's lives have changed dramatically and widely due to the rapid development of artificial intelligence [3]. The progress made in the fields of medicine has a large role to play due to artificial intelligence, as it has a broad role in contributing to the development of wide-ranging diagnoses and treatments for diseases. However, its use is still incomplete, as reliance on the skills of human doctors and experts is still required to make critical decisions

[4]. Although AI is the main supporter of doctors in diagnosing and treating diseases and enhancing patient care, it faces many challenges that must be solved including privacy, bias, and the need for human expertise. Achieving these challenges ensures the responsible and effective use of AI in healthcare[5]. AI has the potential to increase doctors' confidence in their diagnosis by supporting medical practitioners in making informed decisions. However, clinical expertise is indispensable. In the United States, medical errors are the third leading cause of death, and by relying on AI, the accuracy can improve and increase the interpretation and reduce the workload that can lead to missing important details [6]. AI has been applied in the fields of obstetrics and gynecology, including general obstetrics, gynecological surgery, fetal ultrasound, and assisted reproductive medicine. Artificial intelligence can provide good diagnostic results, but clinical examination is still necessary to determine the patient's condition [7]. The use of artificial intelligence finds wide application in gynecological research. The models used stand out effectively, as their results are almost equivalent to those achieved

by highly experienced doctors in this field[8]. Errors resulting from medical negligence have major compensatory consequences, as in addition to legal proceedings, there are long-term economic and social consequences as a result of harmful errors, so the use of artificial intelligence to diagnose diseases is an important step [9]. With the development of artificial intelligence technologies, its applications in the field of medicine have increased and developed, most notably the treatment of gynecological diseases. The aim of this review is to identify how artificial intelligence is used in various fields of gynecology and the various mechanisms, tools and systems that have proven their effectiveness. This research highlights the discussion of different types of systems that work with artificial intelligence, such as supervised and unsupervised machine learning models, expert rules and systems, neural networks and transformer techniques. In addition, it will review the effective role of artificial intelligence in increasing the accuracy of diagnosis to minimize medical errors. The research will also demonstrate how the integration of artificial intelligence has contributed to reducing the workload on doctors, allowing them to make decisions with high accuracy and confidence regarding complex cases to avoid

serious complications of the disease. It will also identify opportunities and challenges in the applications of artificial intelligence in gynecology, and propose new strategies to develop its future uses.

2. Gynecology

Gynecological diseases are those that affect the female reproductive system and have profound effects on women's quality of life and general health, as they pose wide-ranging health and social challenges, and include many hormonal and glandular diseases and disorders, including benign or malignant tumors, infections, and hormonal imbalance. This diversity of gynecological diseases requires special attention and societal awareness, due to its significant effects on women's physical and psychological health and their ability to perform their various roles in life [10]. Gynecological diseases are among the most prominent health challenges and difficulties that women face throughout their lives, as they include disorders that affect the female reproductive system and the woman's psychological and physical life. In[11], a comprehensive vision is presented, explaining the causes, symptoms, and treatment methods for benign and malignant gynecological diseases, as shown in Table 1.

Table 1: The most prominent gynecological diseases and their branches

Types	Branches
Benign diseases	• Polycystic ovary syndrome (PCOS): Ovulation and ovarian function are affected by a hormonal disorder. • Uterine fibroids: Benign (non-cancerous) growths in the wall of the uterus. • Endometriosis: Growth of tissue outside the uterus (similar to the lining of the uterus). • Chronic pelvic inflammatory disease: infection of the reproductive organs. • Ovarian cysts: Sacs that form on the ovary (they contain fluid). • Uterine or bladder prolapse: As a result of muscle weakness, the reproductive organs descend.
Malignant diseases (cancerous)	• Cervical cancer. • Ovarian cancer. • Uterine cancer. • Vaginal cancer. • Vulvar cancer.
Functional disorders	• Hormonal disorders: such as estrogen deficiency. • Menstrual disorders: such as premature menopause and dysmenorrhea.
Infectious diseases	• Sexually transmitted infections (STIs): such as gonorrhea, chlamydia. • Fungal infections (Candidiasis). • Pelvic inflammatory disease (PID).
Reproductive problems	• Recurrent miscarriage. • Infertility. • Ectopic pregnancy.
Diseases related to the urinary system	• Urinary incontinence. • Urinary tract infections.
Endocrine disorders	• Thyroid diseases affect the menstrual cycle.

Improving women's health has positive effects on society and the family, as it supports their role in building a stable family and contributing to development, whether social or economic, which supports the progress of society[12]. Cervical cancer has a profound physical and psychological impact on women, with significant reproductive and mental health challenges. Efforts to improve prevention and treatment, such as vaccine development and self-examination, are essential to reduce the burden, but underfunding and health disparities continue to hinder equitable outcomes globally [13]. The study covered endometrial cancer, ovarian cancer, adenocarcinoma associated with benign gynecological conditions, and rhabdomyosarcoma. The reason for this is the lack of knowledge about the transformation from benign to malignant conditions and the absence of standardized sample repositories. The study revealed significant gaps, emphasizing the development of new diagnostic and preventive models and the importance of historical studies[14].

3. Mechanisms, Challenges, and Future Prospects of Artificial Intelligence Applied for Medicine Purposes: Gynecology Diseases

With the rapid progress of electronic devices and the development of science and technology, the

expansion of knowledge of artificial intelligence greatly contributes to accelerate its integration into the healthcare sector. The use and application of artificial intelligence in the medical field has radically transformed our understanding of traditional medical science over the past years. By improving disease diagnosis and providing personalized treatment plans, AI helps deliver more accurate and effective healthcare, enhancing patients' overall quality of life[15, 16]. Recently, Digital methods and artificial intelligence play an important role in the diagnosis of obstetrics and gynecology, as digital methods enable the processing of ultrasound, MRI and CT images, which helps doctors obtain accurate information about the patient's health. Artificial intelligence is characterized by its ability to process large amounts of data and uncover hidden patterns to achieve an accurate diagnosis [17]. AI models have been developed to predict a wide range of problems, from pre-eclampsia to shoulder dystocia, from postpartum hemorrhage to postpartum depression, covering the optimal situation for pregnancy and childbirth comprehensively[18][19]. Table 2 summarizes the most important AI techniques used in medical and gynecological applications, providing a basic overview before discussing each method in detail.

Table 2: Uses of artificial intelligence (AI) in various medical fields from 2018 to 2023

Reference	Year	Need	Methodology	Disease	Conclusion
[20]	2019	Predicting postpartum depression using machine learning and electronic health records.	Machine learning algorithms were used in the study to predict postpartum depression. These algorithms included: L2 regularized logistic regression, support vector machine, decision tree, naive Bayes, XGBoost, and random forest.	Postpartum depression.	The XGBoost model was able to accurately predict postpartum depression (AUC = 0.79), while identifying important factors such as race, obesity, anxiety, and depression. This suggests that machine learning could be used on electronic health records to improve early screening of mothers at risk for postpartum depression and provide effective interventions.
[21]	2020	Analysis of Chinese women's perceptions	Data source from 45,729 posts on	Cervical cancer associated with	85% of posts are positive or neutral,

		of domestic and imported HPV vaccines.	Sina Weibo platform. The techniques used are data mining, machine learning for sentiment analysis, and semantic network analysis.	human papillomavirus (HPV).	15% are negative. Developed regions prefer imported vaccines, while less developed regions suffer from low awareness.
[17]	2018	To evaluate the potential of using deep learning to detect cartilage lesions (such as chondromalacia, fibrillation, cracking, focal defects, diffuse thinning, and acute cartilage injuries) in the knee joint using magnetic resonance imaging.	Develop an automated system based on CNNs to analyze the MRI data of 175 patients. Use expert interpretation as a reference and evaluate the performance <i>via</i> ROC and k-statistics.	Cartilage lesions	The deep learning-based system achieved high sensitivity and specificity (84.1%-85.2% for the first assessment, 80.5%-87.9% for the second assessment) with good inter-observer agreement, proving its accuracy and reliability in detecting articular cartilage damage.
[22]	2019	Design an expert system for elderly health care (EHC)	Design an EHC system based on a server and three clients.	Common chronic diseases among the elderly and improving the care of the elderly	The system achieved over 95% accuracy in monitoring vital signs of the elderly, such as blood pressure, heart rate and temperature, using smart bracelets equipped with precise medical sensors.
[23]	2022	Improve medical data classification using CGA algorithm to determine optimal weights and biases for MLP network.	Adopting CGA algorithm with DX crossover operator and UM mutation, analyzing five reference medical datasets and comparing performance by accuracy, sensitivity and MSE index metrics.	Various diseases, with a focus on breast cancer (Breast dataset).	CGA+DX showed high efficiency and competitive accuracy, outperforming on three of five datasets. DX+UM achieved the best results in accuracy and sensitivity.
[24]	2022	Development of a new algorithm (LSWT-GA) to improve rTMS scheduling and increase efficiency while reducing errors and taking into	Using LSWT-GA with innovative techniques and simulation experiments to compare its performance with LS-GA and Random-GA.	Treating depression with transcranial magnetic stimulation (rTMS) sessions.	The LSWT-GA algorithm outperformed other methods in reducing execution time and producing optimal schedules, highlighting its potential for

		account patient priority.			improving medical resource management and effective rTMS treatment scheduling.
[25]	2023	A new machine learning-based algorithm to improve the selection of relevant features in medical data. Improving the accuracy of clinical and diagnostic decision-making while reducing data dimensionality.	-Feature extraction: Using LDA. -Feature selection: Using SOC-GA. -Classification: Using RF and SVM. -Performance evaluation: Measure accuracy, precision, recall, and F1.	improve medical classification.	The SOC-GA algorithm showed excellent performance with an accuracy of up to 95% with SVM and 94.6% with RF.
[26]	2021	- Improve the quality of low-contrast MRI images. - Support visual interpretation of affected areas to improve medical diagnosis.	Aggregate Adaptive Histogram Equalization (GAAHE) technique. Image Segmentation. Genetic Algorithm.	Improve medical image quality.	- GAAHE technology improves the quality of medical images while maintaining brightness and reducing information loss. - It provides visual enhancement and operates automatically, enhancing diagnostic efficiency. - Its results showed superiority in parameters such as entropy, PSNR, and adaptability compared to traditional methods.
[27]	2019	Improving the accuracy of survival prediction for patients with differentiated thyroid cancer by using a novel machine learning algorithm called EACCD.	Using SEER data and developing a TNMA model with EACCD algorithm, a machine learning algorithm based on clustering and data analysis techniques.	Differentiated thyroid cancer.	The EACCD TNMA model showed higher survival prediction accuracy than the traditional AJCC system (C-index = 0.8583 vs. 0.8387).
[28]	2018	Developing improved diagnostic systems for breast cancer patients using an innovative machine learning algorithm.	Using the an unsupervised learning algorithm (EACCD) to analyze SEER data (1990-2003) for breast cancer, based on T, N, M,	Breast cancer	The EACCD algorithm-based approach achieves a C-index of 0.7295, demonstrating reliable accuracy in predicting survival for breast cancer patients

			G, ER, PR, and age.		and improving clinical classifications.
[29]	2021	Evaluation of the impact of 3D-CNN on the diagnosis of invasive lung adenocarcinoma by radiologists.	Study of 285 patients. Development and use of a 3D-CNN model for CT image analysis. Comparison of the performance of three radiologists with and without the model.	Lung adenocarcinoma (AIS, MIA, IVA).	3D-CNN improves diagnostic accuracy for less experienced radiologists. A non-invasive and effective diagnostic tool with high sensitivity.
[30]	2021	Developing a TransMed model to integrate CNN and transformers to improve multimodal medical image classification.	CNN for low-level feature extraction. Transformer for learning intermodal relationships. The model was evaluated on parotid gland tumor and knee lesion data.	Parotid gland tumors Knee injuries	TransMed achieved 10.1% and 1.9% accuracy improvements compared to other models. It shows great potential in multimodal medical image classification.

3.1. Rule Based and Expert Systems

Rule-based systems and expert systems are two types of AI systems that are used to represent and process specialized knowledge. The rule-based approach is one of the simplest types of expert systems, and is considered a prototype of artificial intelligence representation. This system relies on the use of rules to encode knowledge extracted from experts, allowing it to mimic the human-like process of thinking and problem-solving. The rule-based system presents guidelines in interactive forms, rather than statically, helping to make the right decisions based on the available options [31]. A rule-based system is typically used to hold and update knowledge in order to interpret data in a useful way. This system includes a rule base, which is a type of knowledge base, usually written in the IF-THEN form (IF < condition > THEN < result >). This approach has the ability to make decisions similar to those made by a human expert, so the IF-THEN rule-based approach is intended to provide solutions to complex problems and can also efficiently infer the knowledge required in intelligent systems[32]. Expert systems are more intelligent and advanced, which are used to simulate human expertise in a particular domain. These systems rely on a knowledge base built with the help of experts, along with an inference engine that extracts solutions to complex problems based on this knowledge. This approach has the ability to make

semi-intelligent decisions, and is used in industry and in areas such as troubleshooting[33]. Medical expert systems work to send effective alerts and inform concerned parties of important health conditions. They were established to meet the urgent need to support doctors and patients in diagnosis and treatment. These systems play a role in enhancing the quality of health care, which leads to accurate diagnosis and providing appropriate therapeutic guidance. These also play an effective role in contributing to rapid intervention and providing continuous care, as they send immediate notifications to doctors and patients about emergency cases or identify any developments, thus becoming an indispensable part in facilitating informed medical decisions by improving doctors' communication with their patients[22]. In the expert systems that help diagnose gynecological and obstetric diseases, a simple model has been designed that addresses ten of the most common diseases that affect women during or outside pregnancy. The system allows guidance towards an accurate diagnosis of the ten diseases, providing appropriate treatment guidelines. The system contains a list of common symptoms for each case, in cooperation with a consultant specialized in gynecology and obstetrics [34].

3.1.1. Challenges and Limitations of Rule-Based and Expert Systems

Although expert systems and rules are widely used in medical applications, they have various limitations in the field of gynecological diagnosis. The most notable of these limitations is their limited diagnostic coverage. These systems often rely on a limited number of cases and therefore cannot solve complex or unusual problems unless they are pre-established. Furthermore, their rule-based models are also too rigid to accommodate diverse patient expressions or evolving symptom patterns. They use static knowledge bases built manually, all of which require to be updated as new medical knowledge becomes available. They are also unable to deal with the uncertainty or probabilistic estimation, as well as have limitations in the natural language understanding (such as requiring exact input from pre-defined lists). Furthermore, most personal health information ontologies are not integrated with clinical or laboratory data and updating and maintaining them are time-consuming, laborious tasks, which constrain their usability and scalability [34, 35].

3.2. Semantic Networks

Semantic networks are one of the Semantic Web technologies that play a vital role in addressing bias in AI. They are used in this context to assess, represent, and mitigate bias in AI systems. By analyzing user interactions and detecting inequality in recommendations, these networks detect bias. In addition, semantic networks increase awareness of bias, capture bias, and can prevent errors by including information about unrepresented groups in the data so that correct decisions can be made. Semantic networks participate in bias mitigation to mitigate its negative impact by modifying learning algorithms, modifying training data, or changing model results to reduce unwanted correlations and prevent its harmful effects in AI systems[36]. By representing relationships between concepts, semantic networks are used to retrieve information, helping machines understand and process word associations and their meanings. They also help organize information, which enhances the effective representation of knowledge. They are essential in natural language processing, such as question answering systems and sentiment analysis systems, where they show how concepts are connected across nodes and edges, making data easier to interpret. Semantic networks map relationships between data, which supports text summarization and knowledge discovery, which enhances computational understanding and advanced analysis[37]. The process of semantic network analysis involves several steps: encoding, visualization, semantic matrix

generation, network statistical indices, module analysis, and sentiment analysis [38]. The analysis contributed to increasing women's awareness of the importance of the HPV vaccine and encouraging them to receive it. Sentiment analysis and semantic network analysis were conducted together on a sample of 45,729 posts. Semantic networks enabled the analysis of the co-occurring patterns of keywords in the posts, which helped build relationships and visualize important word associations. Through semantic network analysis, highly relevant keywords were identified, providing insight into the relationships between words and the sentiments expressed in the posts. This method provided a comprehensive perspective and complemented traditional research methods, proving its value in understanding women's attitudes toward the vaccine in China[21].

3.2.1. Challenges and Limitations of Semantic Networks

Semantic networks face several challenges when used to represent medical knowledge, especially in the context of gynecological diagnosis. These challenges include:

- **Poor scalability:** Networks must be manually and traditionally expanded, making them less usable in large, evolving domains.
- **Complex ontology maintenance:** Obfuscation in the terminological structure can lead to misunderstandings and/or mismatches of concepts.
- **Language ambiguity:** Due to their informal nature, it is difficult to directly match clinical language (unless advanced contextual features are used).
- **Expert-driven construction:** Expert input is critical to network construction and maintenance, reducing its flexibility and scalability.
- **Poor integration with diverse data sources:** These systems struggle to integrate with unstructured data sources, such as reports or text-based physician notes [39].

3.3. Genetic Algorithms

A genetic algorithm (GA) is an algorithm based on the principles of natural evolution such as natural selection, mutation, and trade-off. It is an efficient method for optimizing and searching large and complex spaces for optimal or near-optimal solutions. It is also one of the most prominent optimization algorithms, adapting to systems, and exploring solution spaces currently used in many real-world

applications. The process begins by generating a random set of candidate solutions, and these solutions are then evolved over generations to reach the optimal solution[40]. genetic algorithms are widely used In the medical field to improve and develop the efficiency of medical performance in Diagnosis and treatment, It is used in optimization and classification, medical decision support , scheduling of medical treatment and in medical image enhancement[23][26]. Genetic algorithms were used to select critical features in the prediction of preterm birth using electrohysterogram (EHG) signals. These algorithms proved effective in constructing a robust predictive model with high generalizability and clinical relevance with computational efficiency. The resulting system achieved an F1 score of over 80% when tested on new data, reflecting its ability to accurately predict preterm birth outcomes [41].

3.3.1. Challenges and Limitations of Genetic Algorithms

Genetic algorithms face several challenges when applied to intelligent medical systems. The most prominent of these challenges are:

- **The requirement of fine tuning of parameters:** Sensitive values must be carefully chosen because they influence of the solution quality.
- **Localization:** They occasionally converge to unwanted solutions which limits the diagnostic accuracy of highly diverse examples.
- **Expensive computation:** It is caused by many iterations and constantly evaluating members of an evolutionary population.
- **Initialization sensitive:** The performance is a function of the algorithm's initialization, which is likely to undermine the stability.
- **Transparency and interpretability:** They do not let us to understand how the solutions are actually achieved, which is crucial in clinical applications.
- **Dependence on fitness functions:** Their construction needs specific and accurate knowledge, which is not always accessible in medicine[42].

3.4. Supervised Machine Learning

Machine learning is a branch of science that automatically makes computers intelligent by improving their understanding through experience. This field focuses on systems that learn and make decisions on their own without repeated programming. The machine can adapt to constantly

changing environments[43] . In the machine learning approach to predictive modeling, different from traditional methods, the computer autonomously learns from clinical patterns to improve predictions, while in traditional modeling, clinical data is programmed by humans into the model. Simply put, the computer's role in machine learning is shifting to model development rather than the traditional role as a computational assistant[44]. Machine learning is divided into four categories: supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning. Supervised learning uses labeled datasets to provide predictions and classifications[43]. In the field of cervical cytology, many researchers have applied supervised learning to microscopic images of stained cells to classify cells into normal and abnormal. High-accuracy classification results have often been achieved when analyzing images of single cells, as non-overlapping cells facilitate easy discrimination of the nuclear region in stained cells. The accuracy was 99.78%, For 2-class classification: The accuracy is 99.7% and For 4-class classification: The accuracy is 75.55%[45][46]. The use of supervised learning RF was studied using HPV typing data. Studies shows the data on 522 radioactively associated mutant genes due to widespread human papillomavirus (HPV) infection, in combination with CIN and cancer-sensitive cancer samples, targeting the identification of a novel directionality targeting resistance to CIN 2 or higher using a random forest method. The new biomarker, which reports information on HPV variants, insect mutations, and mitochondrial changes, achieved a perfect predictive score of 0.814 for CIN score 2 or higher[47]. The data of 202 patients with ovarian tumors were registered, and clinical information (such as age, endometrial thickness, body mass index, white blood cell count, menopause, hemoglobin, C-reactive protein, CA 125, CA 19-9, etc.) was analyzed. and CT information (such as tumor size and presence of ascites). Five machine learning classifiers were used to analyze the data: Support Vector Machine, Random Forest, Naive Bayes, Logistic Regression, and XGBoost, in addition to analyzing the importance of 16 features for disease prediction. The XGBoost algorithm, a supervised machine learning model, showed the highest accuracy of 0.80 [48].

3.4.1. Challenges and Limitations of Supervised Machine Learning

Supervised Machine Learning face several challenges, the most prominent of these challenges are:

- **Lack of labeled data:** The model needs relevantly labeled medical data, which is relatively restricted in the clinical context.
- **Sample bias:** Not representing all types destroys generalization ability of the model.
- **Over fitting:** Does not perform well on new data, particularly with small sample sizes.
- **Interpretability is suboptimal:** The decision-making logic (the “explanation”) of most models remains opaque, leading to physician distrust.
- **Dependency of structural data:** Unstructured/erroneous medical text is hard to deal.
- **Poor generalizability:** Models trained on one environment may not generalize to another[49].

3.5. Unsupervised Machine Learning

Unsupervised learning is an approach in machine learning that aims to discover patterns within unlabeled and unstructured data sets. In this approach, The AI system independently and efficiently infers hidden structures and relationships by receiving only input data, without knowing information about the desired outcomes. [50]. The Evolutionary Clustering for Cancer Data (EACCD) is an unsupervised machine learning algorithm developed to build cancer prognostic systems based on survival data alone. It is based on classifying alert groups according to disease-related risk factors through unsupervised clustering. This algorithm can create prognostic groups with similar outcomes, with greater accuracy than traditional staging algorithms, when applied to population data[27][28]. In conjunction with unsupervised machine learning, the researchers used FLIM technology to observe unstained cervical cells, which analyzes FLIM images. This method is characterized by the absence of cell labeling, FLIM-ML greatly enhances the efficiency, specificity, and sensitivity of cervical cancer screening. This technology is a new method for early screening of cervical cancer and follow-up examinations after treatment [51]. Machine learning techniques have outperformed traditional regression-based analyses in predicting multiple clinical parameters related to ovarian cancer (EOC). Ensemble learning methods, such as GBM, CRF, and RF, have shown excellent performance in predicting ovarian cancer. The highest accuracy and value using RF were 92.4% and 0.968, respectively, for separating ovarian cancer from benign ovarian tumors. The accuracy of clinical stage prediction using RF was 69.0% and the AUC value was 0.760. RF can, pre-operatively, predict high-grade serous and membranous histological patterns of ovarian cancer, as well as distinguish between complete

resection and non-complete resection. Unsupervised analysis revealed distinct subgroups among patients with early-stage ovarian cancer, these groups showed significantly lower survival rates than others [52]. Deep learning can directly generate high-level feature representations from raw images, gradually replacing traditional machine learning methods. Increasing studies have shown that artificial neural networks can achieve outstanding performance in detecting and diagnosing cancer [21].

3.5.1. Challenges and Limitations of Unsupervised Machine Learning

Unsupervised Machine Learning face several challenges, the most prominent of these challenges are:

- **Lack of human supervision:** It is hard to interpret and justify model predictions.
- **Strong dependence on similarity measures:** Performance may be highly dependent on the distance measure and the type of features used.
- **Sensitivity to noise:** the model may not be able to efficiently/accurately clean all of the unclean data or structure all of the unstructured data.
- **Low generalization:** Model difficult to apply to new environments with preserved accuracy.
- **Huge computational workload:** Particularly in advanced models[53].

3.6. Neural Networks and Deep Learning

Convolutional Neural Networks (CNNs) are a type of artificial neural network (ANN) that are non-parametric tools in machine learning (ML). Their architecture is based on a structure of interconnected neurons or nodes distributed in multiple layers, which are used to generate predictions such as label classification based on input data such as multi-dimensional images [54]. Deep Learning (DL) consists of multiple layers that learn robust feature representations, which explains the depth of the hierarchy of these layers. Convolutional Neural Networks (CNNs) are a type of deep neural network designed specifically for image analysis. CNNs can be implemented using Graphics Processing Units (GPUs) to increase efficiency. These networks allow direct learning from raw images, because they consist of a hierarchy of layers with learnable parameters. Each layer computes “higher level” features based on representations learned from previous layers, making it easier to extract complex information from images [55]. There is no doubt that deep learning has made a significant impact in various scientific fields in recent years. Modern methods have outperformed traditional methods, achieving impressive results on

tasks previously impossible with automation. These technologies not only accomplish tasks, but also exceed human capabilities in many applications [56]. Deep learning techniques are effective in extracting, classifying and detecting image features. Therefore, it has been widely applied to medical images in recent years. Image recognition using AI is divided into classification and detection. In medical imaging, AI has been introduced in endoscopy, Magnetic Resonance (MR), Computed Tomography (CT), ultrasonography, and pathology imaging[29]. Yanagawa[29] developed aSn algorithm to analyze CT images of 285 lung cancer patients. The results showed that inexperienced radiologists who used deep learning support achieved higher accuracy in diagnosing lung cancer than those who did not use it. Deep learning and neural networks have made remarkable advances in gynecological imaging. In the field of gynecologic cancer imaging, these techniques have become at the forefront of modern technology, particularly in image reconstruction, image processing, and automated analysis[55]. The development of an AI-assisted diagnostic system for colposcopy and a deep learning-based biopsy guide was based on analysis of colposcopy image reports of 19,435 patients from six centers. Biopsies performed with the aid of this system showed higher accuracy compared to those performed by gynecologists alone (82.2% vs. 65.9%, 0.750 vs. 0.516, respectively; $P < 0.001$) [57].

3.6.1. Challenges and Limitations of Neural Networks and Deep Learning

Neural Networks and Deep Learning face several challenges, the most prominent of these challenges are:

- Needs large dataset to produce accurate estimates.
- Our method also has high computational complexity and long training time.
- Over fit of lack of data.
- The decision-making mechanism is not easily interpretable.
- Bias due to quality of training data.
- Generalization when transferring the models to new environments is difficult.
- It has also the drawback that it requires a careful parameter adjustment to obtain an stables performance[58, 59].

3.7. Transformers

Transformer is an attention-based architecture that has become the leading model in the field of Natural Language Processing (NLP). This architecture,

proposed by Vaswani and colleagues, by developing bidirectional transformer representations, has proven to be as superior as the BERT model, which has a robust pre-training approach. Transformer-based models have become at the forefront of innovation as NLP technologies advance[60]. Transformers were first used in natural language processing (NLP) as a deep neural network based on self-attention mechanism. Their use has expanded to computer vision tasks due to their representational capabilities. Transformers have made significant progress in the image domain despite the challenges related to data size and images, such as SETR for semantic segmentation, ViT and DeiT for image classification, DETR for object detection[30]. Recently, transducers are used in the field of disease diagnosis and other clinical symptoms, due to their entry into the field of medical image analysis. For example, using CT or X-ray images, transducers have been used to differentiate between COVID-19 and other types of pneumonia, which helps in treatment quickly and highly effective. Transformers have also achieved success in image segmentation, detection, and synthesis, leading to advanced results in this field [61]. In [62] they produce hybrid transformer architecture for Event Recognition in Laparoscopic Gynecology Videos, It is enhances the accuracy of event recognition by leveraging inter-frame dependencies and managing changes in the surgical scene. The study demonstrates that this approach outperforms traditional architectures such as CNN-RNN, as demonstrated by extensive experiments. Also [63] introduced the Vision Transformer (ViT) to the field of Optical Coherence Tomography (OCT) images, where clinical images acquired by OCT are automatically classified. This approach aims to reduce the medical burden on gynecologists by providing an accurate and efficient tool. Experimental results show that the ViT-P model significantly outperforms both CNN and ViT in case screening on GSM and UCSD datasets, with accuracy reaching astonishing levels of 99.9% and 99.69%, respectively, enhancing the potential for accurate diagnosis in the medical field. [68] designed a CNN-based UF classification (UFCs) system, which was trained on a dataset of 9524 images from 240 patients and 199 healthy individuals. The evaluation results showed that the system achieved a sensitivity of 94.21% and a specificity of 83.76%, outperforming traditional models. This method can be used as an effective tool for computer-aided analysis, highlighting the great potential of deep learning-based methods in supporting clinicians in diagnosing UF and reducing subjective bias in diagnostic results. A new type of AI prediction model uses natural

language processing, seeking to read and understand texts in the same way a human reads them. The technology has seen applications in reading doctors' notes to predict severe maternal conditions, and mining social media data to ensure the safety of pregnancy medications. But its potential extends far beyond these early uses[64].

3.7.1. Challenges and Limitations of Transformers

Transformers have many challenges and limitations that limit their operation, they are:

- High training and operation costs.

- Poor interpretability of model results.
- Data bias can lead to inaccurate results.
- Difficulty adapting to specialized medical language.
- Misunderstanding of precise clinical context.
- Ethical and regulatory concerns related to privacy and liability[65].

Table 3 provides an evaluation of AI techniques in gynecology in terms of their purpose, Methodologies used, diseases, and the Conclusion, all of which are briefly explained.

Table 3: Applications of artificial intelligence in the diagnosis and treatment of gynecological and obstetric disease

Reference	Year	Need	Methodology	Disease	Conclusion
[18]	2020	Developing a machine learning model to predict shoulder dystocia. Improving cesarean section decisions in cases of fetal macrosomia.	Developing a machine learning model for analyzing clinical and biometric data. Training on 686 cases and testing on 2584 cases. Comparison of performance with traditional methods (estimation of fetal weight and diabetes). Risk classification using artificial intelligence algorithms.	shoulder dystocia	The model outperformed conventional methods (AUC = 0.866 vs. 0.784), allowing accurate classification of shoulder dystocia risk. The model could support clinical decisions and improve management of deliveries with suspected fetal macrosomia.
[66]	2019	Developing machine learning-based models for predicting late-onset preeclampsia.	Analysis of records of 11,006 pregnant women. Maternal factors and laboratory data from weeks 14 to 34. Logistic regression, decision tree, naive Bayes, support vector machine, random forest, and stochastic gradient boosting. C-statistics and prediction accuracy measures.	Late preeclampsia	The stochastic gradient boosting model achieved the highest accuracy (0.924) in predicting late-onset preeclampsia. Combining maternal factors with early laboratory data enables effective use of machine learning algorithms to improve clinical diagnosis.
[67]	2020	Develop predictive models using machine	Data from 10 sites in the US Safe	postpartum hemorrhage	Of the 152,279 births, 4.8% had

		learning and statistics to determine the risk of postpartum hemorrhage when a woman is admitted to hospital.	Work Consortium study. Logistic regression, Lasso, Random Forest, and extreme gradient boosting. Performance measured using C-statistics and calibration with temporal and spatial validation.		postpartum hemorrhage. The extreme gradient boosting model performed best (C-statistic: 0.93). The models can be used to improve the preparedness of medical teams and the triage of women at risk.
[68]	2020	Using machine learning to predict the success of vaginal birth after cesarean section.	Analysis of medical records of singleton births. Machine learning with progressive reinforcement. First model based on first visit data, and a subsequent model using prenatal data. Performance comparison <i>via</i> operating curve (AUC). Classification of women into low, intermediate, and high risk.	Risk of failure in vaginal delivery after cesarean section.	Success rates for vaginal birth were 88% among women who attempted labor, highlighting the role of machine learning in providing personalized risk assessment, supporting clinical decisions, reducing cesarean section rates, and improving risk management for better health outcomes.
[69]	2022	Developing a machine learning model to predict vaginal birth using continuous labor data.	Retrospective study, supervised machine learning model construction, ROC-AUC: 0.82, labor data (9385 births).	Complications of labor and cesarean section.	Prediction accuracy: 87.1%. The model improves clinical decisions and reduces labor complications.
[19]	2019	Development and evaluation of the accuracy of cesarean section prediction models using maternal and fetal characteristics during labor.	Secondary analysis of a prospective study using logistic regression to develop prediction models, calculating performance parameters such as area under the curve, diagnostic accuracy, sensitivity, specificity, and positive and negative predictive value.	Cesarean section and possible complications during labor.	Cesarean delivery could be predicted with high accuracy based on labor characteristics, with the accuracy of the model based on labor entry assessments being 76.62% (area under the curve 78.70%), while the accuracy of models including intrapartum assessments was

					88.03% (area under the curve 93.66%).
[34]	2022	An expert who helps women diagnose diseases related to gynecology and obstetrics.	Design an expert system based on a list of common symptoms, correct diagnosis, and treatment of diseases. Designed using CLIPS expert system.	Obstetrics & Gynecology Diseases	The expert system is effective in diagnosing and treating gynecological and obstetric diseases, and has been evaluated by medical students and consultants, who expressed their satisfaction with it. The system provides a simple and effective way to facilitate the process.
[41]	2021	Development of a simple and accurate system for predicting preterm birth using electrohysterogram (EHG) features.	Classification algorithms: KNN, LDA, LR. Feature optimization using genetic algorithms.	Premature birth.	It demonstrated reliable performance with F1 scores of 84.63% (KNN), 89.34% (LDA), 86.87% (LR), and 92.04% for clustering classifier, making it simple and clinically applicable in real-time.
[45]	2021	A machine learning-based method to improve cervical cell classification, by reducing features and increasing accuracy while reducing computational cost.	Feature extraction: Extract 20 features related to shape, color and texture from cervical cells. Feature selection: Reduce features to 9 using Classification and Regression Trees (CART) algorithm. Classification optimization: Improve the performance of Supervised Learning Machine (SVM) using Particle Swarm Optimization (PSO) algorithm.	Cervical cancer (improving its diagnosis).	The CART-PSO-SVM algorithm achieved 99.81% accuracy for seven-factor classification and 99.78% accuracy for binary classification, with reduced features and improved operational performance at lower computational cost, which enhances classification reliability and reduces false diagnosis rates.
[46]	2022	- Improve the accuracy of cervical cell classification to detect abnormal cells.	Cell Segmentation: mPSPnet model for nucleus and cytoplasm segmentation.	Detect abnormal cells associated with cervical cancer.	A new automated framework for cervical cell classification using CNN and stacked

		- Reduce costs and time, and increase productivity in low-resource areas.	Feature Extraction: Analysis of nuclear and non-nuclear features. Classification: Cluster-based stacked classifier using Google Colab and Weka. Evaluation: 99.7% accuracy (binary) and 75.55% (quad).		classifier, achieving high accuracy, reducing manual labor, and improving efficiency with potential to be expanded to classify other cancer cells.
[47]	2019	Development of an effective risk stratification model for cervical lesions to provide accurate triage strategies.	Next generation sequencing (NGS) with a capture panel was used, Random Forest (RF) algorithm was applied in a supervised machine learning framework.	Human papillomavirus infection (HPV+). Cervical lesions (CIN1, CIN2+). Squamous cell carcinoma (SCC).	HPV integration and gene mutations increased with progression to CIN2+. Gene amplification and deletion, with mitochondrial deletion observed in CIN2+ (P=0.009). Predictive model accuracy: 0.814. Capture sequencing with machine learning provides a powerful classification tool to improve screening strategies and clinical management.
[48]	2020	Using artificial intelligence to analyze patient data and pre-operative examinations.	Supervised machine learning using 5 algorithms: XGBoost, Random Forest, Logistic Regression, Support Vector Machine, and Naive Bayes. Data: 202 patients (53 ovarian cancer, 23 borderline malignant tumors, 126 benign tumors). Features studied: 16 features including age, CA125, ascites, C-reactive protein, and other factors	Ovarian tumors.	It achieved the highest accuracy (0.80), with C-reactive protein, albumin, ascites, and CA125 as the most important predictive features. AI supports improved early diagnosis of ovarian cancer, contributing to accurate clinical decisions and enhanced therapeutic management.

			from blood tests and imaging.		
[51]	2022	Improving the accuracy and efficiency of cervical cancer screening using a novel technology that combines fluorescence lifetime imaging microscopy (FLIM) and unsupervised machine learning to analyze cancer cells.	FLIM cell imaging to analyze metabolic state differences <i>via</i> NAD(P)H fluorescence, and using unsupervised machine learning to assess cervical cancer risk.	Cervical cancer.	FLIM-ML demonstrated 90.9% sensitivity and 100% specificity, superior to conventional methods, providing a non-invasive and rapid method for cervical cancer screening and follow-up.
[52]	2019	Development of a machine learning-based predictive system for blood biomarker analysis prior to ovarian cancer surgery.	Study of data from 334 patients with ovarian cancer and 101 with benign tumors. Using 7 machine learning algorithms, most notably Random Forest (RF). Analysis of 32 blood and age parameters for diagnostic and prognostic predictions.	Epithelial ovarian cancer. Benign tumors.	Random Forest (RF) showed an accuracy of 92.4% and an AUC of 0.968. Predictive models help accurately classify patients and improve treatment options.
[57]	2020	Objective: To develop and validate an artificial intelligence system (CAIADS) for grading colposcopic impressions and guiding biopsies.	Deep learning-based AI(CAIADS) was used to analyze colposcopy images and patient data to classify impressions and guide biopsies, with 19,435 patient records divided into training, control, and validation sets to evaluate performance.	Cervical cancer/pre-cancer.	The (CAIADS) demonstrated higher accuracy in biopsy results compared to gynecologists (82.2% vs. 65.9%), with significant improvements in agreement (kappa 0.750 vs. 0.516, $P < 0.001$).
[62]	2024	Developing a hybrid transformer-based architecture for laparoscopic surgery video analysis, with focus on accurate critical event recognition.	Create a laparoscopic surgery dataset with critical event annotations. Use a hybrid transformer architecture with a training-inference framework.	Analysis of surgical procedures in the field of gynecology using laparoscopic techniques	The hybrid architecture enhances temporal resolution and event recognition by exploiting inter-frame dependencies. It significantly outperforms traditional CNN-RNN models.

			Compare performance with CNN-RNN models over extensive experiments. Apply frame sampling to handle scene and skill changes.		
[63]	2021	Development of ViT-P model to improve OCT image classification for screening of genitourinary menopausal syndrome (GSM) and reduce medical burden.	Create GSM dataset. Use zero-order convolution to address class imbalance. Develop ViT-P (Deep Learning-based Transformer AI) model to improve feature extraction using neural networks and channel attention mechanism. Evaluate performance on GSM and UCSD datasets.	Genitourinary menopausal syndrome (GSM).	The ViT-P model outperformed CNN and ViT models in OCT image classification, with an accuracy of 99.9% and 99.69% on GSM and UCSD datasets, demonstrating its great potential in improving medical diagnosis and reducing medical burden.
[70]	2022	Development of UFCs system using CNN and transformers to support uterine fibroid (UF) diagnosis.	UFCs trained on 9524 images (240 patients and 199 healthy). Evaluated on 2312 images (33 patients and 36 healthy). Performance compared with traditional models such as ConvNeXt and Swin Transformer.	Uterine fibroids (UF).	The system achieved a sensitivity of 94.21%, a specificity of 83.76%, and an accuracy of 88.93%. It outperformed traditional models and is an effective tool to support physicians and reduce subjective bias.

3.8. Future Directions and Proposed Strategies

A. Model Interpretability & Explainability

Inexplicably, even for high performing contemporary AI algorithms, is being a barrier in gynecology as a sensitive medical application. Therefore, there is a need in the future to really concentrate on building models with great interpretability, which helps to improve physician's trust in output results. One approach is to develop hybrid rule-based/deep learning models which should be robust and

accurate, and at the same time interpretable. As in the field of predicting prescription errors [71].

B. Domain-Specific Customization

Generic NLP models suffer from poor performance when applied to clinical gynecological texts due to a lack of linguistic and conceptual specificity. Therefore, it is recommended to collect real gynecological medical data and train specialized models, which improves the accuracy of analysis and discrimination between subtle gynecological

symptoms. The study [2] also indicates that customizing BERT models for specialized medical contexts, such as medical specialty classification, improves their accuracy and performance.

C. Integration with Clinical Systems

To implement AI models in clinical practice, it is essential to connect these models to clinical systems, such as electronic health records. This integration will allow direct access to stored clinical information and leverage real-life cases within the clinical workflow, from which the model can learn and interact. Recent research is moving toward training models that use real-time data from electronic health records, such as text, lab results, and medical images. This can be seen in [72].

D. Data Quality and Expansion

Scarcity of good medical data is one of the biggest challenges for implementing AI systems in healthcare, in particular in gynecology, where data is either unstructured or insufficient. The performance of model relies on the symmetry and reality of the data in training. This requires for approaches to capture reliable clinical data across a sufficient diversity of cases, including multiple languages and patient situations. Possible directions for future work are:

- Open-source databases in gynecology.
- Enhancement of data documentation in true clinical environments.

Improving the Arabization and extending its other than English in Arabic. Reference [73] indicate that the lack of quality and diversity of data is one of the most significant obstacles to the development of AI models in healthcare, which calls for efforts to collect reliable and diverse data.

E. Multimodal AI in Gynecology

In gynecological diagnosis, the correctness and rationality of medical diagnosis are an integration of data like the text report, test result, and the medical image, such as the ultrasound and x-ray. Thus, multimodal AI becomes a potential solution combining those heterogeneous data. Proposed strategies include:

- Designing hybrid models which is the fusion of text and image representation, such as the integration of linguistic transformer models and image CNNs.
- Creating datasets with clinical texts and images that related to the same condition.

As in [74], a practical application of integrating information from multiple sources to improve medical diagnosis is shown.

F. Bias and Privacy Handling

AI models are also beset with problems of bias due to imbalance in the training data, leading to inaccurate predictions for disparate populations. The use of health data also raises legal and ethical privacy concerns. Proposed solutions include:

- Attenuation of bias at model design stage.
- Shielding privacy with federated learning.
- Tracking model performance across populations to promote equity.

The study [75] indicates that bias in AI models can lead to disparities in healthcare, calling for effective strategies to identify and mitigate these biases.

3. Discussion

There is no doubt that AI and its clinical applications have had major contributions in modern medicine with regard to increased diagnostic accuracy, faster clinical workflows, and streamlined treatment decisions. According to the aforementioned applications, AI has achieved remarkable results in image-based diagnosis, electronic health record analysis, and predictive modeling. Techniques like supervised learning offer targeted predictions based on annotated datasets, while unsupervised approaches enable hidden pattern detection in unstructured data. In addition, transformer-based models have expanded the repertoire in NLP interpretation and clinical language modeling. In gynecology, AI-based techniques can successfully identify and classify gynecological diseases, for instance cervical and ovarian cancer, pregnancy-associated abnormalities, and hormonal diseases. These approaches provide promising tools for early monitoring and help doctors to personalize treatments. However, despite the increased accuracy and clinical efficiency by AI, it cannot substitute for the role of the doctor. Can be most usefully employed as an assistant to human intelligence, with the purpose of reducing mis-diagnoses and justifying treatment decisions illiterate of data, rather than precluding, substituting or biasing clinician judgement. Yet, there are also hurdles. Data quality, generalizability of model, provision for explanation and ethical boundaries are some of the limitations that need to be overcome for effectively utilizing AI in the actual clinical settings. so, the focus in the future should be on the creation of interpretable, bias-resistant, and clinically validated models designed to complement medical practitioners with the common goal of improving patient outcomes.

4. Conclusions

This study presents recent key developments in application of artificial intelligence (AI) aimed at improving diagnostic accuracy and productivity in women's health from 2018 to 2024, especially in the field of gynecologic risk prediction. The amalgamation of rule based systems, machine learning algorithms and genetic algorithms has improved the feature selection, which in turn increased the credibility of the diagnostic outputs. Remarkably, a high diagnostic value was reached with the binary classification models, and also good diagnostic accuracy was also found with multi-class models considering diverse gynecological diseases. However, the analysis also highlights remaining obstacles such as data quality issues, interpretability of models, and ethical limitations that deserve further exploration. Future directions of research should focus on extending high-quality clinical data, to guarantee generalization of the model to various populations, and to close the gap between algorithmic performance and application to real clinical practices. These initiatives will be critical to increase the clinical relevance of AI-driven diagnostic systems and to prevent the misuse and/or unsafe application of these instruments in gynecological practice.

Funding: This research received no external funding.

Acknowledgements: The authors gratefully acknowledge the academic support provided by the Department of Computer Science, College of Science, Al-Nahrain University. Appreciation is also extended to medical consultants from Al-Iraqia University for their valuable insights on clinical gynecology that informed the review process.

Conflict of Interest: The authors declare no conflict of interest.

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