DOI: 10.6977/IJoSI.202502_9(1).0004
J.I. Nandalwar, P.M. Jaeandhiya./Int. J. Systematic Innovation, 9(1), 44-56 (2025)

A systematic meta-analysis on the role of artificial intelligence and machine learning in detection of gynecological disorders

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(Received 29 July 2024; Final version received 11 October 2024; Accepted 21 October 2024)

Abstract

Globally, one of the major concerns in women's health issues is gynecological disorders such as cancer, which needs to be observed at its early stage. With traditional approaches, it is quite difficult to detect such disorders at its early stages. Therefore, more advanced tools need to be integrated. This paper focuses the advancements of artificial intelligence (AI) and machine learning (ML), exploring their potential in the early detection and diagnosis of these disorders. This paper presents a systematic meta-analysis of AI/ML approaches employed in the diagnosis of gynecological disorders using medical imaging modalities such as magnetic resonance imaging (MRI), ultrasound, etc. The flow for systematic meta-analysis is based on designing the research objective, selection and searching approach with inclusion and exclusion strategy; quality assessment is performed then; and finally, discussion of interpretations is also presented. This paper investigates how ML algorithms can extract characteristics from MRI images and how to use ML to extract and recognize the features from medical images such as MRI, ultrasound, computed tomography (CT) scans, etc. for early detection of gynecological tumors and provision of more personalized risk assessment. However, it is observed that there is a significant impact of advancement of AI/ML on medical technology in the future. Therefore, this paper presents a significant contribution for future medical applications and innovations.

Keywords: Artificial Intelligence, Gynecological Cancer, Machine Learning, MRI, Ultrasound

1. Introduction

Oncologists in practice face an understanding deficit as a result of the exponential growth of information about cancer together with the fast development of human society (Bhattacharjee et al., 2017; Prapty & Shitu, 2020). Researchers have demonstrated that it is quite challenging for physicians to handle clinical workloads in shorter timeframe to gain professional expertise (Denny et al., 2019; Mehrotra et al., 2011). More individuals may take advantage of societal investments in research and development, physicians can promote and embrace innovative prediction, diagnostic, and treatment procedures based on the best available evidence. Artificial intelligence (AI) (Constantinou et al., 2009; Liu et al., 2021) has entered the medical field for academic advancements, followed by an immediate introduction of new tools and techniques. One of the most challenging instances for oncology is the identification of gynecological malignancy. The many malignancy forms, every one of which is named after the body part in which it initially manifests, are shown in Fig. 1 (Basij et al., 2018; Chauhan & Singh, 2021). The goal of AI is to develop intelligent machines that can emulate human cognitive processes (Kajala & Jain, 2020; Ray, 2019). By increasing precision, effectiveness, and scalability, these developments have an opportunity to transform the diagnosis of gynecological cancer (Hou et al., 2022). Over the past decades, AI has been developed to be used for scientific application and medical diagnosis because AI can learn from patterns or knowledge from data and predict accurate outcomes, as compared to conventional techniques (Akazawa & Hashimoto, 2021; Shrestha et al., 2022). Therefore, several types of AI/ML have been used by researchers for early diagnosis of gynecological cancer. For this medical condition, imaging analysis is generally used. Gynecological cancers can be easily detected using radiological imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT) scans, histopathology, and ultrasounds (Zhou et al., 2020). This approach advances the diagnosis performance in women's health also. Apart from imaging technologies, other parameters such as metabolic testing, polycystic ovarian disease (PCOD), and polycystic ovary syndrome (PCOS) can also be used for diagnosis. These AI/ML algorithms can detect risk factors and suggest patient care. While AI/ML has massive potential for detecting gynecological cancer, there are still several research gaps due to inadequate data quality and availability.

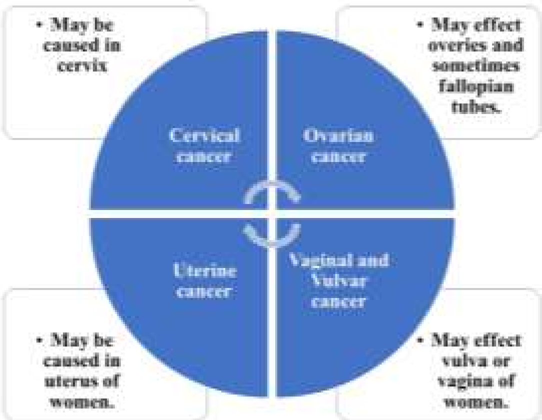

Fig. 1. Types of gynecological cancer

The primary goal of the paper is to give a thorough analysis of the most recent research on AI/ML for automated detection of gynecological cancer. Other objectives are as follows:

To investigate and study the advancement of AI tools and techniques in integrating and analyzing diverse datasets, such as medical imaging, health parameters, and clinical information for enhanced gynecological cancer detection.

To investigate the potential of ML-based approaches in early detection and classification of gynecological malignancies.

To contribute to the body of knowledge in the field of gynecological oncology by providing insights into the potential applications and limitations of AI and ML techniques in cancer detection.

2. Literature Review

In the early 1950s, AI first became a reality. The invention of intelligent robots with human-like capabilities and responses, or AI, has been universally acknowledged as having a significant impact on the industrial sector (Kasture et al., 2021; Tanaka et al., 2016). Medical professionals increasingly integrated AI into the field of medicine after realizing its significance. Therefore, AI can be broadly used in medical field. There are a lot of recent instances of AI being used in medicine. By generating a new field of study to be exploited for precision medicine, ML and radiomics are revolutionizing radiology and medicine. Gynecologic oncologists are hesitant to fall behind as AI continues to advance in the world of medicine. Medical imaging data from MRI and ultrasound scans may be analyzed by AI algorithms to help with the identification and characterization of gynecological cancers. Radiologists may now conduct more precise evaluations and identify small abnormalities that could be difficult to see visually because of the advancements made in AI approaches, notably deep learning. Researchers have reported that recent advancements of AI/ML had revolutionized the assessment and management of risk of gynecological cancer and provide personalized treatment plans (Hu et al., 2023; Lingappa & Parvathy, 2023).

Several studies have highlighted the impact of AI/ML on gynecological cancer diagnosis and risk assessment. For instance, deep learning models, such as Convolutional Neural Networks (CNNs), have shown great promise in the detection of early-stage tumors from MRI and ultrasound scans. Other machine learning techniques, such as Support Vector Machines (SVMs) and Random Forests, have also been employed to improve the classification of cancerous versus non-cancerous tissues. These advancements are transforming the way radiologists and oncologists approach cancer diagnosis, offering more personalized treatment plans tailored to the specific needs of each patient. Deep learning models are highly effective in image analysis but it requires large datasets of labeled medical images to achieve optimal performance. This poses a challenge in gynecological oncology but it has limitation that there is lack of labeled data. Additionally, widespread clinical adoption is another issue related to the interpretability of ML models. Traditional machine learning models, while easier to interpret, may not achieve the same level of diagnostic accuracy as seen in more complex AI systems like deep learning networks.

3. Method Used

In this section, the methodology adopted for performing systematic meta-analysis for the identification of the role of AI/ML in the detection of gynecological tumors or cancer. For this systematic meta-analysis is performed. The flowchart of paper selection for meta-analysis is presented below in Fig. 2.

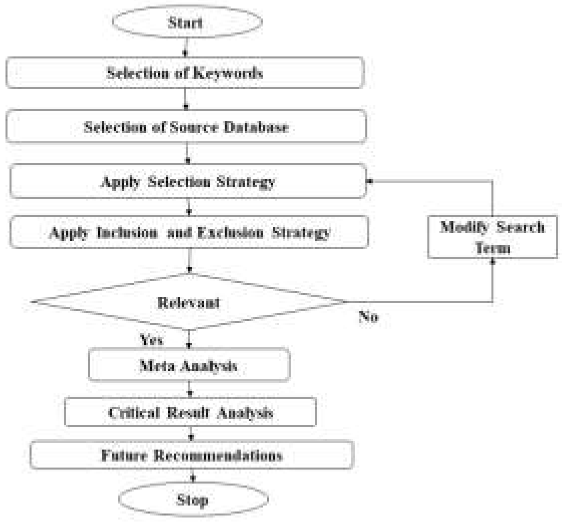

Fig. 2. Methodology used for systematic meta-analysis

The flowchart outlines the systematic meta-analysis process for identifying the role of AI/ML in the detection of gynecological tumors or cancer. The process begins with defining the objective of the systematic meta-analysis. In this paper, the objective is to present a systematic review and meta-analysis for role of AI/ML for automatic detection and correlation of gynecological cancers such as endometrium cancer, cervical cancer, ovarian cancer, etc. This paper aims to analyze the imaging technologies for women health diagnosis by detecting gynecological cancer. To achieve these objectives, relevant keywords are chosen to perform the literature search. These keywords could include terms such as “AI in gynecology,” “machine learning for cancer detection,” “gynecological tumors,” “medical imaging for gynecological tumors detection,” and “AI for gynecological diagnosis.” After determining the keywords, suitable scientific databases were selected for the literature search. Common databases may include IEEE Xplore, Science direct, Springer, Wiley, etc. that contain relevant studies on AI/ML and gynecological cancer detection. A selection strategy was applied to filter relevant research papers from the selected databases. This may involve screening by title, abstract, and keywords to identify studies that align with the research objectives. Then, inclusion and exclusion strategy was applied to further refine the selection. Inclusion criteria could involve selecting studies focused on AI/ML methods for medical imaging in gynecology, while exclusion criteria might omit studies that lack sufficient data or focus on unrelated medical conditions. The filtered studies were assessed for relevance to the research topic. If a study is deemed not relevant, the search is modified to refine the keywords or selection criteria. If the study is relevant, it is included for further analysis. Relevant studies were subjected to meta-analysis and analysis to draw conclusions about the overall impact of AI/ML techniques on the diagnosis of gynecological disorders. After the meta-analysis, the results were critically analyzed to identify the strengths and limitations of the AI/ML approaches.

4. Detection Using Machine Learning Based on MRI Images

For medical diagnosis, MRI findings are considered one of the most important inputs. To better understand the patterns in MRIs, ML extracts characteristics more precisely (Subramanian et al., 2023). These characteristics may be the tissue texture, shape, intensity, and spatial connections. These need to be identified and learned properly to distinguish between healthy and malignant regions in MRI images (Baydoun et al., 2021). To provide the capability of early prediction, ML models may be trained to identify patterns and distinguish certain biomarkers (Zhang & Han, 2020). Additionally, segmentation methods can accurately identify the tumor borders by applying ML techniques that will provide valuable information to doctors for planning, tracking, and treating gynecological disorders (Guo et al., 2019; Visalaxi et al., 2021). Soğukkuyu and Ata (2022) proposed an ensemble strategy for predicting the risk of cervical cancer. Keymasi et al. (2018) categorized pap-smear pictures using various ML techniques to increase prediction accuracy. KNN, SVM, and multilayer perceptron (MLP) are three ML approaches that are combined in the ensemble methodology. Jiang et al. (2021) used multi-parametric MRI data to construct radiomics algorithms that are based on deep learning, which are used for the detection of cervical cancer. Wang et al. (2021) developed a methodology based on deep learning that distinguishes between malignant and benign ovary lesions using CNN as opposed to using conventional MR imaging. A single institution divided 451 patients' 545 lesions—379 normal and 166 malignant—into 7:2:1 training, validation, and evaluation sets. Ghoneim et al. (2020) presented a technique for the identification and classification of cervical cancer cells that is based on CNN. Following this step, the input images are assigned categories using a classifier that is driven by an extreme machine learning (ELM). Transfer learning and fine-tuning are the two methods that are employed to use the CNN architecture. In addition to the ELM, classifiers based on autoencoders and multilayer perceptrons are also being researched as potential replacements. Ratul et al. (2022) carried out a logical analysis to show the efficiency of the MLP method with default hyperparameters and obtained 93.33% prediction accuracy. Wang et al. (2023) offered a unique optical biopsy technique to help surgeons quickly and reliably diagnose ovarian cancer. Khuriwal and Mishra (2018) showed how AI may be used with the UCI Database to identify breast cancer. Kurnianingsih et al. (2019) used a mask regional CNN (Mask R-CNN) on the pap smear dataset to assess the cancerous cells. Arora et al. (2021) used SVM and achieved an accuracy of 95%. The author also used the Gaussian filter for image denoising. Bnouni et al. (2021) suggested an ensemble preprocessing technique to boost a CNN's classification accuracy for cervical cancer. Table 1 presents the overview of recent research on MRI images for detection of gynecological cancer.

5. Detection Using Machine Learning Based on Ultrasound Images

In gynecology, ultrasound imaging is a frequently used diagnostic technique for the identification and assessment of gynecological malignancies. To better analyze ultrasound data and diagnose gynecological cancer, ML algorithms have shown potential (Zhang & Han, 2020). Algorithms are used in ML-based techniques to categorize anomalies, extract useful information from ultrasound pictures, and assist in the early diagnosis of gynecological cancers (Zhang et al., 2023). ML algorithms can examine ultrasound images by identifying characteristics like vascularity, echogenicity, texture, and spatial connections (Ruchitha et al., 2021). Studies have revealed that ML-based methods may improve diagnostic precision by using ultrasound images (Marques et al., 2019). Ultrasound images can be used in environments with minimal resources due to their portability and accessibility (Behboodi et al., 2021). Arezzo et al. (2022) used ML to detect cancer on

Table 1. Recent literature on MRI-based gynecological cancer detection integrated with AI/ ML

Ref.	Year	Methods used	Imaging modality	Type of cancer	Result
Soğukkuyu & Ata (2022)	2022	Multiple ML methods	MRI	Cervical cancer	Accuracy = 97%
Keymasi et al. (2018)	2018	KNN, SVM	MRI	Cervical cancer	Accuracy = 97.83%
Jiang et al. (2021)	2021	Deep learning-based radiomic methods	MRI	Early-stage cervical cancer	AUC = 91.1% Sensitivity = 88.1%
Wang et al. (2021)	2021	CNN	MRI	Ovarian cancer	Accuracy = 87% Sensitivity = 75%
Ghoneim et al. (2020)	2020	CNN, MLP	MRI	Cervical cancer	Accuracy = 99.5%
Ratul et al. (2022)	2022	KNN, DTC, SVM, RFC, MLP	MRI	Cervical cancer	MLP performed best with accuracy = 93.33%
Wang et al. (2023)	2023	End-to-end deep learning	MRI	Ovarian cancer	Accuracy = 99.7%
Arora et al. (2021)	2021	SVM	MRI	Cervical cancer	Accuracy = 95%

ultrasound data. Gao et al. (2022) intended to create a deep CNN system that automates ultrasound image interpretation and makes ovarian cancer detection easier than with current techniques. Srivastava et al. (2020) obtained sample ultrasound pictures of the ovaries from various women and identified the presence or absence of ovarian cysts. The standard VGG-16 model is used in the proposed research and is tweaked using an exclusive dataset of ultrasound images. A 16-layer DL-NN trained on the ImageNet dataset is a VGG-16 model. The last four layers of the VGG-16 network are changed to adjust the network. Kiruthika et al. (2020) presented an artificial neural network to construct an intelligent automated detection and ovarian categorization for ovary detection was given three texture characteristics. Zhou et al. (2021) evaluated the usefulness of tumor feature extraction on DBN for cancer of the cervical cavity patient diagnosis and to accomplish a smart assessment of the impacts of therapy and cervical detection of cancer. This technique was then used to analyze tumors automatically using a DBN architecture.

The proposed framework for tumor extraction of features based on the DBN was shown to have a superior accuracy of 86.36%, sensitivity of 83.33%, and specificity of 87.50 %. Taleb et al. (2022) have shown the capability of ML for accurate recognition of ovarian cancer and its stages. The majority of current studies on ovarian cancer employ a single categorization model, which has poor diagnostic efficacy. Chen et al. (2021) proposed a 3D CNN based on a domain-knowledge-guided temporal attention module and a channel attention module. On a dataset of 221 breast-CEUS patients, the author validated the model. Hyun et al. (2020) proposed a 4-layer CNN to identify MB signatures without causing any damage. Goudarzi et al. (2023) studied the segmentation approach on ultrasound images with a Dice Score Coefficient (DSC) of 0.940.08 and 0.920.06, respectively. The CutMix augmentation technique enhances the generalization performance of the proposed CNN, which is tuned for accurate automated segmentation of tissue layers. Table 2 presents the overview of recent research on ultrasound images for detection of gynecological cancer.

6. Detection Using Machine Learning Based on Metabolic Parameters

Machine learning algorithms may use a variety of health factors in addition to medical imaging to diagnose gynecological cancer. These health indicators include blood test results, metabolic test results, PCOS, PCOD, and other pertinent clinical data (Coffin et al., 2023). To identify risk variables,

Table 2. Recent literature on ultrasound-based gynecological cancer detection in integration with AI/ML

Ref.	Year	Method	Imaging modality	Type of cancer	Result
Arezzo et al. (2022)	2022	RF, LR, KNN	Ultrasound	Ovary cancer	Accuracy = 93.7% Precision = 90% Recall = 90%
Gao et al. (2022)	2022	D-CNN	Ultrasound	Ovary cancer	AUC = 91.1% Accuracy = 86.9%
Srivastava et al., (2020)	2020	VGG-16	Ultrasound	Ovary cancer	Accuracy = 92.11%
Kiruthika et al. (2020)	2020	ANN	Ultrasound	Ovary cancer	Accuracy of 96%
Zhou et al. (2021)	2021	DBN	Ultrasound	Cervical cancer	Accuracy = 86.36% Sensitivity = 83.3% Specificity = 87.50%
Taleb et al. (2022)	2022	SVM, KNN	Ultrasound	Ovary cancer	Accuracy = 98.1% and 97.16%
Chen et al. (2021)	2021	3D CNN	Ultrasound	Breast cancer	Sensitivity of 97.2% and an accuracy of 86.3%.
Hyun et al. (2020)	2020	4-Layer CNN	Ultrasound	Breast cancer	Generalized contrast-to-noise ratio (GCNR) of 0.93 and Kolmogorov-Smirnov statistic (KSS) of 0.86
Goudarzi et al. (2023)	2023	Gated Shape CNN	Ultrasound	Breast cancer	DSC = 94% and 92 %

forecast disease development, and give a tailored risk assessment for gynecological cancer, ML algorithms may combine and evaluate this information. ML algorithms may be used to create prediction models for gynecological cancer risk assessment using health factors like blood test results and metabolic test results. ML models may establish relations among certain biomarkers, patterns, or characteristics that can increase the risk of developing gynecological malignancies (Harish et al., 2023; Tiwari et al., 2022). ML algorithms are capable of enhancing the identification and management of gynecological cancer by analyzing the health metrics or genetic matrices to present personalized risk assessments and treatment recommendations (Harish et al., 2023). ML can analyze medical data to identify risk factors and early signs of cancer and also enable medical experts to provide early interventions like lifestyle adjustments or preventive measures. Bharati et al. (2020) discussed the data-driven approach to diagnosis of PCOS in women. The model has achieved 91.01% of accuracy and 90% of recall value. Poorani and Khilar (2023) categorized whether a woman has PCOS. Denny et al. (2019) provided a method for the timely diagnosis and prognosis of PCOS by making use of clinical and nutritional markers that are ideal and minimal but still helpful in predicting the presence of the condition. The 541 women who participated in this study provided the data sets that were necessary for the construction of this framework. A variety of different ML techniques are used to categorize PCOS utilizing the accumulated set of characteristics that were altered using principal component analysis (PCA). Chitra et al. (2023) diagnosed PCOS via ultrasound images by using transfer learning approaches such as Alexnet and Inception. Harish et al. (2023) identified that PCOS is a serious condition that affects females when their ovaries are fertile, between the ages of 15 and 45. This disease affects 5–10% of reproductive-age females. Despite the difficulty in fully treating this condition, PCOS-affected women may minimize their symptoms by getting the right amount of exercise, eating well, and maintaining a healthy BMI. Random oversampling triumphs when comparing the two equally weighted approaches using accuracy. An enhanced AI classifier for PCOS diagnosis was developed using 594 ovarian ultrasonography (USG) images by (Suha & Islam, 2022). The proposed technique outperforms previous ML-based methods in accuracy and training time. Utilizing the recommended expanded method, the "VGGNet16" pre-trained algorithm uses a CNN architecture as an extractor of features and a stacked ensemble algorithm with the "XGBoost" meta-learner as an image classification. Khanna et al. (2023) have shown an AI method for predicting PCOS in patients with fertile patients utilizing heterogeneous ML/DL approaches. The author investigated a 541-patient open-source dataset. Swapnarekha et al. (2023) proposed a predicting model based on random oversampling that has proved successful in resolving the issue of class imbalance. In this method, the optimal model hyperparameters are selected via Bayesian optimization. Wang et al. (2022) proposed a decision tree-based PCOS-linked cancer detection algorithm. Based on the obtained SMFs, a decision tree is built, and practical simulations are run on separate internal and external cohorts. Bharati et al. (2022) presented the statistical approach for women's PCOS diagnosis. When the traits are graded, the ratio of luteinizing hormone (LH) to follicle-stimulating hormone (FSH) is shown to be the most important factor. While features are being chosen and eliminated, the cross-validation approach is used. Among the classifiers utilized on the dataset are voting hard, voting soft, and CatBoost. Prasher and Nelson (2023) identified the hormone that is most often seen globally is PCOS. The ovaries generate a large number of microscopic fluid-filled sacs known as follicles, which are the root cause of PCOS. The ovaries did not always release the eggs, as was to be anticipated. One of the best ways to diagnose PCOS early and develop a treatment plan for people with this condition is to look for numerous follicles on USG scans. Nasim et al. (2022) predicted the PCOS by applying ML approaches. Based on the CS-PCOS mechanism, a unique feature selection method is suggested. Prolactin, blood pressure (systolic and diastolic), and pregnancy are the key indicators with significant influence on PCOS prediction. Through the early discovery of PCOS, the work assists the medical community in reducing the miscarriage rate and offering women a remedy. Table 3 presents the overview of recent research on metabolic parameters for detection of gynecological cancer.

7. Discussion

The current study provides insights into the role of AI/ML techniques in the detection of gynecological cancers through MRI, ultrasound, and metabolic parameters. The studies used for meta-analysis are

Table 3. Recent literature on metabolic parameters-based gynecological cancer detection in integration with AI/ ML.

Ref.	Year	Methods	Metabolic test	Type of cancer	Result
Bharati et al. (2020)	2020	LR	PCOS	Ovary cancer	Accuracy = 91.01%
Denny et al. (2019)	2019	KNN, SVM	PCOS	Ovary cancer	Accuracy = 89.02%
Chitra et al. (2023)	2023	Inception V3, Resnet50, VGG16 and Hybrid Models	PCOS	Ovary cancer	Accuracy = 93%
Harish et al. (2023)	2023	SVM, XGBOOST, LR, KNN, RF	Polycystic ovary syndrome	Ovary cancer	Accuracy = 96%
Swapnarekha et al. (2023)	2023	SVM, Genetic algorithm, MLP, ELM	Polycystic ovary syndrome	Ovary cancer	Accuracy = 99.31%
Wang et al. (2022)	2022	Decision Tree	PCOS	Ovary cancer	AUC = 96.7%
Bharati et al. (2022)	2022	Ensemble Learning	Polycystic ovary syndrome	Ovary cancer	Accuracy = 91.12%
Prasher & Nelson (2023)	2023	D-CNN	Polycystic ovary syndrome	Ovary cancer	Accuracy = 99.4%
Nasim et al. (2022)	2022	Generative NB	Polycystic ovary syndrome	Ovary cancer	Accuracy = 100%

selected to effectively demonstrate the role of ML and deep learning models for cancer detection.

For instance, high accuracy has been achieved by CNN-based models, as seen in studies by Wang et al. (2021) and Ghoneim et al. (2020). This shows the trend of using CNN for image-based diagnosis. The use of ensemble methods, such as those proposed by Soğukkuyu and Ata (2022) and Keymasi et al. (2018) show promising improvement in prediction accuracy. This indicates a trend toward using hybrid models to address the limitations of single-model approaches. Our review of the studies using MRI-based detection techniques shows that deep learning models like CNNs outperform consistently over traditional ML approaches such as KNN, SVM, and MLP in detecting and classifying gynecological cancers. This is evident in studies by Jiang et al. (2021) and Wang et al. (2021) where CNN models demonstrated its better performance compared to non-deep learning methods. Similarly, ultrasound-based detection techniques also shows the benefit of usage of deep learning. Both Gao et al. (2022) and Srivastava et al. (2020) showed that CNN models can improve the accuracy of ovarian cancer detection compared to traditional methods. However, Taleb et al. (2022) and Chen et al. (2021) used the attention modules or domain-guided approaches that can further enhance performance. In terms of metabolic parameter-based detection, researchers showed that integration of metabolic data with ML techniques provided a significant improvement in cancer risk assessment. Bharati et al. (2020) demonstrated how ML algorithms could effectively combine metabolic data to predict PCOS-related ovarian cancer with high accuracy. This trend highlights the growing importance of using multi-modal data to provide a more comprehensive view of cancer risk and progression.

However, several limitations were also identified:

Many of the studies rely on relatively small datasets. MRI and ultrasound datasets are often limited in size. To mitigate these limitations, there is a need to develop larger and diverse datasets that can help to improve the generalizability of AI/ML models.

While deep learning models such as CNN are “black-box” in nature that presents a challenge for clinical adoption, Ghoneim et al. (2020) and Chen et al. (2021) incorporated more interpretable models such as attention models. Hybrid models that combine multiple AI/ML approaches could yield better outcomes.

8. Practical Implication of Findings

The meta-analysis presented in this paper shows the significant practical implications for the integration of AI/ML techniques in clinical applications. AI/ML models such as deep learning algorithms like CNNs have shown good accuracy for identifying gynecological tumors from MRI and ultrasound images. These models can serve as decision support tools for radiologists and gynecologists for early detection of cancer. By integrating metabolic parameters and health indicators, AI/ML models can provide more personalized risk assessments and treatment recommendations. The use of AI with imaging techniques is particularly promising for resource-limited environment. Such applications can be used in remote areas to facilitate early detection and diagnosis of gynecological cancers. This will reduce the need for immediate specialist intervention. AI/ML systems can minimize diagnostic errors caused by human fatigue, inexperience, or oversight. However, it has some potential barriers also such as lack of large, diverse, and high-quality datasets, hybrid models are black-box in nature, resource limitations, complexity, etc.

9. Conclusion

The use of AI/ML approaches to improve the detection and treatment of gynecological malignancies has gained increasing attention in the past few years. Therefore, the goal of this paper is to describe the current level of AI research for the diagnosis of gynecological tumors using imaging technologies and health metabolic parameters. This paper presents a systematic meta-analysis that explored these aspects. The paper identified that deep learning model as well as hybrid or ensemble learning models outperforms better diagnosis either it is MRI imaging or ultrasound imaging approach. Whereas, on cancer risk assessment, metabolic parameters were also considered and its diagnosis hybrid model also outperforms well. Whereas potential barriers were also identified in this research, such as lack of large, diverse, and high-quality datasets, hybrid models are black-box in nature, resource limitations, complexity, etc. These aspects will need to be focused in future for improvement.

References

Adweb, K. M. A., Cavus, N., & Sekeroglu, B. (2021). Cervical Cancer Diagnosis Using Very Deep Networks Over Different Activation Functions. IEEE Access, 9, 46612–46625.https://doi.org/10.1109/ACCESS.2021.3067195

Akazawa, M., & Hashimoto, K. (2021). Artificial intelligence in gynecologic cancers: Current status and future challenges - A systematic review. Artificial Intelligence in Medicine, 120, 102164. https://doi.org/10.1016/j.artmed.2021.102164

Arezzo, F., Cormio, G., La Forgia, D., Santarsiero, C. M., Mongelli, M., Lombardi, C., Cazzato, G., Ci-cinelli, E., & Loizzi, V. (2022). A machine learning approach applied to gynecological ultrasound to predict progression-free survival in ovarian cancer patients. Archives of Gynecology and Obstetrics, 306(6), 2143–2154. https://doi.org/10.1007/s00404-022-06578-1

Arora, A., Tripathi, A., & Bhan, A. (2021). Classification of Cervical Cancer Detection using Ma-chine Learning Algorithms. 2021 6th International Conference on Inventive Computation Technologies (ICICT), 827–835. https://doi.org/10.1109/ICICT50816.2021.9358570

Basij, M., Yan, Y., Alshahrani, S., Winer, I., Bur-meister, J., Dominello, M., & Mehrmohammadi, M. (2018). Development of an Ultrasound and Photoacoustic Endoscopy System for Imaging of Gynecological Disorders. 2018 IEEE International Ultrasonics Symposium (IUS), 1–4. https://doi.org/10.1109/ULTSYM.2018.8579788

Baydoun, A., Xu, K. E., Heo, J. U., Yang, H., Zhou, F., Bethell, L. A., Fredman, E. T., Ellis, R. J., Podder, T. K., Traughber, M. S., Paspulati, R. M., Qian, P., Traughber, B. J., & Muzic, R. F. (2021). Synthetic CT Generation of the Pelvis in Patients with Cervical Cancer: A Single Input Approach Using Generative Adversarial Network. IEEE Access: Practical Innovations, Open Solutions, 9, 17208–17221. https://doi.org/10.1109/access.2021.3049781

Behboodi, B., Rivaz, H., Lalondrelle, S., & Harris, E. (2021). Automatic 3D Ultrasound Segmentation of Uterus Using Deep Learning. IEEE International Ultrasonics Symposium, IUS, 3–6. https://doi.org/10.1109/IUS52206.2021.9593671

Bharati, S., Podder, P., & Hossain Mondal, M. R. (2020). Diagnosis of Polycystic Ovary Syndrome Using Machine Learning Algorithms. 2020 IEEE Region 10 Symposium (TENSYMP), 1486–1489. https://doi.org/10.1109/TENSYMP50017.2020.9230932

Bharati, S., Podder, P., Mondal, M. R., Prasath, S., & Gandhi, N. (2022). Ensemble Learning for Da-ta-Driven Diagnosis of Polycystic Ovary Syn-drome. 1250–1259. https://doi.org/10.1007/978-3-030-96308-8_116

Bhattacharjee, S., Singh, Y. J., & Ray, D. (2017). Comparative performance analysis of machine learning classifiers on ovarian cancer dataset. 2017 Third International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), 213–218. https://doi.org/10.1109/ICRCICN.2017.8234509

Bhavani, C. H., & Govardhan, A. (2023). Cervical cancer prediction using stacked ensemble algorithm with SMOTE and RFERF. Materials Today: Proceedings, 80, 3451–3457.https://doi.org/https://doi.org/10.1016/j.matpr.2021.07.269

Bnouni, N., Amor, H. Ben, Rekik, I., Rhim, M. S., Solaiman, B., & Amara, N. E. Ben. (2021). Boosting CNN Learning by Ensemble Image Preprocessing Methods for Cervical Cancer Segmentation. 2021 18th International Mul-ti-Conference on Systems, Signals & Devices (SSD), 264–269. https://doi.org/10.1109/SSD52085.2021.9429422

Chang, C.-C., Chen, H.-H., Chang, Y.-C., Yang, M.-Y., Lo, C.-M., Ko, W.-C., Lee, Y.-F., Liu, K.-L., & Chang, R.-F. (2017). Computer-aided diagnosis of liver tumors on computed tomography images. Computer Methods and Programs in Biomedicine, 145, 45–51. https://doi.org/https://doi.org/10.1016/j.cmpb.2017.04.008

Chauhan, N. K., & Singh, K. (2021). Impact of Variation in Number of Channels in CNN Classification model for Cervical Cancer Detection. 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 1–6. https://doi.org/10.1109/ICRITO51393.2021.9596366

Chen, C., Wang, Y., Niu, J., Liu, X., Li, Q., & Gong, X. (2021). Domain Knowledge Powered Deep Learning for Breast Cancer Diagnosis Based on Contrast-Enhanced Ultrasound Videos. IEEE Transactions on Medical Imaging, 40(9), 2439–2451. https://doi.org/10.1109/TMI.2021.3078370

Chitra, P., Srilatha, K., Sumathi, M., Jayasudha, F. V, Bernatin, T., & Jagadeesh, M. (2023). Classification of Ultrasound PCOS Image using Deep Learning based Hybrid Models. 2023 Second International Conference on Electronics and Renewable Systems (ICEARS), 1389–1394. https://doi.org/10.1109/ICEARS56392.2023.10085400

Coffin, T., Wray, J., Sah, R., Maj, M., Nath, R., Nauhria, S., Maity, S., & Nauhria, S. (2023). A Review and Meta-Analysis of the Prevalence and Health Impact of Polycystic Ovary Syndrome Among Medical and Dental Students. Cureus, 15(6), e40141. https://doi.org/10.7759/cureus.40141

Constantinou, I. P., Koumourou, C. A., Neofytou, M. S., Tanos, V., Pattichis, C. S., & Kyriakou, E. C. (2009). An integrated CAD system facilitating the endometrial cancer diagnosis. 2009 9th International Conference on Information Technology and Applications in Biomedicine, 1–5. https://doi.org/10.1109/ITAB.2009.5394424

Coşar Soğukkuyu, D. Y., & Ata, O. (2022). Diagnosing Cervical Cancer Using Machine Learning Methods. 2022 International Congress on Hu-man-Computer Interaction, Optimization and Robotic Applications (HORA), 1–3. https://doi.org/10.1109/HORA55278.2022.9800033

de Carvalho Filho, A. O., Silva, A. C., Cardoso de Paiva, A., Nunes, R. A., & Gattass, M. (2017). Computer-Aided Diagnosis of Lung Nodules in Computed Tomography by Using Phylogenetic Diversity, Genetic Algorithm, and SVM. Journal of Digital Imaging, 30(6), 812–822. https://doi.org/10.1007/s10278-017-9973-6

Denny, A., Raj, A., Ashok, A., Ram, C. M., & George, R. (2019). i-HOPE: Detection and Prediction System For Polycystic Ovary Syndrome (PCOS) Using Machine Learning Techniques. TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), 673–678. https://doi.org/10.1109/TENCON.2019.8929674

Gao, Y., Zeng, S., Xu, X., Li, H., Yao, S., Song, K., Li, X., Chen, L., Tang, J., Xing, H., & Yu, Z. (2022). Articles Deep learning-enabled pelvic ultrasound images for accurate diagnosis of ovarian cancer in China: a retrospective, multicentre, diagnostic study. 179–187. https://doi.org/10.1016/S2589-7500(21)00278-8

Ghoneim, A., Muhammad, G., & Hossain, M. S. (2020). Cervical cancer classification using convolutional neural networks and extreme learning machines. Future Generation Computer Systems, 102, 643–649. https://doi.org/https://doi.org/10.1016/j.future.2019.09.015

Goudarzi, S., Whyte, J., Boily, M., Towers, A., Kilgour, R. D., & Rivaz, H. (2023). Segmentation of Arm Ultrasound Images in Breast Cancer-Related Lymphedema: A Database and Deep Learning Algorithm. IEEE Transactions on Bio-Medical Engineering, 70(9), 2552–2563. https://doi.org/10.1109/TBME.2023.3253646

Guo, Z., Li, X., Huang, H., Guo, N., & Li, Q. (2019). Deep Learning-Based Image Segmentation on Multimodal Medical Imaging. IEEE Transactions on Radiation and Plasma Medical Sciences, 3(2), 162–169. https://doi.org/10.1109/TRPMS.2018.2890359

Harish, K. P., Dhivyanchali, M. N., Devi, K. N., Krishnamoorthy, N., Dhana Sree, R., & Dharanidharan, R. (2023). Smart Diagnostic System For Early Detection And Prediction Of Polycystic Ovary Syndrome. 2023 International Conference on Computer Communication and Informatics (ICCCI), 1–6. https://doi.org/10.1109/ICCCI56745.2023.10128560

Hou, X., Shen, G., Zhou, L., Li, Y., Wang, T., & Ma, X. (2022). Artificial Intelligence in Cervical Cancer Screening and Diagnosis. Frontiers in Oncology, 12, 851367. https://doi.org/10.3389/fonc.2022.851367

Hu, D., Jian, J., Li, Y., & Gao, X. (2023). Deep learning-based segmentation of epithelial ovarian cancer on T2-weighted magnetic resonance images. Quantitative Imaging in Medicine and Surgery, 13(3), 1464–1477. https://doi.org/10.21037/qims-22-494

Hyun, D., Abou-Elkacem, L., Bam, R., Brickson, L. L., Herickhoff, C. D., & Dahl, J. J. (2020). Nondestructive Detection of Targeted Microbubbles Using Dual-Mode Data and Deep Learning for Real-Time Ultrasound Molecular Imaging. IEEE Transactions on Medical Imaging, 39(10), 3079–3088. https://doi.org/10.1109/TMI.2020.2986762

Jiang, X., Li, J., Kan, Y., Yu, T., Chang, S., Sha, X., Zheng, H., Luo, Y., & Wang, S. (2021). MRI Based Radiomics Approach With Deep Learning for Prediction of Vessel Invasion in Early-Stage Cervical Cancer. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 18(3), 995–1002. https://doi.org/10.1109/TCBB.2019.2963867

Kajala, A., & Jain, V. K. (2020). Diagnosis of Breast Cancer using Machine Learning Algorithms-A Review. 2020 International Conference on Emerging Trends in Communication, Control and Computing (ICONC3), 1–5. https://doi.org/10.1109/ICONC345789.2020.9117320

Kapruwan, A., Sharma, S., & Goyal, H. R. (2023). Artificial Intelligence Enabled Diagnostic Digital Cytopathology System for Cervical Intraepithelial Neoplasia Detection: Advantages and Challenges. 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), 669–674. https://doi.org/10.1109/ICAIS56108.2023.10073850

Kasture, K. R., Sayankar, B. B., & Matte, P. N. (2021). Multi-class Classification of Ovarian Cancer from Histopathological Images using Deep Learning - VGG-16. 2021 2nd Global Conference for Advancement in Technology (GCAT), 1–6. https://doi.org/10.1109/GCAT52182.2021.9587760

Keymasi, M., Mishra, V., Aslan, S., & Asem, M. (2018). Theoretical Assessment of Cervical Cancer Using Machine Learning Methods Based on Pap-Smear Test. 1367–1373. https://doi.org/10.1109/IEMCON.2018.8615041

Khanna, V. V., Chadaga, K., Sampathila, N., Prabhu, S., Bhandage, V., & Hegde, G. K. (2023). A Distinctive Explainable Machine Learning Framework for Detection of Polycystic Ovary Syndrome. Applied System Innovation, 6(2). https://doi.org/10.3390/asi6020032

Khuriwal, N., & Mishra, N. (2018). Breast Cancer Diagnosis Using Deep Learning Algorithm. 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), 98–103. https://doi.org/10.1109/ICACCCN.2018.8748777

Kiruthika, V., Sathiya, S., & Ramya, M.M. (2020). Machine learning based ovarian detection in ultrasound images. International Journal of Advanced Mechatronic Systems, 8, 75. https://doi.org/10.1504/IJAMECHS.2020.111306

Kurnianingsih, Allehaibi, K. H. S., Nugroho, L. E., Widyawan, Lazuardi, L., Prabuwono, A. S., & Mantoro, T. (2019). Segmentation and Classification of Cervical Cells Using Deep Learning. IEEE Access, 7, 116925–116941. https://doi.org/10.1109/ACCESS.2019.2936017

Li, Y., Chen, J., Xue, P., Tang, C., Chang, J., Chu, C., Ma, K., Li, Q., Zheng, Y., & Qiao, Y. (2020). Computer-Aided Cervical Cancer Diagnosis Using Time-Lapsed Colposcopic Images. IEEE

Transactions on Medical Imaging, 39(11), 3403–3415. https://doi.org/10.1109/TMI.2020.2994778

Lingappa, E., & Parvathy, L. R. (2023). Image Classification with Deep Learning Methods for Detecting and Staging Bone Cancer from MRI. 2023 International Conference on Networking and Communications (ICNWC), 1–8. https://doi.org/10.1109/ICNWC57852.2023.10127368

Liu, X., Xiao, Z., Song, Y., Zhang, R., Li, X., & Du, Z. (2021). A Machine Learning-Aided Framework to Predict Outcomes of Anti-PD-1 Therapy for Patients With Gynecological Cancer on Incomplete Post-Marketing Surveillance Dataset. IEEE Access, 9, 120464–120480. https://doi.org/10.1109/ACCESS.2021.3107498

Marques, S., Carvalho, C., Peixoto, C., Pignatelli, D., Beires, J., Silva, J., & Campilho, A. (2019). Segmentation of gynaecological ultrasound images using different U-Net based approaches. 2019 IEEE International Ultrasonics Symposium (IUS), 1485–1488. https://doi.org/10.1109/ULTSYM.2019.8925948

Mehrotra, P., Chatterjee, J., Chakraborty, C., Ghoshdastidar, B., & Ghoshdastidar, S. (2011). Automated screening of Polycystic Ovary Syndrome using machine learning techniques. 2011 Annual IEEE India Conference, 1–5. https://doi.org/10.1109/INDCON.2011.6139331

Nasim, S., Almutairi, M. S., Munir, K., Raza, A., & Younas, F. (2022). A Novel Approach for Polycystic Ovary Syndrome Prediction Using Machine Learning in Bioinformatics. IEEE Access, 10, 97610–97624. https://doi.org/10.1109/ACCESS.2022.3205587

Nishio, M., & Nagashima, C. (2017). Computer-aided Diagnosis for Lung Cancer: Usefulness of Nodule Heterogeneity. Academic Radiology, 24(3), 328–336. https://doi.org/https://doi.org/10.1016/j.acra.2016.11.007

Nithya, B., & Ilango, V. (2020). Machine Learning Aided Fused Feature Selection based Classification Framework for Diagnosing Cervical Cancer. 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), 61–66. https://doi.org/10.1109/ICCMC48092.2020.ICCMC-00011

Poorani, B. & Khilar, R. (2023). Classification of PCOS Using Machine Learning Algorithms Based on Ultrasound Images of Ovaries. 2023 Eighth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), 1–7. https://api.semanticscholar.org/CorpusID:259101230

Prapty, A. S., & Shitu, T. T. (2020). An Efficient Decision Tree Establishment and Performance Analysis with Different Machine Learning Approaches on Polycystic Ovary Syndrome. 2020 23rd International Conference on Computer and Information Technology (ICCIT), 1–5. https://doi.org/10.1109/ICCIT51783.2020.9392666

Prasher, S., & Nelson, L. (2023). Follicle Prediction for Polycystic Ovary Syndrome Diagnosis from Ovarian Ultrasound Images using CNN. 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom), 789–793.

Rahman, M. A., Muniyandi, R. C., Islam, K. T., & Rahman, M. M. (2019). Ovarian Cancer Classification Accuracy Analysis Using 15-Neuron Artificial Neural Networks Model. 2019 IEEE Student Conference on Research and Development (SCOReD), 33–38. https://doi.org/10.1109/SCORED.2019.8896332

Ratul, I. J., Al-Monsur, A., Tabassum, B., Ar-Rafi, A. M., Nishat, M. M., & Faisal, F. (2022). Early risk prediction of cervical cancer: A machine learning approach. 2022 19th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 1–4. https://doi.org/10.1109/ECTI-CON54298.2022.9795429

Ray, S. (2019). A Quick Review of Machine Learning Algorithms. 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), 35–39. https://doi.org/10.1109/COMITCon.2019.8862451

Ruchitha, P. J., Sai Richitha, Y., Kodipalli, A., & Martis, R. J. (2021). Segmentation of Ovarian Cancer using Active Contour and Random Walker Algorithm. 2021 5th International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT), 238–241. https://doi.org/10.1109/ICEECCOT52851.2021.9707939

Senthilkumar, G., Ramakrishnan, J., Frnda, J., Manikandan, R., Gupta, D., Tiwari, P., Mohammad, S., & Mohammed, M. (2021). Incorporating Artificial Fish Swarm in Ensemble Classification Framework for Recurrence Prediction of Cervical Cancer. IEEE Access, PP, 1. https://doi.org/10.1109/ACCESS.2021.3087022

Shrestha, P., Poudyal, B., Yadollahi, S., E Wright, D., V Gregory, A., D Warner, J., Korfiatis, P., C Green, I., L Rassier, S., Mariani, A., Kim, B., Laugh-lin-Tommaso, S. K., & L Kline, T. (2022). A systematic review on the use of artificial intelligence in gynecologic imaging - Background, state of the art, and future directions. Gynecologic Oncology, 166(3), 596–605. https://doi.org/10.1016/j.ygyno.2022.07.024

Srivastava, S., Kumar, P., Chaudhry, V., & Singh, A. (2020). Detection of Ovarian Cyst in Ultrasound Images Using Fine-Tuned VGG-16 Deep Learning Network. SN Computer Science, 1(2), 81. https://doi.org/10.1007/s42979-020-0109-6

Subramanian, M., Cho, J., Sathishkumar, V. E., & Naren, O. S. (2023). Multiple Types of Cancer Classification Using CT/MRI Images Based on Learning Without Forgetting Powered Deep Learning Models. IEEE Access, 11, 10336–10354. https://doi.org/10.1109/ACCESS.2023.3240443

Suha, S. A., & Islam, M. N. (2022). An extended machine learning technique for polycystic ovary syndrome detection using ovary ultrasound im-age. Scientific Reports, 12(1), 17123. https://doi.org/10.1038/s41598-022-21724-0

Swapnarekha, H., Dash, P. B., Nayak, J., & Routray, A. R. (2023). An Optimistic Bayesian Optimization Based Extreme Learning Machine for Poly-cystic Ovary Syndrome Diagnosis. In J. Nayak, A. K. Das, B. Naik, S. K. Meher, & S. Brahnam (Eds.), Nature-Inspired Optimization Methodologies in Biomedical and Healthcare (pp. 175–193). Springer International Publishing. https://doi.org/10.1007/978-3-031-17544-2_8

Taleb, N., Mehmood, S., Zubair, M., Naseer, I., Mago, B., & Nasir, M. U. (2022). Ovary Cancer Diag-nosing Empowered with Machine Learning. 2022 International Conference on Business Analytics for Technology and Security (ICBATS), 1–6. https://doi.org/10.1109/ICBATS54253.2022.9759010

Tanaka, Y. O., Okada, S., Satoh, T., Matsumoto, K., Oki, A., Saida, T., Yoshikawa, H., & Minami, M. (2016). Differentiation of epithelial ovarian cancer subtypes by use of imaging and clinical data: a detailed analysis. Cancer Imaging: The Official Publication of the International Cancer Imaging Society, 16, 3. https://doi.org/10.1186/s40644-016-0061-9

Tiwari, S., Kane, L., Koundal, D., Jain, A., Alhudhaif, A., Polat, K., Zaguia, A., Alenezi, F., & Althubiti, S. A. (2022). SPOSDS: A smart Polycystic Ovary Syndrome diagnostic system using machine learning. Expert Systems with Applications, 203, 117592. https://doi.org/https://doi.org/10.1016/j.eswa.2022.117592

Tripathi, A., Arora, A., & Bhan, A. (2021). Classification of cervical cancer using Deep Learning Algorithm. 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), 1210–1218. https://doi.org/10.1109/ICICCS51141.2021.9432382

Visalaxi, S., Punnoose, D., & Muthu, T. S. (2021). An Analogy of Endometriosis Recognition Using Machine Learning Techniques. 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Net-works (ICICV), 739–746. https://doi.org/10.1109/ICICV50876.2021.9388403

Wang, G., Zhan, H., Luo, T., Kang, B., Li, X., Xi, G., Liu, Z., & Zhuo, S. (2023). Automated Ovarian Cancer Identification Using End-to-End Deep Learning and Second Harmonic Generation Im-aging. IEEE Journal of Selected Topics in Quan-tum Electronics, 29(4: Biophotonics), 1–9. https://doi.org/10.1109/JSTQE.2022.3228567

Wang, R., Cai, Y., Lee, I. K., Hu, R., Purkayastha, S., Pan, I., Yi, T., Tran, T. M. L., Lu, S., Liu, T., Chang, K., Huang, R. Y., Zhang, P. J., Zhang, Z., Xiao, E., Wu, J., & Bai, H. X. (2021). Evaluation of a convolutional neural network for ovarian tumor differentiation based on magnetic resonance im-aging. European Radiology, 31(7), 4960–4971. https://doi.org/10.1007/s00330-020-07266-x

Wang, R., Gu, Z., Wang, Y., Yin, X., Liu, W., Chen, W., Huang, Y., Wu, J., Yang, S., Feng, L., Zhou, L., Li, L., Di, W., Pu, X., Huang, L., & Qian, K. (2022). A “One-Stop Shop” Decision Tree for Diagnosing and Phenotyping Polycystic Ovarian

Syndrome on Serum Metabolic Fingerprints. Advanced Functional Materials, 32(45), 2206670. https://doi.org/10.1002/ADFM.202206670

Zahras, D., & Rustam, Z. (2018). Cervical Cancer Risk Classification Based on Deep Convolutional Neural Network. 2018 International Conference on Applied Information Technology and Innovation (ICAITI), 149–153. https://doi.org/10.1109/ICAITI.2018.8686767

Zhang, L., Huang, J., & Liu, L. (2023). Retraction Note: Improved Deep Learning Network Based in Combination with Cost-sensitive Learning for Early Detection of Ovarian Cancer in Color Ultrasound Detecting System. Journal of Medical Systems, 47(1), 20. https://doi.org/10.1007/s10916-023-01915-6

Zhang, Z., & Han, Y. (2020). Detection of Ovarian Tumors in Obstetric Ultrasound Imaging Using Logistic Regression Classifier with an Advanced Machine Learning Approach. IEEE Access, 8, 44999–45008. https://doi.org/10.1109/ACCESS.2020.2977962

Zhou, H., Wang, S., Zhang, T., Liu, D., & Yang, K. (2021). Ultrasound image analysis technology under deep belief networks in evaluation on the effects of diagnosis and chemotherapy of cervical cancer. The Journal of Supercomputing, 77(4), 4151–4171. https://doi.org/10.1007/s11227-020-03421-9

Zhou, J., Zeng, Z. Y., & Li, L. (2020). Progress of Artificial Intelligence in Gynecological Malignant Tumors. Cancer Management and Research, 12, 12823–12840. https://doi.org/10.2147/CMAR.S279990.

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