Artificial intelligence performance in image-based ovarian cancer identification: A systematic review and meta-analysis

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Summary

Background Accurate identification of ovarian cancer (OC) is of paramount importance in clinical treatment success. Artificial intelligence (AI) is a potentially reliable assistant for the medical imaging recognition. We systematically review articles on the diagnostic performance of AI in OC from medical imaging for the first time.

Methods The Medline, Embase, IEEE, PubMed, Web of Science, and the Cochrane library databases were searched for related studies published until August 1, 2022. Inclusion criteria were studies that developed or used AI algorithms in the diagnosis of OC from medical images. The binary diagnostic accuracy data were extracted to derive the outcomes of interest: sensitivity (SE), specificity (SP), and Area Under the Curve (AUC). The study was registered with the PROSPERO, CRD42022324611.

Findings Thirty-four eligible studies were identified, of which twenty-eight studies were included in the meta-analysis with a pooled SE of 88% (95%CI: 85–90%), SP of 85% (82–88%), and AUC of 0.93 (0.91–0.95). Analysis for different algorithms revealed a pooled SE of 89% (85–92%) and SP of 88% (82–92%) for machine learning; and a pooled SE of 88% (84–91%) and SP of 84% (80–87%) for deep learning. Acceptable diagnostic performance was demonstrated in subgroup analyses stratified by imaging modalities (Ultrasound, Magnetic Resonance Imaging, or Computed Tomography), sample size (≤300 or >300), AI algorithms versus clinicians, year of publication (before or after 2020), geographical distribution (Asia or non Asia), and the different risk of bias levels (≥3 domain low risk or <3 domain low risk).

Interpretation AI algorithms exhibited favorable performance for the diagnosis of OC through medical imaging. More rigorous reporting standards that address specific challenges of AI research could improve future studies.

Funding This work was supported by the Natural Science Foundation of China (No. 82073647 to Q-JW and No. 82103914 to T-TG), Liaoning Revitalization Talents Program (No. XLYC1907102 to Q-JW), and 345 Talent Project of Shengjing Hospital of China Medical University (No. M0268 to Q-JW and No. M0952 to T-TG).

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Keywords: Artificial intelligence; Medical imaging; Meta-analysis; Ovarian cancer

Abbreviations: AI, Artificial intelligence; OC, Ovarian cancer; SE, Sensitivity; SP, Specificity; AUC, Area Under the Curve; US, Ultrasound; MRI, Magnetic Resonance Imaging; CT, Computed Tomography; ML, Machine learning; DL, Deep learning; XAI, Explainable artificial intelligence

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Research in context

Evidence before this study

The accurate preoperative differentiation between benign and malignant masses of the ovary is crucial for determining the appropriate treatment strategies and improving the postoperative quality of life. Imaging is an useful tool in medical science and is invoked in clinical practice to facilitate decision making for the diagnosis, staging, and treatment. The advances of artificial intelligence (AI) might help to bridge the gap between the intense demand for diagnostic from imaging and relatively limited healthcare resources. Up to date, there is a lack of quantitative synthesis to comprehensively summarize the available evidence of the AI-based methods on ovarian cancer (OC) detection. The Medline, Embase, IEEE, Pubmed, Web of Science, and the Cochrane library were systematically searched for studies that developed an AI algorithm for the diagnostic performance of OC from medical imaging, published until August 1, 2022. Only English language articles were considered. We performed a systematic review and meta-analysis of published data on diagnostic performance of AI algorithms and radiomics models for OC detection.

Added value of this study

To our best knowledge, this is the first systematic review and meta-analysis specifically dedicated to AI system performance in the diagnosis of OC. We are strictly in line with the guidelines for diagnostic reviews, and conducted a comprehensive literature search in both medical databases and engineering and technology databases to ensure the rigor of the study. After a careful selection of research on relevant topics, we found that AI algorithms excelled in the identification of OC using medical radiography imaging.

Implications of all the available evidence

AI algorithms exhibited favorable performance for the diagnosis of OC through medical imaging. More rigorous reporting standards that address specific challenges of AI research could improve future studies.

Introduction

Ovarian tumors comprise a remarkably heterogeneous group of benign, borderline, and malignant lesions and exhibit extensive morphological characteristics. Among these, ovarian cancer (OC) is the most lethal gynecological malignancy. While malignant ovarian neoplasms may need a more aggressive surgical approach, benign masses can either be safely monitored or undergo simple resection allowing for a fertility- and ovary-sparing approach. Therefore, accurate preoperative differentiation between benign and malignant masses of the ovary is crucial for determining the appropriate treatment strategies and improving the postoperative quality of life.

Imaging is a useful tool in medical science and is invoked in clinical practice to facilitate decision making for the diagnosis, staging, and treatment. The ultrasound (US) is commonly used to recognize the presence of an ovarian mass and to determine between benign and malignant lesions. Magnetic resonance imaging (MRI) plays a significant role in characterizing ovarian tumors due to its high soft-tissue resolution, and it is recommended in assessing the need for surgery for an adnexal mass. Computed tomography (CT) may be helpful for judging the gross extent of hematogenous, peritoneal, and lymphatic spread of OC: because of its ability to evaluate the liver, paraaortic region, omentum, and mesentery. While studies have reported the utility of PET CT in diagnosing ovarian tumors, its cost-effectiveness for this purpose remains unproven. Currently, US and MRI are the most commonly used imaging modalities for the diagnosis and characterization of ovarian tumors. Of note, the diagnosis of OC has been conventionally dependent on the subjective assessment of radiologists or gynecologists who use their clinical practice experience to scrutinize imaging features and examine ovarian tumors with high heterogeneity. Owing to the intricacy generated by inadequate or absent radiology in resource-poor health regions and the influence of wide disparity in the human rater expertise, making a proper and immediate diagnosis from medical imaging is challenging.

The advances of artificial intelligence (AI) might help to bridge the gap between the intense demand for diagnostic from imaging and relatively limited healthcare resources. Meanwhile, as an interesting research hotspot, radiomics is described as a new ‘data-driven’ approach for extracting large sets of quantitative signatures from radiological images. These data can be subsequently analyzed using conventional biostatistics or AI methods. With sophisticated image processing methods, all medical images are transferred to mineable high-throughput image features, which thereafter can be used to correlate these processed feature signatures with pathology diagnoses or treatment responses. Radiomics models and AI algorithms have shown promising results in integrating medical images for the detection of OC. For example, aramendia-vidaurreta et al. emphasized that a machine learning (ML) algorithm based on US images achieved a diagnostic accuracy of 0.98 in one hundred and forty-five patients. Additionally, a deep learning (DL) model was used to automatically discriminate between benign and malignant ovarian tumor images, with high accuracy of 87.6%. Even though, researchers have still tried different ways, including but not limited to improving image quality, expanding sample sizes, and optimizing algorithms, to raise diagnostic accuracy.
Up to date, there is a lack of quantitative synthesis to comprehensively summarize the available evidence of the AI-based methods on OC detection. Therefore, the purpose of this study is to first perform a systematic review and meta-analysis of published data on the diagnostic performance of AI algorithms and radiomics models for OC detection.

Methods

Protocol registration and study design
The study was registered in the PROSPERO (CRD42022324611). The meta-analysis was conducted following the PRISMA,24 MOOSE,35 and CHARMS26 reporting guidelines.

Search strategy and eligibility criteria
The Medline, Embase, IEEE, Pubmed, Web of Science, and the Cochrane library were systematically searched for studies that developed an AI algorithm for the diagnostic performance of OC from medical imaging, published until August 1, 2022. Only English-language articles were considered. Supplementary Note 1 summarizes the search strategy used in each database.

Eligible studies reported the AI technologies for the diagnosis of OC from medical radiology images with diagnostic outcomes, such as sensitivity (SE), and specificity (SP), or detailed information on $2 \times 2$ contingency tables. The following studies were excluded: duplicate publications; reviews; editorials; non-human samples; histopathology images; combining non-image information; no classification task; and no AI model. Two reviewers (H-LX and F-HL) independently screened the titles and abstracts and no AI model. Two reviewers (H-LX and F-HL) were consulted.

Disagreement was discussed with a third author (Q-JW) and subsequently resolved via consensus.

Data extraction
Two reviewers (H-LX and H-YC) extracted study characteristics and diagnostic performance independently using a standardized data extraction sheet. Disagreements were resolved by discussion or a third investigator (F-HL) was consulted.

The diagnostic accuracy data including true-positive (TP), false-positive (FP), true-negative (TN), and false-negative (FN) were extracted directly into contingency tables, and were used to calculate SE and SP. If a study provided multiple contingency tables for the same or different AI algorithms, we assumed that they were independent of each other. Supplementary Table 1 summarizes the contingency tables extracted from included studies.

Study quality assessment
All selected studies were assessed for quality with the use of quality assessment of diagnostic accuracy studies-AI (QUADAS-AI) criteria27 by two independent reviewers (H-LX and T-TG). The details are listed in Supplementary Table 2. This guideline includes four domains (patient selection, index test, reference standard, flow, and timing) in the risk of bias and three domains (patient selection, index test, reference standard) in applicability concerns. This new tool is an AI-specific extension to QUADAS-228 and QUADAS-C,29 providing researchers with a specific framework to evaluate the risk of bias and applicability when conducting reviews that evaluate AI-centered diagnostic test accuracy. Conflicts were discussed with a third collaborator (F-HL).

Meta-analysis
A hierarchical summary receiver-operating characteristic curve (SROC) was fitted to evaluate the accuracy of the AI model. We plotted the combined curve with corresponding 95% confidence region and 95% prediction region around averaged SE, SP, and Area Under the Curve (AUC) estimates in SROC figures. When same or different AI models were tested within the same paper, the proposed model with the best accuracy was used for further meta-analysis. Heterogeneity was assessed using the I² statistic. Subgroup and regression analyses were performed to explore potential sources of heterogeneity. The random effects model was conducted because of the assumed differences between studies. The risk of publication bias was evaluated using funnel plot and regression test.

Seven sub-analysis were performed: (1) according to sample size ($\leq 300$ or $>300$); (2) according to AI algorithms (ML or DL); (3) according to imaging modalities (CT, US, or MRI); (4) according to the pooled performance using the same dataset (AI algorithms or human clinicians); (5) according to the year of publication (before or after 2020); (6) according to the geographical distribution (Asia or non Asia); (7) according to different risk of bias levels ($\geq 3$ domain low risk or $< 3$ domain low risk).

The methodological quality of included studies was evaluated using the QUADAS-AI by RevMan (Version 5.4). A cross-hairs plot was also produced (R V.4.2.1) to better display the variability between sensitivity/specificity estimates.30 All other statistical analyses were conducted in Stata software (Version 15.0) with two-tailed probability of type I error of $0.05$ ($a = 0.05$).

Role of the funding source
Our study was funded by the Natural Science Foundation of China, the Liaoning Revitalization Talents Program, and the 345 Talent Project of Shengjing Hospital.

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Results

Study selection and characteristics of eligible studies
A total of 1212 records were retrieved on initial search and 513 duplicates were removed, and of these 642 studies were excluded based on screening of titles and abstracts, resulting in 57 studies for full-text review. Finally, 34 articles were included in the present systematic review and 28 had sufficient data for meta-analysis (Figure 1).

Majority of the studies (n = 31) were based on retrospective patient data except four studies. Only two studies using prospective data. One studies used images from public databases. Eight studies excluded low quality images, while twenty-six studies did not mention this process. Only three studies using out-of-sample dataset to perform external validation, of which two studies did not provide data of our concern for integrated analysis. Eight studies compared AI model with clinicians in the same dataset. Moreover, imaging modalities were classified as US (n = 19), MRI (n = 10), CT (n = 3), MRI and US (n = 1), and MRI and CT (n = 1). Furthermore, the distribution of the number of studies on AI algorithms in the present study is as follows: DL (11 studies) and ML (23 studies). Tables 1–4 show the detailed characteristics of these including studies.

Pooled performance of AI algorithms
The SROC curves for 28 included studies with 160 contingency tables are provided in Figure 2a, the combined SE and SP were 88% (95%CI: 85–90%) and 85% (82–88%), respectively, with an AUC of 0.93 (0.91–0.95) for all AI algorithms. When the highest accuracy
| Author [ref], year | Participants | Inclusion criteria | Exclusion criteria | N  | Mean or median age (SD; range) |
|-------------------|--------------|-------------------|-------------------|----|-------------------------------|
| Liu et al,31 2022a | Patients with no previous pelvic surgery; patients with no previous gynecological disease history; patients who had MRI examinations performed at our institution before pelvic or laparoscopic surgery. | Patients with previous pelvic surgical history or radiation history; patients whose MRI data were unavailable either due to the examination being performed at another institution or due to claustrophobia; patients whose data lacked histological results. | 196 | 46.3 |
| Gao et al,22 2022a | Consecutive adult patients (aged ≥18 years) who presented with adnexal lesions in ultrasound in ten hospitals between September 2003, and May 2019. | Duplicated cases; postoperative patients who were deprived of adnexa; patients without histological diagnosis. | 1,07,624 | NR |
| Saida et al,32 2022a | Aged above 20 years for ethical reasons; pelvic MRI scan obtained as per the protocol followed at our hospital between January 2015 and December 2020; pathologically proven malignant epithelial tumors (i.e., carcinomas) or borderline tumors of the ovary for the malignant group; pathologically proven or clinically apparent benign lesions in the non-malignant group. | Malignant tumors in the pelvis other than the ovary; history of surgery of the uterus or ovaries other than caesarean section, chemotherapy, or radiation therapy of the pelvis; malignant ovarian epithelial tumors mixed with non-epithelial components. | 465 | 50 (20–90) |
| Guo et al,33 2022a | Definite pathological diagnosis after operation; MRI and ultrasound were performed and the data were complete; the images could be used for diagnostic analysis; patient informed consent. | Incomplete ultrasound, MRI, or pathological data; combined with severe organic diseases, such as coagulation dysfunction, renal insufficiency, heart failure, and other surgical contraindications; history of ovarian surgery; combined with other pelvic diseases, such as endometrial cancer and rectal cancer. | 207 | NR |
| Li et al,34 2022a | Patients with ovarian tumor confirmed by histopathology; no history of malignant tumors other than ovarian tumor; patients who were undergoing pelvic CT examination within half a month before surgery. | Those who had received radiotherapy, chemotherapy, or radiotherapy—chemotherapy before CT examination; patients diagnosed with inflammatory diseases; patients with low image quality. | 140 | NR |
| Wang et al,35 2021a | A histologic diagnosis of benign, borderline, or malignant SOTs between March 2013 and December 2016; availability of diagnostic-quality preoperative US images; US scanning before neoadjuvant therapy or surgical resection. | No ultrasound results or the ovarian mass was not completely in the images; mucinous, clear cell, endometrioid, or metastatic cancer. | 265 | 51 (15–79) |
| Chiappa et al,36 2021a | Diagnosis of OM; execution of a preoperative ultrasonographic examination within 2 weeks before surgery; surgery performed. | Age<18 years; absence of ultrasonographic images stored; consent withdrawn. | 241 | 55 (18–84) |

Table 1 (Continued)
| Author [ref], year | Participants | N | Mean or median age (SD; range) |
|-------------------|--------------|---|-----------------------------|
| Jian et al,37 2021 | All patients were histopathologically proven to have either BEOT \((n = 165)\) or MEOT \((n = 336)\). | 501 | NR |
| Wang et al,38 2021 | Benign or malignant ovarian lesions confirmed by either pathology or imaging follow-up; available pre-operative MRI examination including T1C and T2WI; the quality of images was clear without motion or artifacts and were fit for analysis. | 451 | 45.7 |
| Hu et al,39 2021 | Patients with poor image quality; patients without enhanced scanning; patients with unclear boundary and unable to outline | 110 | NR |
| Yu et al,40 2021 | SBOTs and SMOTs were diagnosed by postoperative pathology; SBOTs and SMOTs were in an early stage \(I\) and \(II\) according to the guideline of the FIGO; the images were of sufficient quality for radiomics analysis. | 182 | 47.7 |
| Ştefan et al,41 2021 | A lesion with a minimum diameter of at least 20 mm; the availability of conventional B-mode images; lack of imaging artifacts; and the existence of a patient's serial number. | 120 | 38.2 |
| Christiansen et al,42 2021 | Surgery within 120 days after the ultrasound examination or ultrasound follow-up for a minimum of 3 years or until resolution of the lesion. | 758 | NR |
| Akazawa et al,43 2020 | Patients were ovarian tumors which had been diagnosed pathologically after surgical resection. | 202 | 51 (14–84) |
| Martinez et al,44 2019 | NR | 384 | NR |
| Zhang et al,45 2019 | No previous pelvic surgery; no previous gynecological disease history; MRI examinations before pelvic or laparoscopic surgery were performed at our institution. | 438 | 52.7 |

**Table 1 (Continued)**
| Author [ref], year | Inclusion criteria | Exclusion criteria | N  | Mean or median age (SD; range) |
|-------------------|-------------------|-------------------|----|-----------------------------|
| Mol et al,45 2001a | Women who had surgery for an adnexal mass between January 1991 and December 1998 were included. | NR | 170 | 46 (20–89) |
| Liu D et al,46 2017a | Patients with histologically proven diagnosis of EOCs; patients complete CT or MRI examination before operation in two weeks. | Surgery was performed outside our institution without definite histological diagnosis, incomplete clinical or CT and MRI records preoperatively. | 65 | 56.4 |
| Kazerooni et al,47 2017a | Patients were scheduled for surgical removal of suspicious ovarian masses and postoperative histopathological assessment within 2 weeks of MRI exam. | NR | 55 | 38.4 |
| Acharya et al,48 2014a | NR | Women with no anatomopathological evaluation. | 20 | 49.5 |
| Acharya et al,49 2013a | NR | Patients with no anatomopathological evaluation. | 20 | 49.5 |
| Acharya et al,50 2012a | NR | NR | 20 | 49.5 |
| Umar et al,51 2012 | NR | NR | 24 | NR |
| Acharya et al,52 2012a | NR | Patients with no anatomopathological evaluation. | 20 | 49.5 |
| Al-Karawi et al,53 2021a | All ovarian tumors were given a histological diagnosis label. | NR | 232 | NR |
| Jian et al,54 2021 | Histologically proven EOC; MRI performed within 1 month prior to gynecological operation; all four axial MRI sequences obtained: fast spin-echo T2-weighted imaging with fat saturation(T2WI FS), echo-planar DWI with gradient b factors of 0 and 600, 800, or 1000 s/mm², ADC map, and 2D volumetric interpolated breath hold examination (VIBE) contrast enhanced T1-weighted imaging with FS (CE-T1WI) in the late phase (150–190 s after the intravenous administration of contrast agent); absence of prior gynecological operation or chemotherapy prior to MRI scanning. | Patients without definitive histopathology or with poor MRI image quality (image has artifacts that cannot outline the tumor). | 294 | (51.2–57.2) |
| Li et al,55 2020 | Histologically proven BEOT or MEOT from January 2010 to June 2018; MRI performed within 2 weeks prior to gynecological operation. | Lacking any one of these four axial MRI sequences; prior gynecological operation and/or chemotherapy before MRI scanning; poor MRI image quality with artifacts that affected the delineation of the tumor. | 501 | (47.2–51.6) |
| Acharya et al,56 2014a | NR | NR | 20 | NR |
| Pathak et al,57 2015a | NR | NR | 120 | NR |

Table 1 (Continued)
| Author [ref], year | Participants | Mean or median age (SD; range) |
|-------------------|--------------|-----------------------------|
| **Inclusion criteria** | **Exclusion criteria** | **N** |
| Ameye et al,58 2009a | NR | Exclusion criteria were pregnancy, inability to tolerate transvaginal sonography, and surgery performed more than 120 days after sonographic assessment. | 1573 | 46 (9−94) |
| Jian et al,59 2022a | Inclusion criteria were as follows: patients with 1) BEOT or MEOT that was proven by surgery and histopathology from January 2010 to June 2018; 2) an MRI performed within 2 weeks before gynecological operation which included the following three axial MRI sequences: fast spin echo T2-weighted imaging with fat saturation (T2WI FS), echo planar diffusion-weighted imaging (DWI) with apparent diffusion coefficient (ADC) maps generated from maximum b-value imaging if images with multiple b-values available, and 2D volumetric interpolated breath-hold examination of contrast-enhanced T1-weighted imaging (CE-T1WI) with FS in the late phase (150−190 seconds after the intravenous administration of contrast agent); and 3) no history of gynecological operations or chemotherapy prior to the MRI scan. | Patients with poor quality images were excluded (based on the evaluation of the radiologist with 10 years’ experience in gynecological imaging) because artifacts could affect the observation of the tumor. | 501 | 58.92 (14.05) |
| Alqasemi et al,51 2012a | NR | NR | 24 | NR |
| Chen et al,60 2012a | Inclusion criteria were as follows: patients with at least one persisting ovarian tumor detected at US (except for physiologic cysts) from January 2019 to November 2019, patients who underwent a surgical procedure with histopathologic results, an interval of 30 days between US examination and surgery, and patients who had no previous history of ovarian cancer. | Exclusion criteria were histopathologic analysis—confirmed uterine sarcomas or nongynecologic tumors, inconclusive histopathologic results, or poor US image quality. | 422 | 46.4 (14.8) |
| Zheng et al,61 2022 | Patients with either SBOTs or SMOTs, who underwent preoperative MRI scans and confirmed by post-operative pathology. | Exclusion criteria were as follows: (1) solid tissue <80% in lesion (25); (2) the tumor had significant metastases; (3) significant image artifacts. | 1260 | 61 (20−79) |

**Table 1: Participant demographics for the 35 included studies.**

Abbreviation: BEOT: borderline epithelial ovarian tumor; CT: computed tomography; EOC: epithelial ovarian cancer; FIGO: International Federation of Gynecology and Obstetrics; MEOT: malignant epithelial ovarian tumors; NR=not reported; MRI: magnetic resonance imaging; OM: ovarian mass; SBOT: serous borderline ovarian tumors; SMOT: serous malignant ovarian tumors; SOT: serous ovarian tumors; T1C: T1-weighted contrast-enhanced sequence; T2WI: T2-weighted sequence; US: ultrasound.

- **Studies (n = 28) included in the meta-analysis.**
contingency table was selected from these 28 studies, the pooled SE and SP were the same as 91% (84−95%) and 94% (89−97%), respectively (Figure 2b). A cross hairs plot shows reported point estimates and confidence intervals in Figure 3.

Quality assessment
The quality of included studies was determined by the QUADAS-AI (Supplementary figure 1). The detailed assessment results are presented with a diagram in Supplementary figure 2. Over half of the studies showed a high risk or an unclear risk of bias respectively for patient selections (n = 23) and index test (n = 31) because these studies did not clarify description of included patients detailing previous testing, presentation, setting, the intended use of the index test and lack of adequate external evaluation.

Subgroup meta-analyses
Considering the stage of development of the algorithm and the difference in nature, we categorized them into ML and DL algorithms and did a sub-analysis. The results demonstrated a pooled SE of 89% (95%CI: 85−92%) for ML and 88% (95%CI: 84−91%) for DL, and a pooled SP of 88% (95%CI: 82−92%) for ML and 84% (95%CI: 80−87%) for DL (Supplementary figure 3a, b).

Table 2: Model training and validation for the 35 included studies.
Abbreviation: AI: artificial intelligence; NR=not reported.
Studies (n = 28) included in the meta-analysis.

| Author [ref], year | Reference standard | Type of internal validation | External validation | AI versus clinicians |
|--------------------|--------------------|-----------------------------|---------------------|----------------------|
| Liu et al,31 2022a | Histopathology     | NR                          | No                  | No                   |
| Gao et al,32 2022a | Histopathology     | Random split sample validation | Yes                 | Yes                  |
| Said et al,33 2022a | Histopathology     | NR                          | No                  | Yes                  |
| Guo et al,34 2022a | Histopathology     | K-fold cross validation     | No                  | No                   |
| Li et al,35 2022a  | Histopathology     | Ten-fold cross-validation   | No                  | No                   |
| Wang et al,36 2021a | Histopathology     | Three-fold cross validation | No                  | No                   |
| Chiappa et al,37 2021a | Histopathology   | Ten-fold cross validation   | No                  | No                   |
| Jian et al,38 2021  | Histopathology     | Random split sample validation | No                  | No                   |
| Wang et al,39 2021a | Histopathology     | Cross validation            | No                  | Yes                  |
| Hu et al,40 2021a  | NR                 | Ten-fold cross-validation   | No                  | No                   |
| Yu et al,41 2021a  | Histopathology     | NR                          | No                  | No                   |
| Ştefan et al,42 2021a | Histopathology  | NR                          | No                  | No                   |
| Christiansen et al,43 2021a | Histopathology | NR                          | No                  | Yes                  |
| Akazawa et al,44 2020 | Histopathology   | K-fold cross validation     | No                  | No                   |
| Zhang et al,45 2019 | Histopathology     | Ten-fold cross validation   | No                  | No                   |
| Martinez et al,46 2019 | Histopathology | Cross validation            | No                  | No                   |
| Zhang et al,47 2019 | Histopathology     | Leave-one-out cross-validation | No                 | Yes                  |
| Mol et al,48 2001a | Histopathology     | Cross validation            | No                  | No                   |
| Liu D et al,49 2017a | Histopathology     | Cross validation            | No                  | No                   |
| Kazerooni et al,50 2017a | Histopathology  | Leave-one-out cross-validation | No                 | No                   |
| Acharya et al,51 2014a | Histopathology   | Ten-fold cross validation   | No                  | No                   |
| Acharya et al,52 2013a | Histopathology   | Ten-fold cross validation   | No                  | No                   |
| Acharya et al,53 2013a | Histopathology   | Ten-fold cross validation   | No                  | No                   |
| Umar et al,54 2012 | Histopathology     | NR                          | No                  | No                   |
| Acharya et al,55 2012a | Histopathology  | K-fold cross validation     | No                  | No                   |
| Al-Karawi et al,56 2021a | Histopathology | Random split sample validation | No               | No                   |
| Jian et al,57 2021 | Histopathology     | NR                          | Yes                 | Yes                  |
| Li et al,58 2020 | Histopathology     | NR                          | Yes                 | Yes                  |
| Acharya et al,59 2014a | NR                 | Ten-fold cross validation   | No                  | No                   |
| Pathak et al,60 2015a | NR                 | Cross validation            | No                  | No                   |
| Ameye et al,61 2009a | Histopathology     | NR                          | No                  | Yes                  |
| Jian et al,62 2022 | Histopathology     | NR                          | No                  | No                   |
| Alqasemi et al,63 2012a | Histopathology  | NR                          | No                  | Yes                  |
| Chen et al,64 2012a | Histopathology     | NR                          | No                  | Yes                  |
| Zheng et al,65 2022 | Histopathology     | Ten-fold cross validation   | No                  | No                   |
Seventeen US studies had a pooled SE of 91% (87–93%), a pooled SP of 87% (82–91%), and with an AUC of 0.95 (0.93–0.97). Six MRI studies with a pooled SE of 83% (77–88%), pooled SP of 84% (80–87%), and an AUC of 0.90 (0.87–0.92). Three CT studies that had a pooled SE of 75% (68–81%), pooled SP of 75% (67–82%), and an AUC of 0.82 (0.78–0.85) (Supplementary figure 4a, b, c).

Eight studies presented the diagnostic accuracy between AI algorithms and human clinicians in the same dataset. The pooled SE was 82% (77–87%) for AI algorithms, and human clinicians had 77% (73–80%). The pooled SP was 86% (83–89%) for AI algorithms, and 80% (75–84%) in human clinicians. The AUC was 0.91 (0.88–0.93) and 0.85 (0.81–0.88) for AI algorithms and human clinicians, respectively (Supplementary figure 5a, b).

Fifteen studies had sample sizes ≤ 300 and thirteen studies had sample sizes > 300. The pooled SE was 85% (81–88%) for sample size ≤ 300, and 93% (89

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**Table 3: Indicator, algorithm, and data source for the 35 included studies.**

| Author [ref], year | Indicator definition | Algorithm | ML/DL | Transfer learning applied |
|-------------------|----------------------|-----------|-------|---------------------------|
| Device            | Exclusion of poor-quality imaging | Heatmap provided | Architecture | |
| Liu et al,31 2022a | MRI | NR | No | LASSO | ML |
| Gao et al,22 2022a | US | Yes | No | DCNN | DL |
| Saida et al,32 2022a | MRI | NR | Yes | CNN | DL |
| Guo et al,33 2022a | MRI, US | NR | No | LR | ML |
| Li et al,34 2022a | CT | Yes | No | LR | ML |
| Wang et al,35 2021a | US | NR | Yes | DCNN | DL |
| Chiappa et al,36 2021a | US | NR | No | SVM | ML |
| Jian et al,37 2021 | MRI | NR | No | MAC-Net | DL |
| Wang et al,38 2021a | MRI | Yes | No | CNN | DL |
| Hu et al,39 2021a | CT | Yes | No | LR | ML |
| Yu et al,90 2021a | CT | Yes | Yes | SVM | ML |
| Ștefan et al,91 2021a | US | NR | No | KNN | ML |
| Christiansen et al,92 2021a | US | NR | No | MLP | DL |
| Akazawa et al,93 2020 | US | NR | No | SVM, KNN, RF, NB, XGBoost | ML |
| Martinez et al,94 2019a | US | NR | No | KNN, LD, SVM, ELM | ML |
| Zhang et al,95 2019a | MRI | NR | No | LASSO | ML |
| Mol et al,96 2001a | US | NR | No | LR, NN | ML |
| Liu D et al,37 2017a | CT, MRI | NR | No | RF | ML |
| Kazerooni et al,97 2017a | MRI | NR | No | SVM, LDA | DL |
| Acharya et al,98 2014a | US | NR | No | PNN | ML |
| Acharya et al,99 2013a | US | NR | No | DT | ML |
| Acharya et al,100 2012a | US | NR | No | SVM | ML |
| Umbar et al,101 2012 | US | NR | No | SVM | ML |
| Acharya et al,103 2012a | US | NR | No | DT | ML |
| Al-Karawi et al,104 2021a | US | NR | No | SVM | ML |
| Jian et al,105 2021 | MRI | Yes | No | LASSO | ML |
| Li et al,106 2021 | MRI | NR | No | LR | ML |
| Acharya et al,107 2014a | US | NR | No | PNN | ML |
| Pathak et al,108 2015a | US | NR | No | SVM | ML |
| Ameye et al,109 2009a | US | NR | No | LR | ML |
| Jian et al,110 2022a | MRI | Yes | No | MICNN | DL |
| Alqasemi et al,111 2012a | US | NR | No | SVM | ML |
| Chen et al,112 2012a | US | Yes | No | ResNet | DL |
| Zheng et al,113 2022 | MRI | NR | No | LASSO | ML |

Abbreviation: AI: artificial intelligence; CNN: convolutional neural network; CT: computed tomography; DCNN: deep convolutional neural network; DL: deep learning; DT: decision tree; DNN: deep neural network; ELM: extreme learning machine; KNN: k-nearest neighbor; LASSO: least absolute shrinkage and selection operator method; LD: linear discriminant; LR: logistic regression; ML: machine learning; MRI: magnetic resonance imaging; NB: naive bayes; NR—not reported; PNN: probabilistic neural networks; RF: random forest; SVM: support vector machine; US: ultrasound.

*Studies (n = 28) included in the meta-analysis.*
| Author [ref], year | Source of data | Number of images for training/testing | Data range | Open access data |
|------------------|----------------|----------------------------------------|------------|----------------|
| Liu et al.[31] 2022a | Retrospective study, data from Gynecological and Obstetric Hospital, School of Medicine, Fudan University, Shanghai, China. | 99/97 | 2014.01–2017.12 | No |
| Gao et al.[22] 2022a | Retrospective study, data from Tongji Hospital, Tongji Medical College, Huazhong University of Science and Technology, and seven other hospitals, Jingshou First People’s Hospital and Xiangyang Central Hospital. | 575930/8416/7929 | 2003.09–2019.05 | No |
| Saida et al.[32] 2022a | Retrospective study, data from Faculty of Medicine, University of Tsukuba. | 3663/100 | 2015.01–2020.12 | No |
| Guo et al.[33] 2022a | Retrospective study, data from Qilu Hospital. | 138/69 | 2018.04–2021.04 | No |
| Li et al.[34] 2022a | Retrospective study, data from the First Affiliated Hospital of Nanchang Medical College. | 99/41 | 2017–2020 | No |
| Wang et al.[35] 2021a | Retrospective study, data from Tianjin Medical University Cancer Institute and Hospital. | 195/84 | 2013.03–2016.12 | No |
| Chiappa et al.[36] 2021a | Retrospective study, data from Fondazione IRCCS Istituto Nazionale dei Tumori di Milano. | NR | 2017.01–2019.12 | No |
| Jian et al.[37] 2021 | Retrospective, data from eight clinical centers in China. | 282/119 | NR | No |
| Wang et al.[38] 2021a | Retrospective study, data from one large academic center in the United States. | 384/161 | NR | No |
| Hu et al.[39] 2021a | Retrospective study, data from Lishui Hospital of Zhejiang University | 76/34 | 2010.01–2018.12 | No |
| Yu et al.[40] 2021a | Retrospective study, data from the Affiliated Hospital of Qingdao University. | 127/55 | 2017.12–2020.06 | No |
| Ştefan et al.[41] 2021a | Retrospective study, data from University of Medicine and Pharmacy | NR | 2017.10–2019.02 | No |
| Christiansen et al.[42] 2021a | Retrospective study, data from Karolinska University Hospital (tertiary referral center) and Sodersjukhuset (secondary/tertiary referral center) in Stockholm, Sweden. | 508/250 | 2010–2019 | No |
| Akazawa et al.[43] 2020 | Prospective study, data from Tokyo Women’s Medical University Medical Center East. | 141/61 | 2013.12–2019.01 | No |
| Martinez et al.[44] 2019a | Retrospective study, data from the University Hospital of the Catholic University of Leuven. | NR | NR | No |
| Zhang et al.[45] 2019a | Retrospective study, data from Gynecological and Obstetric Hospital, School of Medicine, Fudan University, Shanghai, China. | NR | 2014.01–2017.12 | No |
| Mol et al.[46] 2001a | Prospective study, data from in the Saint Joseph Hospital in Veldhoven. | NR | 1991.01–1998.12 | No |

*Table 4 (Continued)*
−95%) for sample size > 300. The SP for ≤ 300 was 82% (80–85%) and 91% (84–96%) for > 300. The AUC was 0.90 (0.87–0.92) for ≤ 300 and 0.97 (0.95–0.98) for > 300 (Supplementary figure 6a, b).

Thirteen studies were published before 2020. Fifteen studies were published after 2020. The pooled SE was 89% (84–93%) for published before 2020, and 88% (85–90%) for published after 2020. The SP was 89% (83–93%) and 89% (80–85%), respectively. The AUC was 0.95 (0.93–0.97) and 0.92 (0.89–0.94), respectively ((Supplementary figure 7a, b).

Fifteen studies were geographically distributed in Asia and thirteen studies were geographically distributed outside Asia. The pooled SE was 87% (84–90%) and 90% (85–93%), respectively. The SP was 85% (80–86%) and 89% (82–93%), respectively. The AUC was 0.92 (0.89–0.94) and 0.95 (0.93–0.97), respectively (Supplementary figure 8a, b).

There were ten studies with low risk in more than three evaluation domains and eighteen studies with high risk. The pooled SE was 86% (78–91%) and 89% (87–91%), respectively. The SP was 92% (88–95%) and 81% (76–85%), respectively. The AUC was 0.93 (0.90–0.95) and 0.93 (0.91–0.95), respectively (Supplementary figure 9a, b).

**Heterogeneity analysis**

The meta-analysis results of 28 studies suggested that AI algorithms were beneficial for the diagnosis of OC from medical imaging from random-effects model. However, there was substantial heterogeneity among the included studies, SE had an $I^2 = 94.68\%$, while SP had $I^2 = 97.50\%$ ($p < 0.01$). The detailed results of subgroup and meta-regression analyses exploring the potential source of between-study heterogeneity are shown in Table 5 and Supplementary figure 10-23. The results highlighted a statistically significant difference. Visual inspection of funnel plots suggested there was no publication bias ($p = 0.83$) (Supplementary figure 24).

**Discussion**

With the widespread application of AI in medical imaging during recent years, radiomics and AI models are now being actively evaluated for diagnostic accuracy in a variety of malignancy types. To our best knowledge, this is the first systematic review and meta-analysis specifically dedicated to AI system performance in the diagnosis of OC. We are strictly in line with the guidelines for diagnostic reviews, and conducted a comprehensive

| Author [ref], year | Source of data | Number of images for training/testing | Data range | Open access data |
|-------------------|---------------|--------------------------------------|------------|-----------------|
| Liu et al, 2017a  | Retrospective study, date from Department of Radiology, Shanghai Tenth People’s hospital of Tongji University. | NR | 2009.01–2015.10 | No |
| Kazerooni et al, 2017a | Prospectively study, NR. | NR | NR | No |
| Acharya et al, 2014a | Retrospective study, NR. | 2340/260 | NR | No |
| Acharya et al, 2013a | Retrospective study, NR. | 1800/200 | NR | No |
| Acharya et al, 2012a | Retrospective study, NR. | 1800/200 | NR | No |
| Umar et al, 2012a | Retrospective study, NR. | NR | NR | No |
| Acharya et al, 2012a | Retrospective study, NR. | 1800/200 | NR | No |
| Al-Karawi et al, 2021a | Retrospective study, data from the IOTA research. | 150/148 | 2005.11–2013.11 | No |
| Jian et al, 2021a | Retrospective study, eight centers. | 144/75/75 | 2010.01–2019.02 | No |
| Li et al, 2016a | Retrospective study, NR. | 250/92/159 | 2010.01–2018.06 | No |
| Acharya et al, 2014a | Retrospective study, NR. | 2340/260 | NR | No |
| Pathak et al, 2015a | Retrospective study, NR. | 70/50 | NR | No |
| Ameeyo et al, 2009a | Retrospective study, data from the IOTA research. | 754/507 | 1999–2006 | No |
| Jian et al, 2013a | Retrospective study, NR. | 342/159 | 20102018 | No |
| Alqasemi et al, 2012a | Retrospective study, NR. | 400/95 | NR | Yes |
| Chen et al, 2012a | Retrospective study, data from the Ruijin Hospital affiliated with Shanghai Jiaotong university School of Medicine. | 296/41/85 | 2019.01–2019.11 | Yes |
| Zheng et al, 2022a | Retrospective study, data from the Tianjin Medical University General Hospital from November 2010 to May 2020. | 125/31 | 2010–2020 | No |

Table 4: Data source for the 35 included studies. Studies (n = 28) included in the meta-analysis.
literature search in both medical databases and engineering and technology databases to ensure the rigor of the study.

After a careful selection of research on relevant topics, we found that AI algorithms excelled in the identification of OC using medical radiography imaging, which manifested an equivalent or even better performance than independent detection by human clinicians. This study also described the performance of the different imaging modalities, sample size, the year of publication, geographical distribution, and the different risk of bias levels. Potential sources of inter-study heterogeneity were identified based on the above subgroup and meta-regression analyses. More importantly, we rigorously rated study quality and risk of bias using an adapted QUADAS-AI assessment tool, which is a strength of this systematic review and will also better guide future related studies.

Advances in ML techniques may facilitate processing of large amounts of medical image data. Notwithstanding their utility, ML methods are known to have limitations related to: manual extraction and selection of features, this is a fundamental task in order to find a group of significant variables to predict and correlate with outcome; Poor performance when dealing with imbalanced datasets. DL is the newest class of ML and

**Figure 2.** (a, b). SROC curves of all studies included in the meta-analysis (28 studies). a: SROC curves of all studies included in the meta-analysis (28 studies with 160 tables). b: SROC curves of studies when selecting contingency tables reporting the highest accuracy (28 studies with 28 tables).

Abbreviations: AI: artificial intelligence; SROC = summary receiver operating characteristic; SENS = summary sensitivity; SPEC = summary specificity.

**Figure 3.** Cross-hair Plot of all studies included in the meta-analysis (28 studies with 160 tables).
| No. of studies | Sensitivity | P value | I² (95%CI) | P value | I² (95%CI) |
|----------------|-------------|---------|------------|---------|------------|
| Overall        | 0.88 (0.85—0.90) | < 0.05  | 94.68 (94.16—95.19) | 0.85 (0.82—0.88) | < 0.05  | 97.50 (97.31—97.69) |
| Algorithm      |             |         |            |         |            |
| Machine learning | 0.89 (0.85—0.92) | < 0.05  | 95.11 (94.49—95.72) | 0.88 (0.82—0.92) | < 0.05  | 97.69 (97.46—97.92) |
| Deep learning  | 0.88 (0.84—0.91) | < 0.05  | 95.48 (94.84—96.11) | 0.84 (0.80—0.87) | < 0.05  | 95.84 (95.28—96.41) |
| Imaging modality |             |         |            |         |            |
| Ultrasound     | 0.91 (0.87—0.93) | < 0.05  | 96.58 (96.22—96.94) | 0.87 (0.82—0.91) | < 0.05  | 98.55 (98.43—98.66) |
| Magnetic resonance imaging | 0.83 (0.77—0.88) | < 0.05  | 85.72 (82.32—89.12) | 0.84 (0.80—0.87) | < 0.05  | 83.47 (79.37—87.58) |
| Computed tomography | 0.75 (0.68—0.81) | 0.43    | 0.00 (0.00—100.00) | 0.75 (0.67—0.82) | 0.83    | 0.00 (0.00—100.00) |
| Sample size    |             |         |            |         |            |
| ≤ 300          | 0.85 (0.81—0.88) | < 0.05  | 91.75 (90.61—92.90) | 0.82 (0.80—0.85) | < 0.05  | 83.00 (80.08—84.93) |
| > 300          | 0.93 (0.89—0.95) | < 0.05  | 97.96 (97.72—98.20) | 0.91 (0.84—0.96) | < 0.05  | 99.42 (99.38—99.47) |
| Risk of bias   |             |         |            |         |            |
| Low            | 0.86 (0.78—0.91) | < 0.05  | 97.49 (97.14—97.84) | 0.92 (0.88—0.95) | < 0.05  | 97.31 (96.92—97.69) |
| High           | 0.89 (0.87—0.91) | < 0.05  | 91.78 (90.70—92.87) | 0.81 (0.76—0.85) | < 0.05  | 95.94 (95.51—96.37) |
| Geographical distribution |             |         |            |         |            |
| Asia           | 0.87 (0.84—0.90) | < 0.05  | 94.48 (93.74—95.22) | 0.83 (0.80—0.86) | < 0.05  | 95.00 (94.35—95.65) |
| Non Asia       | 0.90 (0.85—0.93) | < 0.05  | 96.36 (95.91—96.82) | 0.89 (0.82—0.93) | < 0.05  | 98.17 (97.99—98.36) |
| Year of publication |             |         |            |         |            |
| Before 2020    | 0.89 (0.84—0.93) | < 0.05  | 96.26 (95.81—96.71) | 0.89 (0.83—0.93) | < 0.05  | 97.89 (97.68—98.10) |
| After 2020     | 0.88 (0.85—0.90) | < 0.05  | 94.63 (93.87—95.39) | 0.83 (0.80—0.85) | < 0.05  | 95.12 (94.45—95.79) |

Table 5: Summary estimate of pooled performance of artificial intelligence in image-based ovarian cancer detection.

a P-Value for heterogeneity within each subgroup.
b P-Value for heterogeneity between subgroups with meta-regression analysis.
has been found to be advantageous to other forms of ML.\(^{64}\) DL employs multiple layers of neural networks, leading to expanded ‘neuronal’ complexity, to significantly enhance computational power. However, with DL methods being more prone to overfitting and hence often requiring more data. Considering the stage of development of the algorithm and the difference in nature,\(^{65,66}\) we also carried out a sub-analysis by the different algorithms, where no significant difference was observed. This may be attributed to the small dataset of included studies, most of which collected a few hundred data, limiting the advantages of DL.

Although great promise has been shown with AI algorithms in a variety of tasks across radiology and medicine as a whole, these systems are far from perfect, we should also critically consider some methodological issues:

First, data continues to be the most central and crucial component for learning AI systems.\(^{67}\) Exploiting radiology report databases by using modern information processing technologies may improve report search and retrieval and help radiologists in diagnosis.\(^{68}\) We need to call for advocacy for creating interconnected networks of identifying patient data from around the world and training AI on a large scale according to different patient demographics, geographic areas, diseases, etc. In addition, we emphasize that rare cancers, including OC, require more diverse image databases. In fact, maximization of the power of AI will require the deposition of medical data with sufficient annotation in large-scale databases.\(^{59}\) However, such data are rarely curated, and this represents a major bottleneck in attempting to learn any AI model.\(^{70}\) International collaborative projects (such as The Cancer Imaging Archive [http://www.cancerimagingarchive.net]) that build large, labeled datasets should make a substantial contribution to meeting this challenge. Curation can refer to patient cohort selection relevant for a specific AI task but can also refer to segmenting objects within images.\(^{70-71}\) Curation ensures that training data adheres to a defined set of quality criteria and is clear of compromising artefacts. It can also help avoid unwanted variance in data owing to differences in data-acquisition standards and imaging protocols, especially across institutions, such as the time between contrast agent administration and actual imaging.\(^{71-73}\) Only in this way can we create an AI that is socially responsible and benefits more people.

Second, as the advent of AI-based diagnostic test studies, there has been a parallel increase in the number of systematic reviews summarizing such findings.\(^{74,75}\) Noteworthy, 94% studies have been performed in the absence of an AI-specific quality assessment criteria in those published systematic reviews.\(^{59}\) During the past decade, the most frequently utilized tool is the QUADAS-2.\(^{28}\) However, QUADAS-2 does not address the particular terminology that arises from AI diagnostic test studies, nor does it consider other issues that appear in AI research, such as the setting of the data set, sources of bias, etc.\(^{72}\) Therefore, Sounderajah, V et al. proposed an AI-specific risk of bias tool, termed QUADAS-AI in 2021.\(^{73}\) This tool provided us with a specific instruction to assess the risk of bias and applicability of the present study. Not surprisingly, most of the relevant studies were more often designed or conducted prior this guideline. We therefore accepted the low quality of some of the studies and the heterogeneity between the included studies. It also makes sense that we assume that patient selection, index test and flow and timing of studies used to evaluate the diagnostic performance of AI models will be optimized soon.

Third, although no publication bias was noticed in the present study, we must be honest about the fact that the available AI research is often a publication of positive results. We venture to guess that this phenomenon stems from reporting bias by researchers, which may have skewed the dataset and not conducive to the comparison between AI models and clinicians.\(^{74,75}\) One more point, the extraordinary applications of AI technology in medicine will require healthcare workers to enhance their clinical workflow combination. Of the included studies, only two evaluated the performance of integrating AI with clinicians. It has been suggested that scientific research should shift from an AI-physician dichotomy to a combination of AI and clinicians, which would be more in line with realistic medical workflows.

Fourth, 28 of the 34 studies that met the inclusion criteria for this systematic review provided information of our concern for the development of contingency tables. There is a broad range of indicators employed in AI research to report diagnostic abilities. Metrics such as SE, SP, and accuracy are the most applied in numerous studies. If the number of subjects with/without disease is shown in the study, we can combine SE and SP to derive TP, TN, FP, and FN for the construction of the contingency table. Other metrics like precision, dice ratio, F1 score and recall, which are frequently used in computer science, also present as the default standard of measurement in some studies.\(^{57}\) However, these metrics are not all-encompassing and alone we do not receive sufficient information to build a contingency table. Well-defined metrics at the intersection of health care systems and computer science are also prudent to consider for future research. Additionally, for AI based models, the obtained heatmaps show what aspects of the images are important for a given classification,\(^{72}\) whereas few included studies provide such information. To reduce bias, we emphasize reporting information about segmentation properties or heat maps in AI model-based studies to draw conclusions about the elements of interest in AI models.

Fifth, there is a disagreement around the critical terminology applied in AI research. Different papers have
defined the same terminology in different ways. For example, for an AI-based model, the sample set is generally grouped into several separate sections, including a training set and a test set for evaluating the effectiveness of the model. Although the term ‘validation’ is used in a causal sense, some researchers used this phrase to denote the dataset used to assess the diagnostic performance of the ultimate model. Other investigations have described it as a dataset with a tweaking function in the exploitation process. The inconsistency of naming renders it challenging to determine whether the set is independent. It is vital that the validation set comprises data isolated from training data and is exclusively dedicated to assess the final model. It has been proposed to classify the sample data set into a training set, a tuning set and a validation set, whose functions are to be applied for training the model, for tuning the parameters and for assessing the performance of the model, respectively. Considering the different sorts of validation sets, Altman et al. designated the datasets used for in-sample validation as internal validation set and those for out-of-sample validation as external validation set, suggestions which are very realistic and contribute to the quality of the study. Researchers concerned with the application of AI in healthcare should be careful about the phenomena and optimize it for future research.

Sixth, within a purely image-based setting, AI can achieve on par or superior performance to physicians, thereby highlighting its potential as a decision support system with immediate clinical implications. Although a fairly good evaluation can be made in this way, it does not take into account all the information that radiologists rely on when evaluating a difficult examination. Nonimaging-based patient characteristics, such as demographic information, history of cancer, and genetic information, may be integrated into the model. Given a sufficiently large data set, AI could use these pieces of information in conjunction with the image data to identify women at high risk of cancer.

Seventh, the high performance of AI model comes at the cost of high complexity and vast number of parameters. We may be unable to understand and explain why an AI model has made certain classifications in image analysis. This type of algorithm is often referred to as a “black box”. Compared with AI techniques, explainable artificial intelligence (XAI) can provide both decision-making and explanations of the model. Some research have been conducted into XAI to overcome the limitation of the black-box nature of AI methods. For example, Laios et al. have pioneered the implementation of XAI models in the field of gynecological oncology. They presented an ensemble AI-based model that predicted the outcomes following cytoreductive surgery for OC with high accuracy, and an XAI strategy that explained the patient and surgery-specific factors that led to that risk. The team also made a pioneering attempt to implement XAI models to explain the prediction of surgical effort at OC cytoreduction, by feeding the models with features that also include human factors. However, most of radiomics extraction and imaging biomarkers analyses included in this review are used as “black box”, and their application in clinical practice still lacks reliability and interpretability. This phenomenon is understandable given that the use of XAI in oncology is still in its infancy. Understanding the principles and applications of AI in medical imaging will facilitate assimilation and expedite advantages to practice. We encourage future researches to consider the interpretability of AI models in modeling, to address challenges, and to find clinical approaches for the development of AI in the field of radiomics.

Eighth, most studies were carried out in a single center with limited data availability. Only three of the included studies have external validation, which refers to validating the performance of the model with out-of-sample datasets from other institutions. However, among the three included studies with external validation, only one was included in the meta-analysis. This precluded a subgroup meta-analysis in the present study, but emphasized the necessity for rigorous and reliable evaluation of AI performance in external datasets. The included studies are more likely to group an institution’s dataset into a training set, a test set or an internal validation set. The performance was judged by the test set or internal validation. As the intention of the validation was to examine the performance of the model applied to patients from different populations, it is preferable to obtain a new dataset from a different organization. The lack of an external validation set may potentially lead to overestimation of the results, which could compromise the generalizability of the model. Several reviews in the AI field reported that studies with internally validated AI models outperform externally validated models in the detection of cervical cancer, breast cancer and tumor metastases. However, this is not surprising as the samples in the same dataset are often homogeneous and the diagnostic performance of the algorithm can easily be misjudged. Rigorous external validation is warranted in the design of AI-related diagnostic studies. Multicentric studies will have an significant role in this research field. The use of interoperable standards and uniform protocols will also be needed prior to conducting such a study. AI methods can provide valuable models for quality assurance, personalized and predictive medicine. For this purpose, the contribution of clinicians and researchers in the interpretation of models and their application has a crucial role in the daily clinical practice.

Additionally, limited prospective studies were carried out in real clinical environments. Most of the included studies were based on retrospective data and whose patients chosen from hospital medical records. It is well known that prospective studies would provide more
favorable evidence, and we anticipate more prospective AI research to emerge in the future. And only considering the inclusion of English articles may omit important information from other language studies. Another limitation is that we did not contact the authors because most of the studies included in full-text screening (93%) provided the necessary data.

The present study represents a summary of the enormous potential of AI algorithms that are useful for detecting OC using medical radiology imaging. However, it is also acknowledged that this finding is derived from relatively low methodological quality research, which inevitably overestimates the accuracy of the algorithm. The research of AI-based systems in diagnosing OC needs to be further improved in terms of study design.

Contributors
H-LX, T-TG, H-ZS, YS, Y-HZ, and Q-JW contributed to the conception and design of the study. H-LX, F-HL, and H-YC contributed to the literature search and data extraction. H-LX, F-HL, and T-TG contributed to risk of bias evaluation. H-LX, T-TG, H-ZS, YS, SC, T-TG, and Q-JW wrote the first draft of the manuscript and edited the manuscript. All authors contributed to critical revision of the manuscript. All authors approved the manuscript. H-LX and T-TG contributed equally to this work.

Data sharing statement
The search strategy was shown in Supplementary Note 1, and the contingency tables of 28 studies included in the meta-analysis were shown in Supplementary Table 1. The results of risk of bias and publication bias were separately provided in the Supplementary Figure 8 and 9. Additional data are available on request.

Declaration of interests
All authors declare no competing interests.

Acknowledgments
This work was supported by the Natural Science Foundation of China, the LiaOing Revitalization Talents Program, and the 345 Talent Project of Shengjing Hospital of China Medical University.

Supplementary materials
Supplementary material associated with this article can be found in the online version at doi:10.1016/j.eclinm.2022.101662.

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