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Review article

Application of artificial intelligence in the diagnosis, treatment, and recurrence prediction of peritoneal carcinomatosis

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ABSTRACT

Peritoneal carcinomatosis (PC) is a type of secondary cancer which is not sensitive to conventional intravenous chemotherapy. Treatment strategies for PC are usually palliative rather than curative. Recently, artificial intelligence (AI) has been widely used in the medical field, making the early diagnosis, individualized treatment, and accurate prognostic evaluation of various cancers, including mediastinal malignancies, colorectal cancer, lung cancer more feasible. As a branch of computer science, AI specializes in image recognition, speech recognition, automatic large-scale data extraction and output. AI technologies have also made breakthrough progress in the field of peritoneal carcinomatosis (PC) based on its powerful learning capacity and efficient computational power. AI has been successfully applied in various approaches in PC diagnosis, including imaging, blood tests, proteomics, and pathological diagnosis. Due to the automatic extraction function of the convolutional neural network and the learning model based on machine learning algorithms, AI-assisted diagnosis types are associated with a higher accuracy rate compared to conventional diagnosis methods. In addition, AI is also used in the treatment of peritoneal cancer, including surgical resection, intraperitoneal chemotherapy, systemic chemotherapy, which significantly improves the survival of patients with PC. In particular, the recurrence prediction and emotion evaluation of PC patients are also combined with AI technology, further improving the quality of life of patients. Here we have comprehensively reviewed and summarized the latest developments in the application of AI in PC, helping oncologists to comprehensively diagnose PC and provide more precise treatment strategies for patients with PC.

1. Introduction

Peritoneal carcinomatosis (PC) is a type of secondary cancer caused by the metastasis of tumor cells from the primary tumor to the peritoneum via the bloodstream [1]. About 15 % of patients with colorectal cancer will eventually develop PC. The incidence even increases to 24 % and 45 % in patients with gastric cancer and those with ovarian cancer, respectively [2,3]. Unlike metastatic tumors

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in other sites, PC followed by malignant ascites is associated with impaired quality of life and poor prognosis, with a median overall survival (OS) of 2–5 months. And current treatment strategies for PC are mostly palliative and limited [4]. Due to the aggressive behavior of PC, early detection and reduction of recurrence are becoming increasingly important. Artificial intelligence (AI) is a new intellectual capability that can simulate and replicate human intelligence and judgement through data-driven algorithms [5,6]. Machine learning (ML), as one of the branches of AI, analyzes massive training data to teach machines, find out the rules and complete the learning process. Then, ML can automatically learn and continuously improve its performance accuracy to solve the desired data without human intervention [7]. Deep learning (DL) is an implementation technology of ML that is an effective approach for automatically extracting information from massive medical images and performing detection or classification tasks [7,8]. Convolutional Neural Networks (CNNs) are the most widely used DL architecture in the field of medical imaging. CNNs are sophisticated models with multiple hidden layers that can analyze various input data, extract, and classify internal features from massive data, and provide prediction outputs [5,9] (Fig. 1). In summary, based on the powerful learning ability and efficient computational power of AI, it has been widely applied in PC for diagnosis, treatment, and recurrence prediction. Therefore, we aimed to review and summarize the development of the application of AI in the field of PC based on current literature findings. In addition, the current evidence on the application of AI in peritoneal carcinomatosis over the past 6 years is summarized in Table 1.

2. Research methodology

Previous relevant articles using AI in cancer were identified from the literature. The core databases, including PubMed databases and Web of Science, were systematically searched from the inception dates to 2024, using the keywords "deep learning," "machine learning," “artificial intelligence”, “"peritoneal cancer”, and "peritoneal carcinomatosis". Studies that involved the relationship between artificial intelligence and peritoneal carcinomatosis were included.

3. Diagnosis of peritoneal carcinomatosis

3.1. Imaging diagnosis

The clinical manifestations of PC are atypical, making early diagnosis difficult. Traditionally, PC is often discovered incidentally during surgical exploration [33,34]. Specifically, PC can be observed in 15 % of patients with colorectal cancer during abdominal exploration. And in patients with gastric cancer, the proportion reaches almost 40 % [33]. Computed tomography (CT) is the most used imaging modality for the detection of peritoneal nodules. Some CT imaging features, including peritoneal thickening and massive ascites, suggest the presence of peritoneal metastasis. However, these classic imaging features usually appear at a late stage of the disease. The overall sensitivity of CT is only 28.3%–50.9 %. And it is difficult for CT to detect small tumor smaller than 5 mm [35,36].

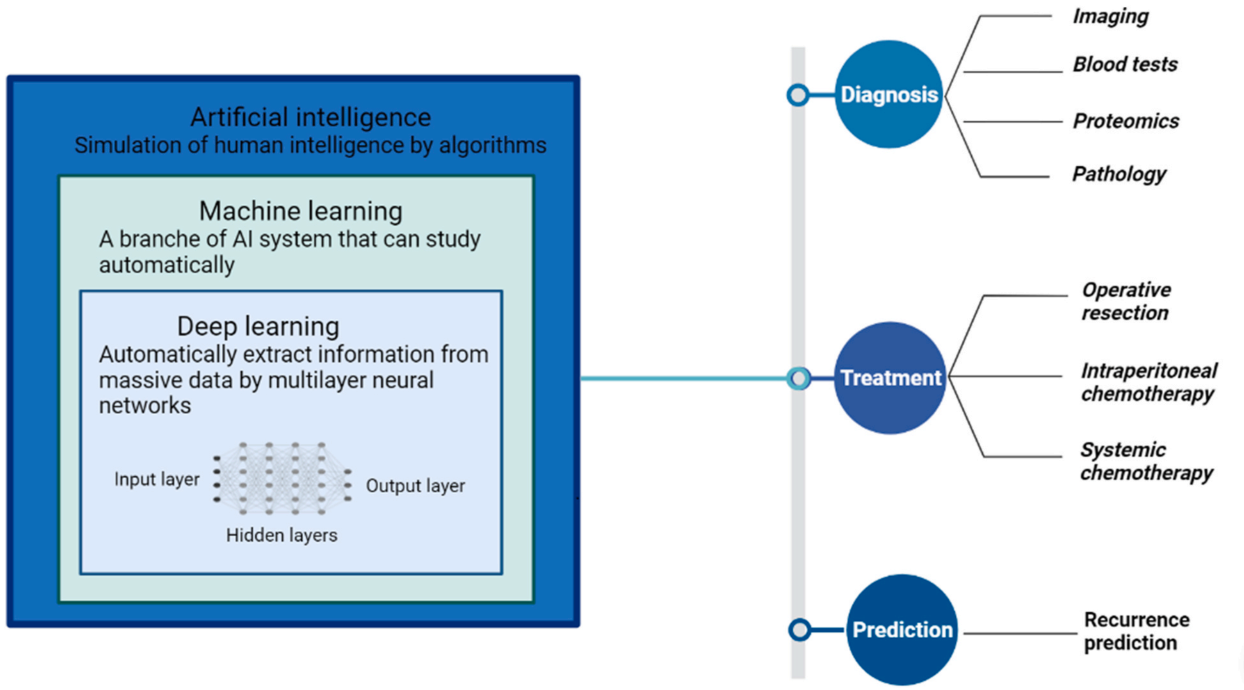

Fig. 1. The relationships among artificial intelligence (AI), machine learning (ML), with deep learning (DL) and the applications of AI technologies in the diagnosis, treatment, recurrence prediction of peritoneal carcinomatosis.

Table 1
Summary of clinical studies for artificial intelligence in peritoneal carcinomatosis in recently 6 years.

Reference	Study type	Number of cases	Tumor type	Methods	Results	Year
Diagnosis						
Dong D et al. [10]	Retrospective	554 advanced gastric cancer patients	GC with PC	Radiomic nomogram	AUC: 0.920	2019
Zixing Huang et al. [11]	Retrospective	554 patients	GC with PC	DCNN	AUC: 0.900 Sensitivity: 81.0 % Specificity: 87.5 %;	2020
Menglei Li et al. [12]	Retrospective	779 patients	CRC with PC	Clinical-radiomics model	AUCs: up to 0.855	2020
Zixing Huang et al. [13]	Retrospective	At least 109 cases	GC with PC	DCNN	NR	2020
Chengmao Zhou et al. [14]	Retrospective	1080 patients with postoperative GC	GC with PC	ML	AUC: up to 0.938 Accuracy : up to 90.9 %	2020
Ruijiang Li et al. [15]	Multicenter	1978 patients	GC	DCNN + PMetNet	AUC: 0.920–0.946 Sensitivity: 75.4%–87.5 % Specificity: 92%–98.2 %	2021
Bin Zheng et al. [16]	Retrospective	159 patients	GC with and without PC	ML	AUC: 71.2 % Sensitivity: 43.10 % Specificity: 87.12 %	2021
Xinyu Jin et al. [17]	Retrospective	11408 images from 131 patients	PC	Meta-learning-based DL	AUC: 0.877 Sensitivity: 73.4 % Specificity: 95.2 %	2022
Lili Wang et al. [18]	Retrospective	810 patients	GC	ML	AUCs of clinical models: 0.902–0.969 AUCs of radiomics models: 0.896–0.975	2022
Valentin Bejan et al. [19]	Retrospective	NR	CRC	ML	Optimal accuracy: 0.75.	2022
Zixu Yuan et al. [20]	Retrospective	19,814 images from 130 patients	CRC with and without PC	DL	AUC: 0.922 Sensitivity: 93.75 % Specificity: 94.44 % Accuracy: 94.11 %	2022
Dailun Hou et al. [21]	Multicenter	88 peritoneal tuberculosis and 90 PC patients	PC	ML	AUC: 0.914–0.971	2023
Yanyan Chen et al. [22]	Retrospective	25 patients	GC with and without PC	Proteomic analysis	NR	2023
Jihong Liu et al. [23]	Retrospective	98 laboratory tests and clinical feature	Ovarian cancer	AI model	AUC of 0·949	2024
Treatment						
Milad Shamsi et al. [24]	Retrospective	NR	PC	Computational model	NR	2018
J M Bereder et al. [25]	Retrospective	373 cases	PC	ML	Accuracy: close to 98 %	2019
Alexandros Laios et al. [26]	Retrospective	154 cases	OC	ML	Accuracy: 66 %	2020
Nicholas et al. [27]	Retrospective	60 cases	OC	ML	NR	2021
Mohsen et al. [28]	Retrospective	NR	PC	Mathematical model	MCDT increased penetration depth more than 13 times	2022
Mohamed A. et al. [29]	Retrospective	1959 CRS-HIPEC procedures	PC	ML model	AUC: 0.74	2023
Diederick De Jong et al. [30]	Retrospective	508 patients with ovarian cancer	OC	ML and explainable AI	AUC: 0.91	2023
Predicting recurrence						
Ruijiang Li et al. [31]	Retrospective	2320 patients with gastric cancer	GC	Multitask DL model	AUC: 0.843–0.857 C-index: 0.610–0.668	2022
Sun, Zepang et al. [32]	Retrospective	584 quantitative features from 2005 patients	GC	Radiomics	AUC: 0.721–0.732	2023

Abbreviation: PC: peritoneal carcinomatosis; AUC: area under curve; DCNN: deep convolutional neural network; ML: machine learning; DL: deep learning; NR: not reported; AI: artificial intelligence; GC: gastric cancer; CRC: colorectal cancer; OC: Ovarian cancer; CRS-HIPEC: cytoreductive surgery and hyperthermic intraperitoneal chemotherapy; MCDT: magnetically controlled drug targeting; PMetNet: peritoneal metastasis network.

Although clinical imaging has diagnostic value, it lacks the sensitivity to detect microscopic or small tumor. And the sensitivity for radiologists to detect PC is still insufficient [37]. Therefore, more accurate diagnostic methods for PC are urgently needed.

Due to the sensitive screening techniques of AI, it has been successfully applied in various approaches in the PC diagnosis process. DL and ML have shown great potential in image processing due to the automatic extraction function of the convolutional neural network (CNN) and the learning model based on ML algorithms [38,39]. The data consisting of massive medical images have been used to train the neural networks, which can further detect diseases using CT or MRI through pattern recognition [40]. Several studies have investigated the application of DL and AI in the detection of peritoneal metastasis [10,11,15]. J-F Ji et al. constructed a radiomic nomogram reflecting CT features of the primary tumor and adjacent peritoneum based on 266 quantitative image features from 554 patients with advanced gastric cancer (AGC). And they found the CT features with Lauren type can help in early detection of occult peritoneal metastasis with an area under the curve (AUC) of 0.920 (95%CI 0.862–0.978) [10]. In a multicenter retrospective cohort study, image data from 1225 surgically treated gastric cancer patients were included and a deep convolutional neural network (DCNN)-based peritoneal metastasis network (PMetNet) was developed. External data from 753 patients which were collected by other independent centers were used to validate the model with a sensitivity of 75.4 % and 87.5 % and an AUC of 0.946 and 0.920 in two external validation groups, respectively. According to the multivariable logistic regression analysis, PMetNet was an independent predictive factor for occult PC [15]. In another retrospective study [16], a radiomics-based ML model was developed using 315 image features from 159 patients. Then, five feature selection methods (including selection operator, recursive feature elimination, random projection algorithm, etc.) were used to optimize the ML model for predicting PC in gastric cancer patients from preoperative CT images. And the ML model which embedded with the random projection algorithm (71.2 %) was associated with significantly higher detection accuracy than that of other models ($p < 0.05$). Furthermore, a retrospective study described the preoperative CT imaging of colorectal cancer with synchronous PC and extracted the characteristics of the adjacent peritoneum to build a ResNet3D + SVM classifier for the detection of synchronous PC [20]. The ResNet3D + SVM classifier is associated with fast, non-invasive, and accurate features, which spent only 34 s for analyzing the images with AUC of 0.922 (0.912–0.944), specificity of 94.44 % and sensitivity of 93.75 %. The ResNet3D + SVM classifier was associated with a higher accuracy rate than routine CT identified by senior radiologist and junior radiologists (AUC: 0.922 vs 0.791 vs 0.780) [20]. Xinyu Jin et al. [17] proposed a novel model trained by meta-learning and extracted features using multimodal DCNN with enhanced CT to identify PC with an accuracy of 87.5 %. This model outperformed the routine PC prediction model based on DL method and logistic regression (AUC: 0.877 vs 0.827 vs 0.795). Some studies combine imaging and clinical characteristics to predict PC and achieve optimal efficacy. Menglei Li et al. [12] develop a radiomics signature, which included imaging characteristics of the primary site and the adjacent largest lymph node, and further used logistic regression analysis for selecting significant clinical factors to develop a clinical radiomics model. And the model is superior to the clinical-only and radiomics-only models (AUC: 0.855 vs 0.771 vs 0.764) for preoperative prediction of synchronous PC. These non-invasive AI strategies identify patients with occult PC, which may benefit the optimal treatment selection making and avoidance of unnecessary curative surgery.

It is difficult for CT imaging alone to differentiate PC from peritoneal tuberculosis [41]. Although laparoscopic biopsies are considered as the most sensitive method to differentiate the two diseases. However, laparoscopy is expensive and invasive, which limits its application [42]. Therefore, it is necessary to develop a convenient and non-invasive tool for identification diagnosis. Dailun Hou et al. developed a ML model using CT to differentiate PC from peritoneal tuberculosis with an AUC of 0.971 and 0.923 in the training and test cohorts, respectively. There were significant differences between the two diseases in the following aspects, including massive ascites, calcified or ring enhancement of lymph nodes, irregular thickening or cake-like thickening of the peritoneum, scalloping sign and so on [21]. The diagnostic accuracy of PC will be improved and the physician's workload will be significantly reduced by the automatic learning ability and repeated assessment capabilities of AI.

3.2. Blood tests

Early prediction of PC through ML models using basic blood parameters is non-invasive and convenient, which may benefit patient management and reduce mortality and morbidity caused by aggressive surgery [14]. Valentin Bejan et al. [19] conducted a study to use different ML strategies, including random forests (RF), artificial neural networks (ANNs), and support vector machines (SVM), to verify the influence of routine blood tests (hematocrit, white blood cell count, platelet count, hemoglobin levels, neutrophil and lymphocyte counts) in the presence of PC. They found that the sensitivity analysis of the RF model can be applied to verify the influence of each parameter in the occurrence of PC with an optimal accuracy of 0.75. And the following parameters, including age, hemoglobin, and hematocrit, were associated with higher sensitivity. This study opens a promising study direction, more research is required to explore the predictive effect of basic blood parameters in the occurrence of PC.

3.3. Proteomics

Proteomics is the study of a large collection of proteins expressed by an organelle, cell type, tissue or even an organism at a given time [43]. Proteomic information plays an important role in identifying cancer stage, discovering tumorigenesis mechanisms, predicting recurrence, tumor aggressiveness, selecting individual treatment, reducing of cell resistance, in various tumors, such as breast cancer [44,45]. The proteomic features can also predict the presence of PC and further predict the characteristic of tumor immune microenvironment. Yanyan Chen et al. [22] developed a proteomic signature by whole-exome sequencing and proteome profiling in PC and PC-free of gastric cancer. They selected 10 proteins (MSRB3, TBC1D14, PLCB1, ITGA7, LIMS1, RAB6B, SMTN, TADA1, DUOXA2, SEMA3C) through the ML algorithms from the PC-related cohort for predicting the occurrence of PC and achieved an AUC of 0.83. They further established a PC risk score based on this 10-protein signature and divided gastric cancer patients into three cohorts: high-risk, moderate-risk, and low-risk groups according to the PC risk score. In contrast to the low-risk cohort, the high-risk cohort was associated with a higher percentage of regulatory T cells, M2 macrophages, and resting $CD4^+$ memory T cells and a lower percentage of $CD4^+$ naive T cells, plasma B cells, and eosinophils. This result showed that there is an association between PC risk score and tumor immune microenvironment and that PC risk score may be a predictive factor for immunotherapy response.

3.4. Pathological diagnosis

Histopathology through laparoscopic or laparotomy biopsy and cytopathology of malignant ascites remains the gold standard for the diagnosis of PC [46,47]. Recently, DL image analysis has used to identify morphology-based representations caused by molecular alterations in some tumors, including colorectal cancer, melanoma, breast cancer, prostate Cancer, and lung cancer [48–50]. Digital pathology has made significant progress due to the following advantages, including immediate availability of cases, remote diagnosis, and more convenient consultation with pathologists [51]. Faster slide scanning, cheaper data storage, and increased computing power have enabled the development of large-scale slide scanning as well as image analysis, and promoted the application of ML to address biological issues through combining tumor morphology with histology [48,52]. Machine learning is also associated with higher accuracy in error-prone tasks such as metastasis identification [51].

In cytopathology, whole slide scanners convert cytopathology into high resolution images [53]. In addition, DL-based models have been used in ascites cytology. Feng Su et al. [54] generated a novel database of peritoneal effusion cytopathology images and developed a DL model for ascites cytopathology. Based on Region-based CNN, they established Detection-Net for automatic cell detection and Classification-Net for cell classification. The average accuracy of the detection Net was 0.8316. And the Classification-Net showed outstanding performance in cell classification with an AUC of 0.8851, precision of 96.80 %. The DL model, which combined Detection-Net and Classification-Net, showed good performance in ascites cytopathology. With the application of AI in cytopathology, CNN can be used for pre-screening of ascites cytology, significantly reducing the burden on pathologists, and improving the accuracy.

4. Treatment

4.1. Operative resection

Cytoreductive surgery (CRS) and hyperthermic intraperitoneal chemotherapy (HIPEC) are regarded as the mainstay of treatment, but have limited efficacy in patients with PC [55]. In cytoreductive surgery, surgeons attempt to remove all macroscopic neoplasm (R0) from the peritoneal surface. Sometimes it may be necessary to remove heavily involved organs to achieve radical resection [56]. HIPEC is recommended only after complete CRS, and a survival benefit has been observed [57]. Recently, AI has been used in surgical procedures. Due to the improved accuracy and stability, high-definition 3D vision, and good ergonomic experience of Da Vinci robotic surgery, it is being used more widely in surgery [58].

Postoperative mortality and morbidity are also relatively high, making the selection of cytoreductive surgery a challenging issue. And accurate prediction of surgical effect and identification of R0 resection patients are important to improve patient prognosis and survival. ML and eXplainable Artificial Intelligence (XAI) are also used to predict R0 resection in ovarian cancer [26,30,59]. In a single institution study, two predictive models based on the eXtreme Gradient Boosting (XGBoost) and Deep Neural Network (DNN) algorithms were developed and compared to predict the probability of complete cytoreduction. Patients with a surgical complexity score greater than 5 were associated with a higher likelihood of incomplete cytoreduction on a receiver operator characteristic (ROC) curve with an AUC of 0.644, sensitivity of 34.1 %, and specificity of 86.5 %. And DNN scoring is inferior to XGBoost for predicting surgical efficacy (AUC: 0.739 vs 0.77) [59]. XAI technology is important for a more comprehensive understanding of the AI framework and to encourage the application of AI in the medical field. A retrospective study investigated the performance of the k-nearest neighbor (k-NN) classifier, an AI system, in predicting R0 resection in advanced ovarian cancer [26], and the k-NN algorithm relatively outperformed conventional logistic regression with a mean predictive accuracy of 66 %. More recently, Diederick De Jong et al. [30] developed a novel intraoperative score to capture anatomical fingerprints of disease (ANAFI score) and discovered that the presence of cancer dissemination in the following areas, including the colonic serosa, small bowel mesentery, and diaphragmatic peritoneum, was associated with higher predictive accuracy of CC0 than the existing scoring tools, including the intraoperative mapping for ovarian cancer (IMO) and the peritoneal carcinomatosis index (PCI). Early assessment of the above anatomical sites by ML and AI during surgery procedure can guide the selection of surgical approaches. Accurate identification of patients with complete resection can help in the selection of individualized treatment.

A previous study showed that patients undergoing CRS-HIPEC with major complications were associated with a higher 3-year OS rate than those with minor complications (62 % vs 28 %, $p < 0.01$) [60]. Mohamed A. Adam MD et al. established a risk score to predict the severity of 90-day complications of CRS with HIPEC using a data-driven ML model [29]. They used the comprehensive complication index (CCI) score, a continuous scale from 0 (no complication) to 100 (death), to identify the severe complications. And the CCI >61 was identified as severe complications with an AUC of 0.74. And the following factors, including PCI score, symptomatic status, and having undergone pancreatectomy, were positively associated with severe complications.

4.2. Intraperitoneal chemotherapy

Intraperitoneal (IP) chemotherapy delivers cytotoxic drugs directly into the peritoneal cavity, reducing the toxicity of systemic chemotherapy and enabling peritoneal lesions to be exposed to high concentrations of anticancer agents [61]. However, because of the poor penetration depth of cytotoxic drugs into the tumor tissue, and only tumor periphery cells can be in full contact with the high concentration of chemotherapy drugs, so IP chemotherapy is associated with limited efficacy [62]. It is necessary to develop new drug delivery systems to increase the depth of drug penetration and improve the efficacy of therapy. Recently, magnetically controlled drug targeting (MCDT) has been developed to improve the efficacy of IP therapy. In MCDT, drug-coated magnetic nanoparticles (MNPs) are targeted to tumor tissue through an external magnetic field [63,64]. Amir Sanati-Nezhad et al. established a computational model [24] for predicting the predictability and feasibility of magnetically assisted IP chemotherapy. The computer reconstructed drug delivery barriers, including a spatially heterogeneous construct of non-functional lymphatic vessels, increased interstitial fluid pressure, leaky vasculature, and denser extracellular matrix. Compared to IP-free cytotoxic drugs, the MCDT method increases agent penetration into large tumor tissue and significantly increases the final intra-tumoral concentration of cytotoxic drugs. Similarly, Kaamran Raahemifar et al. [28] also developed a mathematical modelling and confirmed the efficacy of MCDT. Compared with conventional IP injection, MCDT increased the drug penetration area by more than 1.4 times and the penetration depth by more than 13 times, and significantly enhanced the proportion of killed cancer cells (6.5 % vs 2.54 %).

Recently, some preclinical and clinical studies have investigated the efficacy of various IP immunotherapies in PC, including catumaxomab, chimeric antigen receptor (CAR)- T cells, immune stimulators, immune checkpoint inhibitors, cancer vaccines, and radioimmunotherapy [55]. More AI-based models are needed to predict the efficacy of different intraperitoneal immunotherapies and to guide drug selection in PC.

4.3. Systemic chemotherapy

Systemic chemotherapy may be considered for some patients who are unable to undergo surgery [65]. Chemotherapy drug resistance is a challenge issue in cancer treatment, caused by insufficient drug concentration reaching the tumor tissue through the blood circulation. AI can use its learning ability to predict the sensitivity of chemotherapeutic drugs, improve therapeutic decisions, and increase the effectiveness of therapy by individualizing therapy [58]. A retrospective study [27] generated a signature to predict cisplatin sensitivity using the Genomics of Drug Sensitivity in Cancer and The Cancer Genome Atlas databases to identify four biomarkers, including S100A14, CYTH3, ERI1, and GALNT3. Using ML, they found that ovarian cancer patients with lower expression of CYTH3 and S100A14 and negative lymph node status were associated with a low risk of platinum resistance. Close monitoring of response and relapse is required for tumors predicted to be chemo-resistant, and second-line chemotherapy should be considered if relapse is confirmed. PC arise from different primary tumor sites and are amenable to different chemotherapeutic agents. AI can help predict the therapeutic response to drugs and guide drug selection in PC. In addition, the AI technologies had been widely used in the various aspects of drug field, including new drug development, drug target identification and validation, and drug repurposing and so on [66].

4.4. Recurrence prediction of peritoneal carcinomatosis

Physicians need to predict the survival and recurrence rates of cancer patients by assessing their clinical characteristics. However, this prediction has great contingency and uncertainty, and often requires rich experience of doctors. With the application of AI in cancer recurrence prediction, the prediction accuracy will be improved. Peritoneal recurrence is the main site of relapse in gastric cancer patients who had undergone radical operation. Accurate prediction of peritoneal recurrence is important to identify patients who may benefit from local treatment or intensified systemic therapy [67,31]. DL models usually perform a single task, such as predicting survival endpoints. In contrast, multitask learning models perform multiple tasks simultaneously using a single model. Based on preoperative CT images, a retrospective study developed a multitask DL model that simultaneously predicts disease-free survival (DFS) and peritoneal recurrence for gastric cancer after radical operation. The AUC is 0.857 in the training cohort, 0.856 in the internal validation cohort, and 0.843 in the external validation cohort for predicting peritoneal recurrence. And the model performed well in predicting DFS with a C-index of 0.654, 0.668, and 0.610 in the training cohort, internal validation cohort, and external validation cohort, respectively [31]. The study also showed that the predictive accuracy of the multitask DL model was significantly higher than that of the traditional single-task DL-based model. In addition, the predictive models are also associated with response to adjuvant chemotherapy. Adjuvant chemotherapy can significantly improve DFS in stage II-III gastric cancer patients with a high risk of peritoneal recurrence. While chemotherapy had no effect on DFS in patients with a low predicted risk [31]. More recently, a multi-center study extracted 584 quantitative characteristics of the intra-tumoral and peritumoral regions on enhanced CT images and combined different algorithms, including penalized Cox regression algorithm, SVM-RFE, and LASSO, for generating a radiomics signature. This study enrolled 2005 patients with gastric cancer after surgical resection and developed an AI model to predict PC recurrence according to preoperative CT images with an AUC of 0.732 in the training cohort. Notably, this model helps doctors with 5–15 years of clinical experience to increase the PC diagnostic accuracy by 10.13 %–18.86 % [32]. AI can screen for features associated with peritoneal recurrence by comparing images with PC and cancer without PC, and integrate these features into a radiomic signature for clinical prediction, which will optimize the patient management and treatment.

4.5. Emotion analysis of patients with peritoneal carcinomatosis

The severity and lethality of PC has a profound impact on the mental health of patients, resulting in the production of depression, anxiety, and even suicidal psychology. Patients with these psychological problems are always resistant to cancer therapy, which seriously affects the therapeutic effect [68–70]. Therefore, accurate prediction of the patient's psychology and prompt counselling interventions are very vital for cancer treatment. Recently, the AI techniques have also been used to analyze patients' emotions. Compared with general verbal or pictural stimulation, virtual reality (VR) technology is more effective to induce emotions for diagnosis [71]. Li, ZB et al. [72] constructed a computational affection-based OCC-PAD-OCEAN federation cognitive modelling (OPO-FCM), which can capture expression features by training a deep neural network, map expression features to the PAD emotion space by the established expression–emotion space mapping connection, and complete the mapping of the average emotion during a period. Liu, TT et al. [73] found that the integration of AI in the research of emotions of loneliness, depression, and anxiety (EMO-LDA) research is a promising direction for addressing mental health. In general, AI technology is a powerful tool to diagnose and support mental health in cancer patients.

5. Discussion

Our analyses pooled data from the core database PubMed databases and Web of Science. We included studies that involved the association between AI and PC. We concluded that the application of AI technologies in different approaches in the field of PC. AI increases the diagnostic accuracy and treatment efficacy in PC. And recurrence prediction and emotion evaluation of PC patients are also combined with AI technology. However, our study also has limitations. Firstly, the literature on the use of AI in PC is not extensive, and some of the data in our review represent the conclusions of individual studies, which are not very rigorous. In addition, the studies we enrolled are almost retrospective datasets, the information of some clinical factors may be questionable, which may affect the accuracy. Future inclusion of more prospective studies could further strengthen the evidence. There are few studies on the application of AI in PC, and our center have conducted related study to expand the application prospect of AI in carcinoma.

6. Conclusions and perspectives

PC is a type of secondary cancer that is not sensitive to conventional intravenous chemotherapy. And treatment strategies are usually palliative and limited. Therefore, early diagnosis and sensitive treatment are needed for PC. Recently, AI has made rapid progress in the field of cancer, including PC. Due to the development of deep neural networks and machine learning algorithms of AI, it is generally applied in the diagnosis, recurrence assessment, and treatment of PC. However, the application of AI in PC still has some problems, such as the immature technology, the high cost, and the controversies in moral and ethical direction. And most of the current studies are retrospective studies. In the future, more prospective and rigorous studies are needed to enroll larger sample size to combine AI technology with different aspects of cancer, and apply AI in PC more systematically and normatively. Specifically, more radiomic nomograms based on imaging phenotypes were required to serve as a feasible approach for non-invasive prediction of suspicious PC. Researches using machine learning methods to select treatment strategies is needed, so that clinicians can better individualize treatment regimens to maximize survival benefits. And some of the models mentioned in our review need to be further validated by a larger prospective external center.

Ethics approval and consent to participate

Not applicable.

Data availability statement

No data was used for the research described in the article.

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CRediT authorship contribution statement

Gui-Xia Wei: Writing – original draft. **Yu-Wen Zhou:** Writing – original draft. **Zhi-Ping Li:** Writing – review & editing. **Meng Qiu:** Writing – review & editing.

Declaration of competing interest

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

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