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REVIEW PAPER

Artificial intelligence in the treatment of cancer: Changing patterns, constraints, and prospects

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Abstract

Purpose Artificial intelligence (AI) has contributed to the advancement of medical research, particularly cancer research. AI technology is an inclusive science comprising computer science, cybernetics, psychology, neurophysiology, medical science, and dialectology.

Methods In the present review, we first addressed the new developments of AI in the oncology-related area and its application in the progression of anticancer drugs and treatment. Then, we discuss the state-of-the-art status and progress outlook of AI.

Results Comprehensive Cancer Information from the National Cancer Institute (NCI) suggests that AI, deep learning (DL), and machine learning (ML) can be utilized to improve patient outcomes in cancer care. AI technology can be used to anticipate the action of anticancer drugs and/or aid in the development of anticancer drugs. AI technology can aid physicians in making accurate treatments, decreasing nonessential surgeries, and assisting oncologists in progressing treatment plans for cancer patients. Thus, AI can improve the speed and accuracy of cancer detection, assist with clinical decision-making, and result in better health outcomes.

Conclusions We conclude by summarizing the challenges and possible future directions—along with their limitations—of AI-assisted anticancer medication research in the context of cancer. The application of AI in cancer research has a significant future in prognostication and decision-making given the expanding tendency.

Keywords Artificial intelligence · Machine learning · Deep learning · Cancer diagnosis · Treatment interference

1 Introduction

Artificial intelligence (AI) refers to the intelligence that is discovered by machinery built by a human being. AI technology is an inclusive science comprising computer science, cybernetics, psychology, neurophysiology, and dialectology. In 1950, Alan Turing was the first person to think up the idea of using computers to emulate intellectual activities and perilous thinking [1]. In 1956, AI was invented at the Dartmouth conference. Subsequently, the continuous progression of the connotation of AI has constantly increased, and generally, it has developed in various names, such as artificial neural networks, machine learning (ML), and deep learning (DL) [2]. AI appears to be linking the gap of accession to data and their notable understanding of cancer. These methods have revealed better exceptional capabilities and deteriorated approaches [3]. DL is a vital part of AI, which can automatically remove features from large volumes of data. Furthermore, DL can discover the data in images that cannot be recognized by the human eye [4]. This is of inordinate meaning for the initial diagnosis of cancer based on the image data. Additionally, AI can aid in the diagnosis and treatment of cancer [5]. Similarly, AI can directly create rapid and instinctive decisions to clear up difficulties. This is not a problem because AI can intensely augment the present patterns of cancer research. To provide a complete representation of the present situation of the actions

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played by AI in the treatment of cancer, a regular appraisal was performed to scrutinize the devices related to AI, which has already acquired an authorized agreement for inflowing into oncology medical practice, including its connected areas. To this goal, scientists have recovered entirely AI-based machines that have received Federal Drug Administration (FDA) approval in cancer-associated areas, removing entirely potential data by investigating official FDA databases. Such kinds of data were also combined with all earlier connected reviews and/or comments. Complete data were arranged to be distinctly presented by the precise oncological regions in the script in the figure below (Fig. 1) [6].

John McCarthy 1956 invented the term AI, as today's science and engineering technologies produce intelligent devices [7]. Currently, AI signifies a developing and quickly growing pattern that regards diverse technical areas, which are also dedicated to the treatment of cancer [8]. It can be understood as a general idea representing the capability of a device to acquire and identify designs and connections from an adequate quantity of illustrative models and to apply this evidence for enhancing the present method regarding the method of decision-making in a particular area [9].

In oncology, AI is reforming the current situation, aiming to assimilate the enormous quantity of data obtained from multiomics scrutinizes with present developments in good presentation calculating and revolutionary DL approaches [10]. In particular, the uses of AI are increasing and include innovative methods for cancer detection, diagnosis, screening the depiction of cancer genomics, scrutiny of the cancer microenvironment, and analysis of biochemical markers [11].

For a good understanding of present roles as well as future views of AI, two vital terms that are strongly related to AI should be rational: ML and DL. ML is a universal concept that indicates the aptitude of a device in learning and hence developing the designs and models of scrutiny, while DL specifies an ML method that uses multilayered and deep networks to accomplish an enormously prophetic concert. It is well known that these two ideas are essential in AI in the treatment of cancer.

In the present review, we first addressed the new developments of AI in the oncology-related area and its application in the progression of anticancer drugs and treatment. Then, we went on to discuss the state-of-the-art status and progress outlook of AI. The related literature was studied and analyzed, and a systematic review was performed. We searched the significant and high-quality literature from high-ranked journals for significant interpretation. Simultaneously, we scrutinize additional literature to enhance authentication. We discuss cancer diagnostics in the oncology-associated area wherein clinically AI already has shown an enormous effect. We concluded by outlining the difficulties and potential future paths of AI-assisted anticancer drug research, with limitations, and future directions in cancer.

2 Conventional cancer diagnosis and treatment approaches

Traditionally, a patient seeks medical attention from a doctor when they have symptoms such as hard lumps on their bodies or strange patterns on their skin. The clinic compiles the patient's clinical history, screening exams, and medical imaging as the initial step in the cancer detection

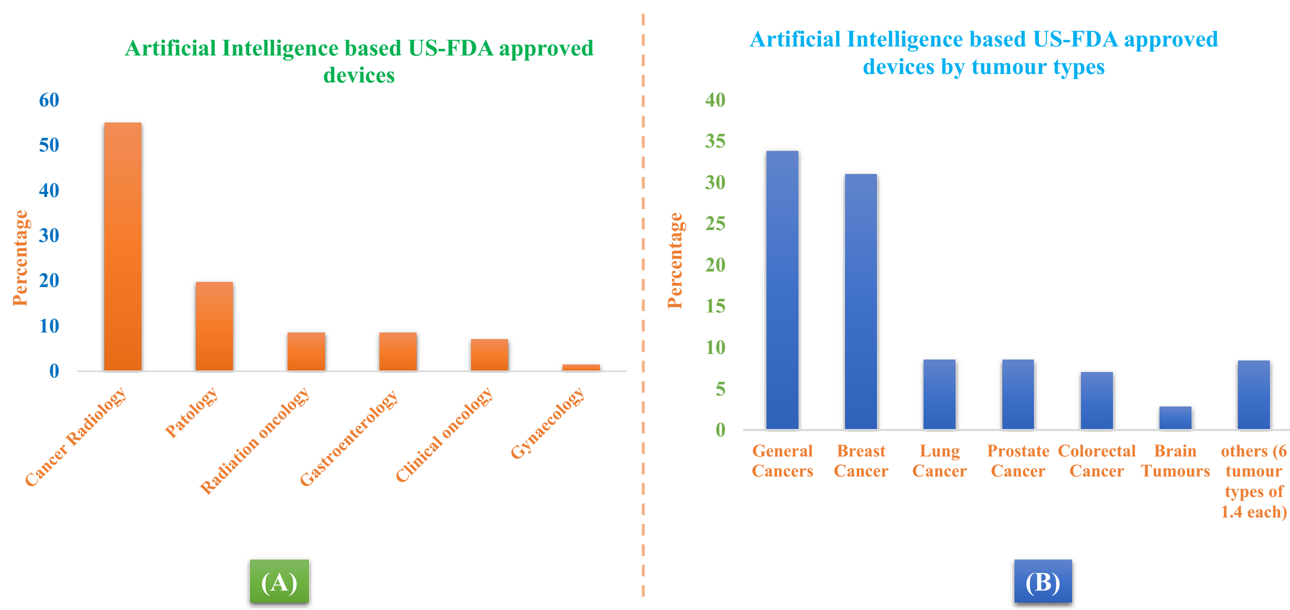

Fig. 1 Present status of AI in cancer and its associated areas. Outline the images of the FDA-approved AI-based devices. "Reproduced with permission from which was published under Creative Commons Attribution 4.0 International License [6]"

process. The screening test looks for people who have cancer or precancer but have not yet displayed any symptoms to quickly refer them for further testing and treatment if necessary. Several scan modalities can be used to perform a prestage analysis. This is carried out as a preventative measure to avoid cancer in a high-risk population being discovered too late. After a questionable discovery, tissue samples from the affected area are collected and examined in a lab. For additional information on the findings, medical professionals are consulted [12, 13]. They compile, synthesize, and analyze the pertinent data while also recommending a diagnosis. The appropriate course of therapy is suggested, and the patient is advised of the current diagnosis and prognosis. With possibilities for speedy diagnosis and the capacity to learn from mistakes, this procedure is advantageous for patients as well as the healthcare system. Nevertheless, this procedure has room for error and is adaptable based on the medical specialty.

Early detection is recognized as a crucial goal by many international institutions, including the World Health Organization (WHO) and the International Alliance for Cancer Early Detection (ACED). Screening can increase early cancer diagnosis and mortality, according to several studies. However, discussions about patient selection and risk-benefit trade-offs persist, and concerns are raised about what is perceived as a "one size fits all" approach that is at odds with the objectives of personalized medicine, even in disease groups such as breast cancer that have long-standing screening programmes in place [14–16]. Risk assessment and patient selection provide significant obstacles to screening initiatives. Shortly thereafter, AI algorithms may play a part in streamlining this process because of their ability to handle enormous amounts of multimodal data and discover signals that would otherwise be challenging to detect [17–19]. Additionally, AI can help discover cancer early on by automating clinical workflows in situations when capacity is limited and starting an investigation or referral in patients who have been screened based on clinical characteristics [20]. This study discusses the potential applications of AI for early cancer diagnosis in both symptomatic and asymptomatic patients. Special emphasis is placed on the types of data that can be used and the clinical areas most likely to undergo changes in the near future. We discussed the areas where AI is anticipated to have clinical influence in the near future using exemplar cancer groups as examples (Fig. 2).

With increased concerns about the lack of diagnostic staff and infrastructure, particularly in the wake of the COVID-19 pandemic that disrupted diagnostic workflows and halted screening programmes, it is expected that AI-based workflow triage will play a larger role in the near future [22, 23]. Based on risk, these systems are meant to filter diagnostic test results and assign cases for specialist examination by pathologists or radiologists, for example, to prevent the large number of routine or low-risk tests from being escalated (Fig. 3).

Gehrung et al. recently published a paper [25] that used deep learning to triage pathology workflows. Reflux-induced epithelial metaplasia, or Barrett's esophagus (BE), is a risk factor for esophageal cancer that necessitates extensive diagnostic resources for monitoring endoscopies and biopsies [26]. The advent of novel nonendoscopic techniques, such as Cytosponge, enhances the patient experience but makes the pathology resource shortage worse because it generates cellular material that needs to be reviewed by a pathologist [27]. These studies offer solid proof that AI systems may be effectively incorporated into clinical workflows and that, with the right risk thresholding, they can improve triage and lessen the workload associated with diagnosis.

The amount of time that medical experts can devote to making a diagnosis is often limited, and it could be challenging to make inferences from nonstandardized data from several modalities. Additionally, the process could take longer than anticipated [28] because a diagnosis needs to be made by several experts from various medical disciplines. The difficulty of conventional cancer treatment stems from the need to try and test patient-specific therapy combinations. Mechanical, physical, chemical, and biological therapies are the main approaches used to treat patients with malignant disorders. The prescribed customized treatment plan includes one or more conventional modalities, such as chemotherapy, surgery, and radiation.

AI will develop and become more widely used in the medical industry in the future (Fig. 4) because of ongoing advancements in computer hardware and software as well as AI algorithms.

3 Role of artificial intelligence in cancer management

3.1 Development of anticancer drugs and AI

Nowadays, AI is used to many aspects of cancer research, including image classification of aberrant cancer cells [29], target protein structure prediction [30], and drug-protein interaction prediction [31, 32]. These findings show how artificial intelligence methods can completely transform the way anti-cancer drugs are designed. Figure 5 illustrates some applications of artificial intelligence in anti-cancer drug design processes.

AI technology can be used to anticipate the action of anticancer drugs and/or aid in the development of anticancer drugs. Several types of cancers and the same medications have various responses, and data from large screening methods frequently expose the association between genomic erraticism of cancer cells and drug

Fig. 2 AI in clinical settings for early cancer detection. "Reproduced with permission from [21]". NLP: natural language processing; EHR: electronic health record. NGS: next-generation sequencing; DL: deep learning; ML: machine learning

action. Lind et al. developed a random forest model by assimilating screening data and ML, the model can anticipate the action of anticancer agents according to the mutation state of the cancer cell genome [34]. Wang et al. developed a drug sensitivity estimation model based on an ML model termed an elastic net regression model [35]. The literature has reported that ML effectively predicts drug sensitivity in ovarian and gastric cancer patients [35] as well as endometrial cancer [36].

These cancer patients were predicted through the ML model to be resistant, such as ovarian, gastric and endometrial cancer patients treated with anticancer drugs such as tamoxifen, 5-FU, and paclitaxel, respectively. The abovementioned cancer patients were shown to have a

Fig. 3 A sample triage pathway for diagnostics. Each examination is given a risk category and confidence estimate by the AI model, and scans that are deemed high risk or have low diagnostic confidence are forwarded to a professional for review. "CT scans from the publicly available LUNGx dataset [24]"

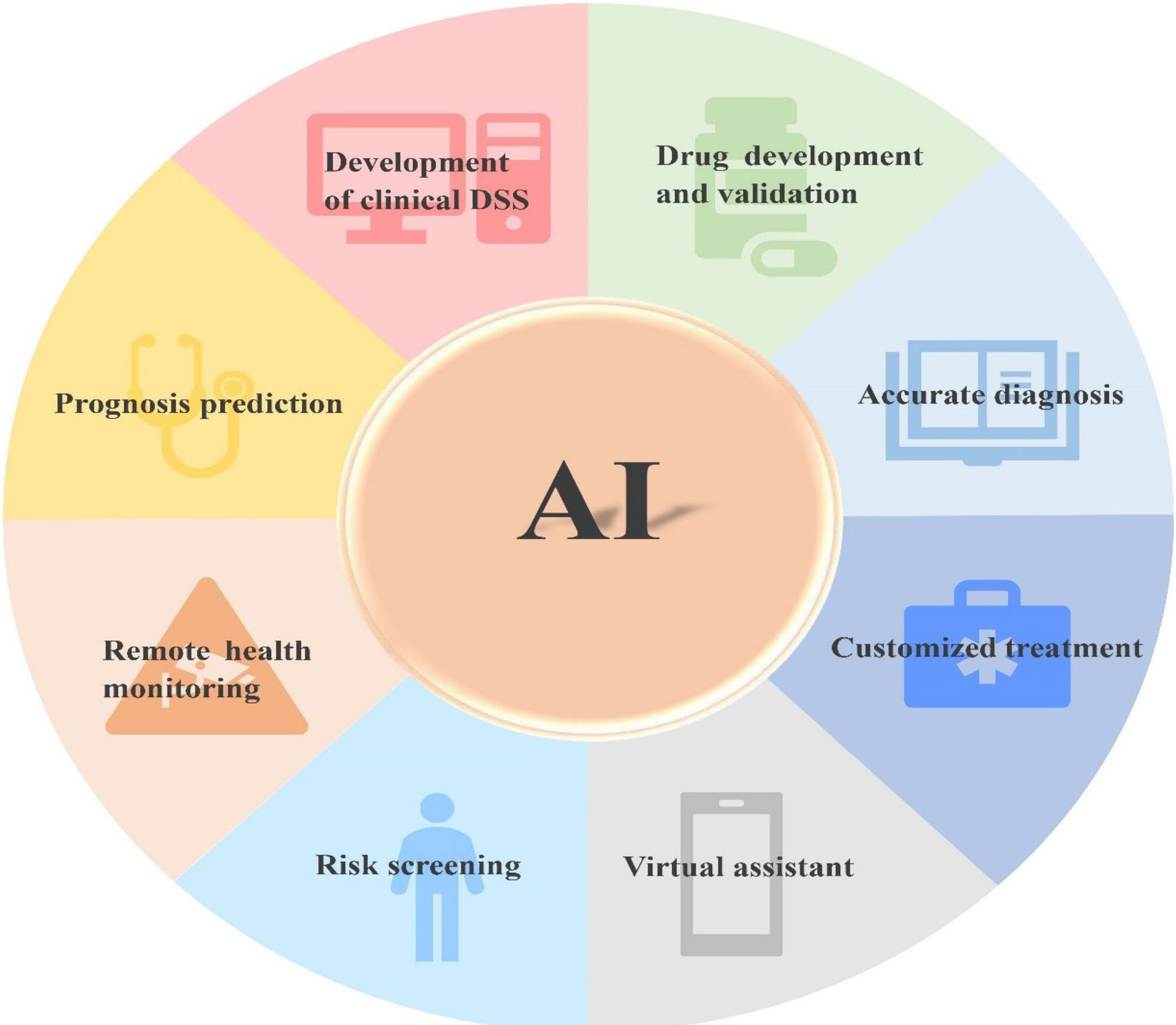

Fig. 4 AI's potential for use in cancer. "Reproduced with permission from which was published under Creative Commons Attribution 4.0 International License [30]"

poor prognosis. Authors suggest AI-technology has high potential in anticipating the sensitivity of chemotherapeutic agents. Additionally, AI can play an outstanding role in inscribing drug resistance in cancer patients [37]. AI can rapidly comprehend in what way cancer cells develop resistance to anticancer drugs through learning and analyzing data on enormous drug-resistant cancers, which can assist in enhancing anticancer agent development and enhancing the management of drug applications in cancer.

AI can control the application of anticancer agents and estimate the tolerance of anticancer agents, thus improving the regimen of cancer treatment. AI technology can aid physicians in making accurate treatments, decrease nonessential surgeries, and assist oncologists in progressing treatment plans for cancer patients [38].

AI mostly concentrates on assessing the therapeutic impact and aiding doctors in regulating therapeutic strategies in cancer immunotherapy. Scientists established an AI platform based on ML to precisely forecast the treatment impact of apoptotic cell death protein 1 (PD-1) inhibitors. This platform can efficiently estimate the impact of immunotherapy in patients with progressive solid tumors who are sensitive to PD-1 inhibitors [39]. The authors developed an ML technique based on the human leukocyte antigen (HLA) mass spectrometry database that can boost the recognition of cancer neoantigens and enhance the effectiveness of cancer immunotherapy [40].

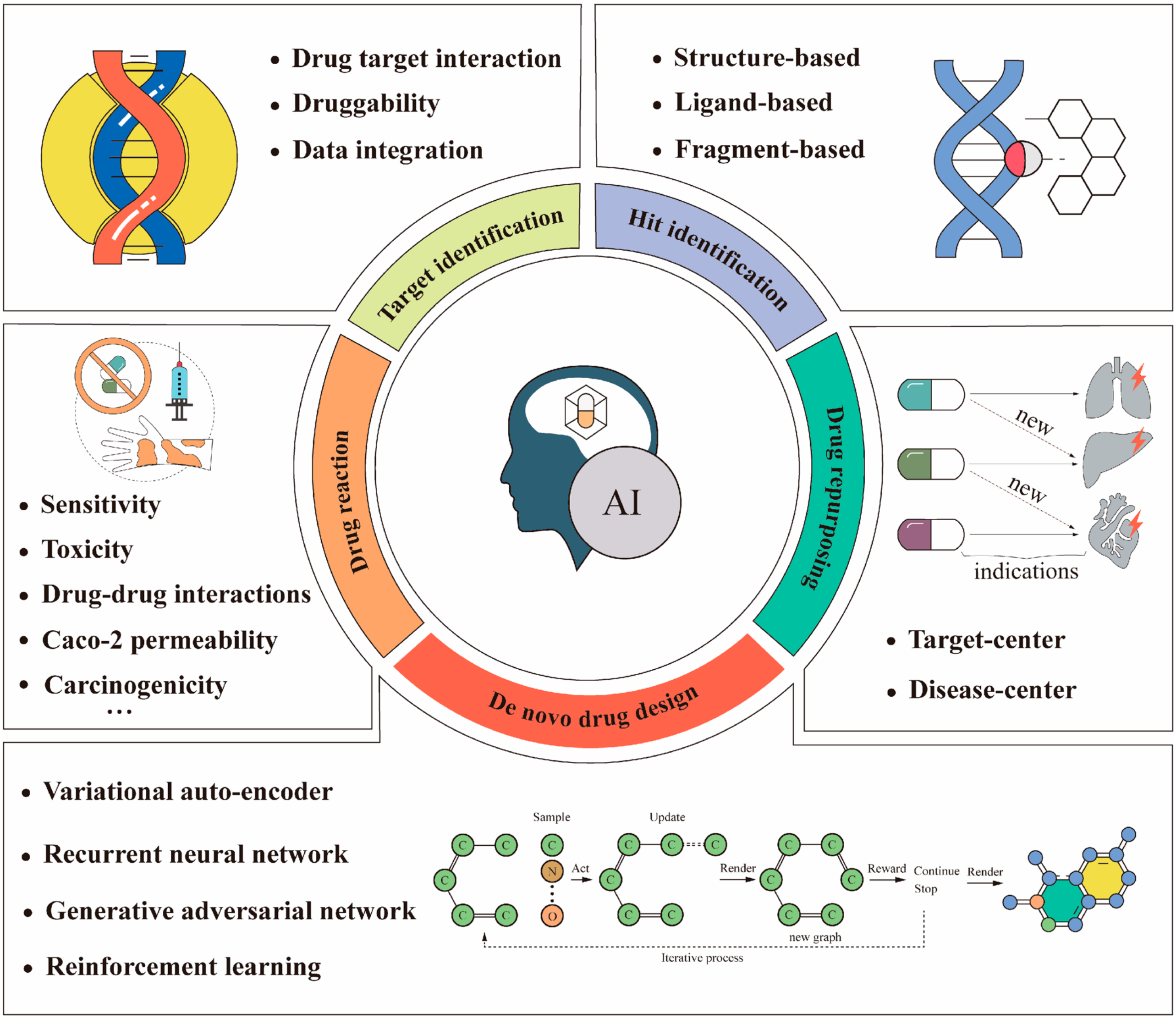

Fig. 5 Some of the uses of AI in the development of anti-cancer medications. The models based on deep learning mentioned above are typically used to implement the bottom (de novo drug design). Reinforcement learning has been widely applied recently. An iterative chemical graph generating method is demonstrated in the workflow example of a graphical chemical structure with an O–C–O relationship above. "Reproduced with permission from which was published under Creative Commons Attribution 4.0 International License [33]"

3.2 The role of AI in cancer chemotherapy

AI technology mostly concentrates on the interaction between chemotherapy and cancer patients in cancer chemotherapy. The major applications of AI include the treatment of cancer by chemotherapeutic agents, estimation of anticancer drug tolerance, and optimization of cancer treatment programs. AI technology can adjust the application of anticancer agents and estimate the tolerance of anticancer agents, thus augmenting the administration of chemotherapy. AI can aid physicians in providing accurate treatment decisions, decrease needless surgeries, and assist doctors in progressing cancer therapy strategies [41].

AI can efficiently and quickly accelerate the combination chemotherapy process for cancer. Researchers used "CURATE, AI" to examine the best doses of medications, such as zen-3694 and enzalutamide, which improved the efficacy and tolerability of the combined therapy [42]. When Gulhan et al. created DL, they showed that it can identify cancer-infected cells with HR deficit with 74% precision. They also calculated that poly adenosine diphosphate-ribose polymerase (PARP) inhibitors could assist patients [43]. The author developed an ML process that can interpret the tolerance of breast cancer to anticancer drug treatment. Earlier literature stated the association between chemotherapeutic agents and genetic materials of cancer patients, which was able to differentiate between the impacts of two chemotherapeutic agents such as Taxol and gemcitabine [44].

Moreover, studies suggest that the DL process is crucially higher than the Epstein−Barr Virus-DNA-based model in the danger stratification and supervision of introduction treatment for nasopharyngeal cancer [45]. This indicates that the supervisory function of the DL technique can be applied as a promising indicator to estimate the initiation of chemotherapy for progressive nasopharyngeal cancer [46].

ML procedures can be accomplished on high-quantity screening data to progress models that can estimate the feedback of cancer cell lines as well as cancer patients to innovative medicines and/or drug combinations [47]. Researchers are quickening drug discovery by applying ML to produce and make inverse synthesis pathways for drugs. The entire method of generating an innovative medication generates a large amount of data. ML suggests a large chance to process chemical data and generate outcomes that may assist us in the progression of drugs [48]. ML can also aid us in processing data collection throughout the years and/or in a very short period [49]. Additionally, it will aid us in building further decisions that would otherwise have to be made by forecast and investigation [50].

DL is an exceptional ML system that has accomplished the highest performance in drug discovery and various fields [51]. These kinds of models have an inimitable feature that may create those more appropriate for multifaceted responsibilities of modeling drug responses based on biological as well as chemical data, but the use of DL in the response of drug prognostication has only newly been investigated (Fig. 6) [52].

AI interventions in cancer research can be more effective if proper data are available for developing ML and DL models. Figure 7 shows the broad approaches to cancer research using AI.

3.3 AI and radiotherapy

Lin et al. applied the 3D convolutional neural network (3DCNN) to accomplish an automatic explanation of nasopharyngeal cancer, with a precision of 79%, which is equivalent to radiotherapy [55]. The function of AI technology in radiation oncology is presented in Table 1.

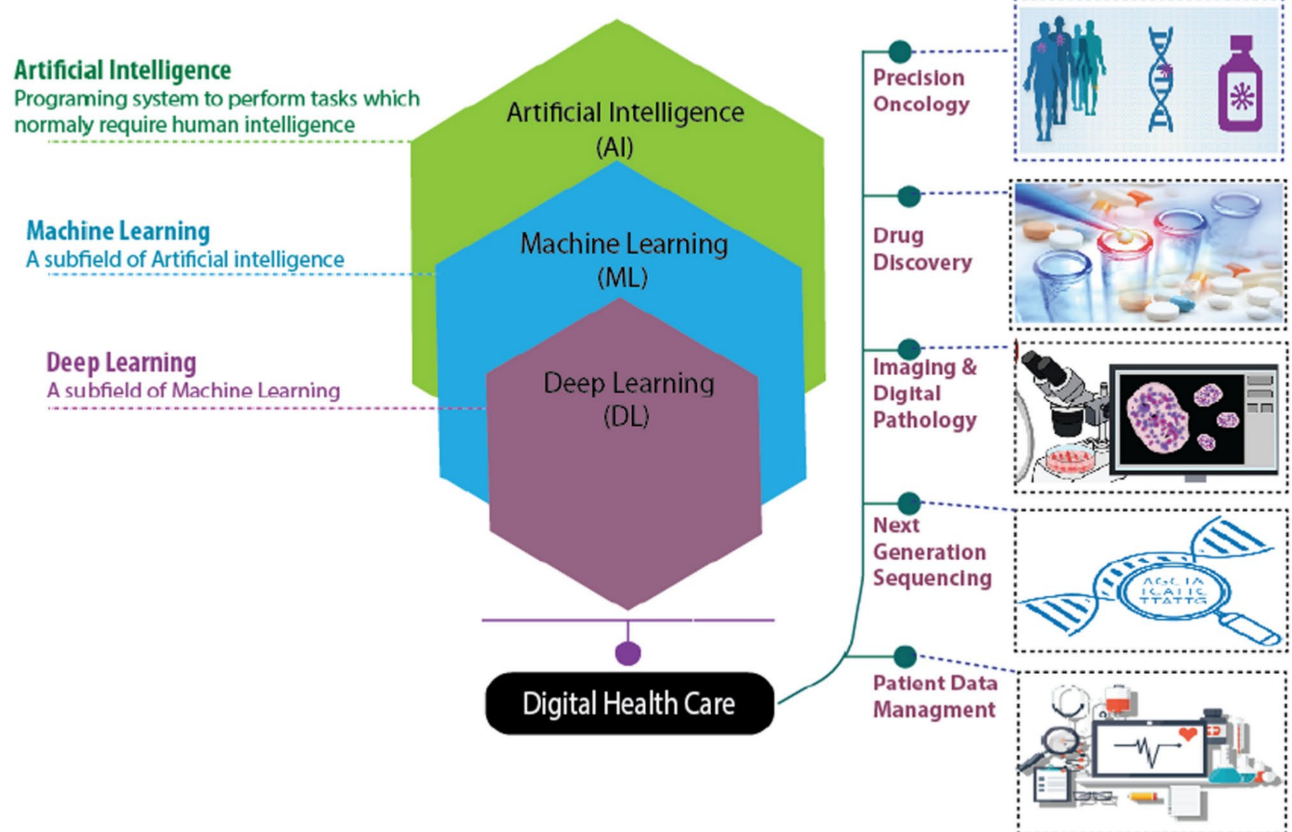

Fig. 6 Usages of AI, ML, and DL in digital healthcare and cancer to settle healthcare problems and anticipate optimum therapy results. "Reproduced with permission from which was published under Creative Commons Attribution 4.0 International License [53]"

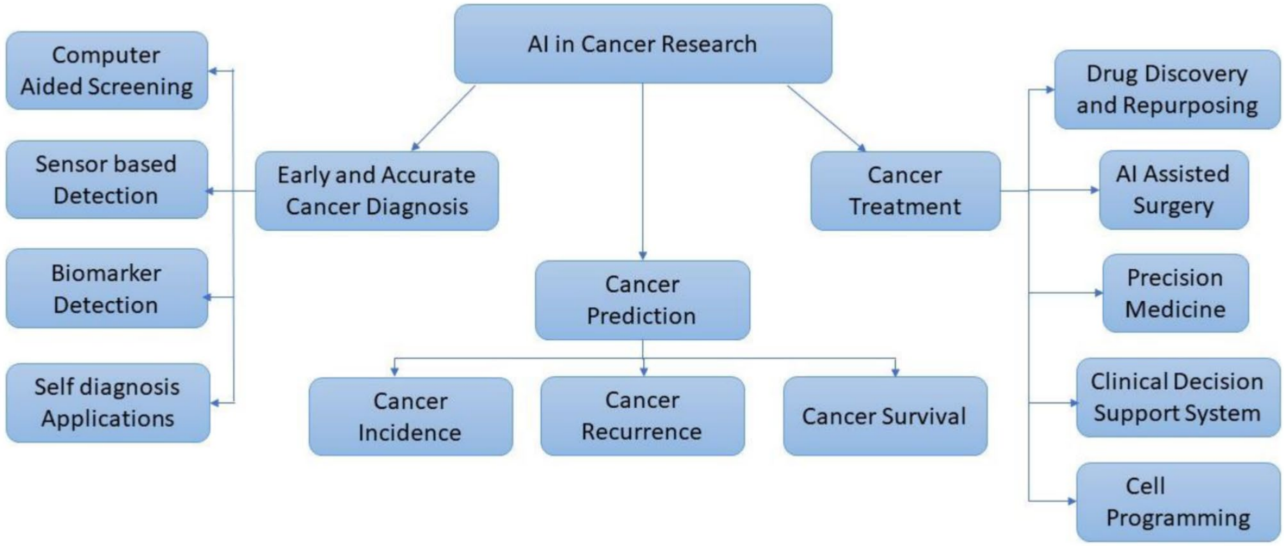

Fig. 7 Methods for cancer research utilizing AI. "Reproduced with permission from which was published under Creative Commons Attribution 4.0 International License [54]"

Scientists developed automatic software based on the DL system that abridged the time it took to strategy radiation treatment to a short time. The AI software generated a treatment plan that was comparable to the patient's conformist therapy strategy [61, 62], and the time was seriously decreased (Fig. 8). Cha et al. developed a predictive model that evaluates the response to bladder cancer therapy by combining the DL approach with radiomics [63].

3.4 AI and cancer imaging are seeing better with complicated neural networks

Image scrutiny has been shown to be among the most effectual approaches in that AI has a wedged society. Assuming that a large quantity of digital imaging data exists within the medication, there is cumulative exhilaration about the use of the same methods for imaging within oncology (Table 2). This cycle in image investigation was catalyzed through the progression of a specific DL technology, the convolutional neural network (CNN). CNNs analyze pixel-level data from images. CNN-based models have recently been shown to be equivalent to human beings in picture categorization and object detection [64]. Furthermore, there has been interest in the application of DL to estimate the toxicity of cancer therapy. Recently, a CNN method has been used to anticipate the toxic impacts of combination databases of protein–protein and drug-protein interactions [65].

3.5 AI and clinical consequences

In interior medical oncology, AI has progressively been used to connect the power of the electronic health record (EHR)

Table 1 The function of AI in radiation oncology

Stage of the workflow	Current AI role	Current and future inferences	Ref
Tumor segmentation	DL technique in outline OAR and target tissue	Quicker, more reliable outline; and obliging in adaptive planning	[55]
Image acquisition	Progression of CT scan from MRI images	No necessity for distinct development CT; and greater for image registration	[56]
Image registration	DL approaches	Quicker and better accuracy image registration than intensity-based processes	[57]
Radiation planning	Voxel-based dose determination and dose monitoring	Quicker and better specific planning process	[58]
Radiation delivery	Utilizing soft resort activator regulatory flexion of the neck	Reduced intrafraction motion	[59]
	Applying DL for assessing breathing pattern	Precise tumor followed by slight errors of lag and predictive estimate	[60]

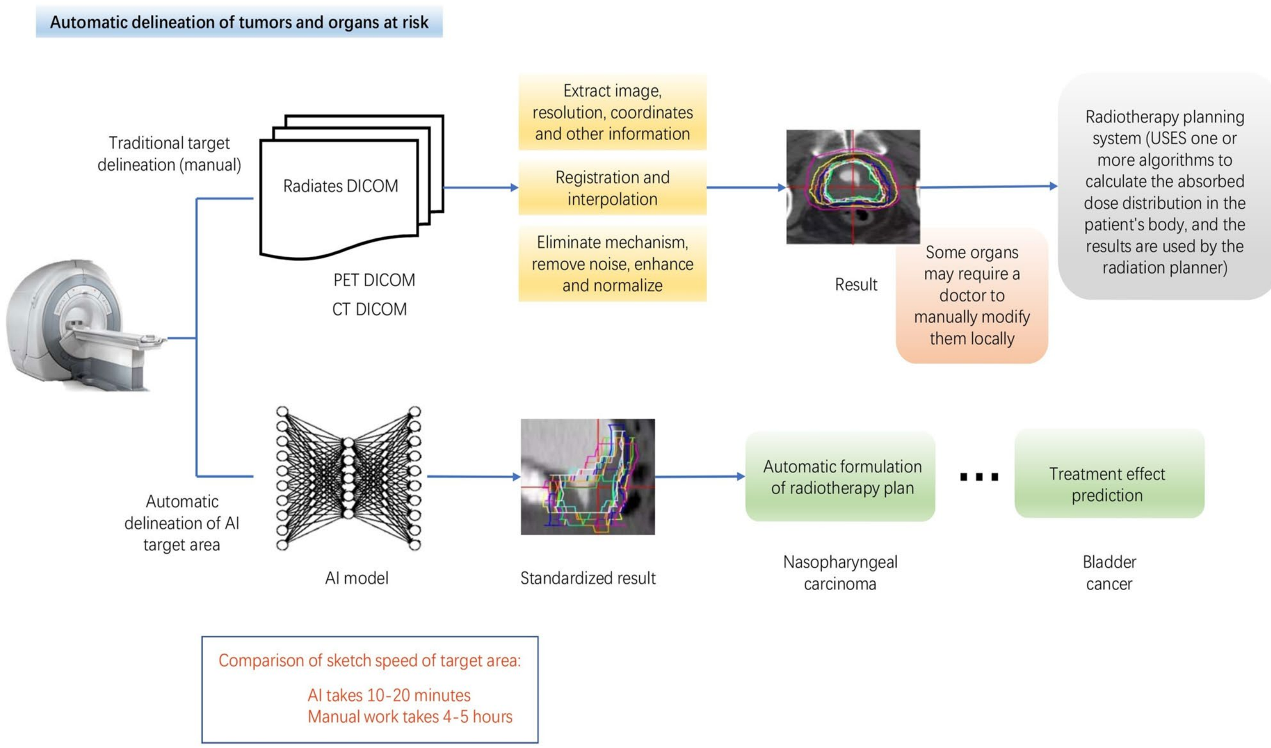

Fig. 8 Automatic description of cancers and organs at threat. The use of AI technology in radiotherapy mostly comprises cancer target areas, the delineation of organs in danger, and the automatic preparation of radiotherapy strategies. AI technology can automatically understand the intelligent delineation of radiative images without manual registration interpolation and other operations. “Reproduced with permission from which was published under Creative Commons Attribution 4.0 International License [125]”

(Table 3). Specifically, AI-based usual language processing methods have revealed potential in forecasting the expansion of ailments across enormous healthcare systems. Mount Sinai stated that a DL-based AI process modeling EHR was able to anticipate the progression of various ailments with 93% precision in general, comprising cancers of the prostate [74].

This study discovers five novel drug−drug interaction estimations, and finally, those were found to have supported scientific proof. The toxic effect of predicted radiotherapy has created important interest in a few years using AI [75]. Basic neural networks, CNNs, and other ML techniques have stated the use of medical and dosimetric data to forecast the toxicity of the urinary system resulting from prostate radiotherapy outcomes [76], hepatobiliary toxicity after hepatic radiotherapy, and rectal toxicity for cancer patients who received radiotherapy for the treatment of cervical cancer [77].

AI is starting to develop in the translational oncology area. To predict protein structure, DL neural networks have also been applied [85] to categorize cells into a separate step of mitosis and to even forecast the future lineage of parent cells based on microscopy images [86].

The progression of drugs and reuse has become an attractive choice for DL. One cluster utilized DL Artificial neural network (ANN) skilled in transcriptomic retort to medicines to estimate with better precision the probability of unsuccessful clinical trials of more than two hundred examples of medicines [87]. One more application of ANN to anticipate the sensitivity of cancer cells in the treatment of genomic as well as chemical properties has been reported [88]. Additionally, CNNs have been used to anticipate peptide-major histocompatibility complex binding [89], which may have implications for oncological immunotherapy expansion. Table 4 outlines the uses of AI technology in translational oncology that have been investigated.

Scientists developed a process that can scrutinize the digital images of women’s cervix and precisely recognize the precancerous wounds that are essential for treatment, which leads to a decrease in unnecessary treatment for cancer patients [93]. Authors developed an ML device that can decrease the overtreatment of wounds doubted of breast cancer. The device can analyze that more dangerous breast wounds are likely to become cancer, aiding physicians in making accurate decisions for treatment and diminishing unnecessary operations [94].

3.6 AI and clinical decision making

Assuming the cumulative quantity and stage of published work, clinical research registration, drug development, and

Table 2 Applications of AI in imaging

Disease Site	AI Task	Method	Ref
Head and Neck	Lymph node categorization and histopathologic forecast (CT)	DL	[55]
Lung	Histopathologic categorization and genetic mutation estimation (histopathology)	DL	[58]
Colorectal	Polyp recognition and categorization (endoscopic)	DL	[66]
Brain	Brain tumor classification and genetic mutation prediction (MRI)	DL	[67]
Colorectal	Lymph node identification and classification (MRI)	DL	[68]
Breast	Tumor recognition and classification (mammogram)	DL	[69]
Head and Neck	Tumor autosegmentation (CT)	DL	[70]
Prostate	Prostate gland autosegmentation (MRI)	DL	[71]
Skin	Skin scratch classification and histopathology forecast (photograph)	DL	[72]
Prostate	Tumor classification and Gleason Score estimation (MRI)	SVM/ Adaptive Boosting	[73]

SVM support vector machine

biochemical marker detection in cancer in recent years, there is a better chance than ever for AI to help in creating these data and supervising decision-making. Numerous saleable uses in progression use DL and natural language processing to this goal [95].

These utilizations are being planned to connect patient data to databases of clinical trials and to match patients to suitable clinical trials countrywide. One more algorithm uses ML to choose the accurate research medicine expansion for a specified patient. There has also been interest in using AI integrated with patient data and national therapeutic strategies to supervise cancer treatment, with the greatest protuberant example being IBM's Watson for Oncology (WFO) [96]. Whereas this area of AI use is in its promising steps, to enhance continuous performance, there is also a large potential to progress medical practice.

The DL technique builds cancer therapy selections more intellectually. AI can find the most appropriate therapeutic strategy for oncologists by learning from clinical big data [97]. Advanced a Clinical Decision Support System (CDSS) based on DL technology that can extract and assess a large quantity of clinical data and create decisions regarding cancer therapy. The study reported the significance of AI technology in aiding oncologists to boost cancer treatment strategies [98].

4 Challenges and constraints

4.1 Data admittance and equity

Directly contributing to this complication of overfitting are problems with information access and excellence. DL neural networks, more than other ML systems, need large quantities of data. This can cause a problem in health care when striving to use AI for an ailment process with low prevalence. These problems are beginning to be addressed, with increasing emphasis on efficient data capture [99] and several various institutional data sharing contracts [100]. Strategies have been anticipated to encourage findable, accessible, interoperable, and refillable (FAIR) data use [101], and there are now chances for research clusters to publish their data itself, which may boost openness [102].

4.2 The ethical concern of AI and ML-based therapy

Artificial intelligence has a big impact on healthcare systems. It may cause distress in terms of diagnosis and therapy, exhibiting a high degree of moral thought. ML healthcare employs a range of techniques, from fully autonomous AI for cancer diagnosis to nonautonomous mortality predictions to oversee budget allocations in healthcare. AI and ML treatment options are expanding, ranging from community-based robots to simulated psychotherapists for a range of issues [103]. Transparency is the main issue with AI today. It is challenging to characterise and evaluate a variety of AI and ML systems, primarily deep image inspection methods. Even medical professionals and/or scientists who are aware of this process are unable to explain it. Researchers have argued that continual use of AI and ML in therapy may create damaging effects, thereby suggesting that select data will not match current clinical data and would lead to imprecise conclusions [104]. AI can also be used in psychological practice to both increase and decrease patient autonomy. These technologies are required in order to educate patients and ensure that they do not mislead AI systems intended for human usage. Furthermore, consenting to uses outside of the healthcare environment raises issues about suffering [105].

AI is vulnerable to misjudgment and improper risks. Naturally, the brain of a human being has a low capability to process a large volume of data and existing information

Table 3 Uses of AI in clinical consequence prediction

Disease Site	AI Task	Method	Ref
Lung	Immunotherapy response using CT images and histopathology	Elasticnet Linear Regression	[63]
Multiple	Patient disease classification and outcome prediction	DL	[74]
Prostate	Acute radiotherapy toxicity prediction	Artificial Net/SVM	[76]
Breast/ Brain/ Renal	Survival prediction using genomic and clinical data	DL	[78]
Cervical	Acute radiotherapy toxicity prediction	DL	[79]
Brain	Survival prediction using MRI images	DL	[80]
Head and Neck/ Lung	Disease outcome prediction and classification using CT images	DL	[81]
Colorectal	Chemoradiation response using CT images	DL	[82]
Liver	Survival prediction using RNA and miRNA sequencing and methylation data	DL	[83]
Prostate	Late radiotherapy toxicity prediction	Artificial Neural Net	[84]

SVM support vector machine

[106]. The scientific community reported that DL devices have adequate problems at the micro and macro levels in the medical area. These problems, such as unfettered exercise set procedures, unsupervised learning accomplishments, and patient data privacy, require significant attention in the direction of human–computer interfaces (HCIs) and the application of AI [107]. The reproducibility of a clinical study is a major problem at the molecular level of drug discovery, which takes several centuries for the inauguration of effective preparation in the sooq after clinical trials [108]. Assessment of an enormous volume of intricate and varied healthcare data can be achieved through the scrutiny of big data and ML devices to diminish limitations and false-positive data [109].

Table 4 Applications of AI in translational oncology

AI Task	Method	Ref
Cell cycle reconstruction and disease progression prediction	DL	[60]
Polypharmacy side effect prediction	DL	[65]
Drug-target interaction strength prediction	DL	[90]
Cancer cell drug sensitivity prediction	Artificial neural network/random forest	[88]
Peptide-MHC binding prediction	DL	[89]
Anticancer drug synergy prediction	DL	[91]
Transcriptomic-based drug repurposing prediction	DL	[92]

MHC major histocompatibility complex

4.3 Interpretability of black box problem, limitations and future instructions

One of the fundamental problems is to the acceptance of AI in health care is the concern that these models, despite normally accomplishing high presentation, are to some extent opaque. For example, a DL model may properly estimate that a patient will grow pancreatic cancer based on his past two years of EHR data. Currently, we are inadequate in our ability to assess the accurate logic behind DL-based predictions. This is frequently stated as the "black box" problem [110]. In medical practice, it has usually been vital in clinical decision-making to know the logic for each decision. In contrast, DL uses formless input data, and vast knowledge creation occurs within the concealed layers. Thus, it becomes a problem to assess the precise characteristic of the input data contributing to the consequence. This interpretability challenge has enormous implications for the acceptance of AI-based systems in healthcare, both from doctor and supervisory outlooks [111]. Undertaking the black box problem has now become a focus of research [112].

In AI image scrutiny processes, numerous approaches have been improved, including feature imagining, salience maps, and sensitivity scrutinizes, where certain portions of the image are concealed to the impact on prediction [113]. Although these approaches have developed in a few years, further work is needed to better clarify the decision-making logic with deep neural networks.

Owing to AI's diverse applications, it would be practically impossible and extremely laborious to review every research paper on the subject. The papers included in the survey were chosen carefully for their AI-related substance and significance. Newer research is prioritized more when providing interested researchers with an overview of current trends. Thus far, four primary domains of attention have been distinguished: a means of providing an explanation for intricate black-box models, neural network performance and analysis, boosting the acceptance of white-box models among developers, and strategies to eliminate prejudice and increase equity [114]. Investigating novel ideas broadens one's meta-information and aids in the assessment of local algorithms' individual class predictions [115]. The significance of each concept rises when it is broken down and dissected. AI will have an impact on people's daily lives in both positive and negative ways, as life's ups and downs will inevitably bring. The effects of this technology are numerous. It must be implemented by all organizations for their websites, operating algorithms, games, etc. Governance, new technologies, and ethics will be important to the future. Elite companies are always developing Artificial Intelligence (AI)-based products via rigorous technological application.

Whereas AI technology is quickly assimilated into the scientific research of cancer, the rest of the work is to be done to interpret these works into real-world, medically significant uses. One of the major fences is in exterior authentication as well as evidencing the generalizability of DL uses. Certain intricacies of neural networks and the tremendously enormous quantity of variables, where there is a greater propensity for neural networks to make overfitted models that do not generalize throughout the various populaces. Moreover, since there is a substantial volume of heterogeneity of clinical data throughout the institutions, several exterior authentication groups might be needed for the evidence of the accomplishment of an application [116].

The fact that many AI models have not undergone the same thorough evaluation as would be needed for other medical therapies is arguably the most important critique of AI. First, as was already said, certain technologies have been utilized in clinical settings without being published in a peer-reviewed journal, which means they have not been exposed to the kind of rigorous adversarial input that the scientific community expects. Furthermore, considering assertions that academia is still experiencing a reproducibility crisis, it is troubling that a methodology that is not published cannot be replicated [117]. Additionally, there are surprisingly few prospective studies despite the sharp increase in AI publications using very large datasets [118].

The existing techniques of cancer detection and treatment have drawbacks, including greater rates of false-positive test results that suggest that someone does not have lung cancer. For instance, in CT scans, some noncancerous lung abnormalities closely resemble cancer. Additionally, an early diagnosis may mean that certain malignant nodules found during the scan are not apparent to the human eye. The patient experiences more pain during therapy as a result of the increased number of treatment trials and related costs. There is a significant risk associated with repeatedly subjecting individuals to radiation for routine screening [119]. AI developments have been shown to reduce the limitations of current cancer diagnostic and treatment methods, and they have the potential to bring about revolutionary advances in the field of cancer healthcare.

5 Discussion and future outlook

The current paper provides a comprehensive review of the status and applications of AI in cancer-related fields, specifically narrating the devices related to AI technology that have already received official approval to enter medical practice. AI has demonstrated cross-cutting significance in all scientific branches since its inception, indicating promising future development. As stated in the review, this advancement has piqued the interest of researchers in cancer and related fields. In general, the use of FDA-approved machines has not been considered superfluous of standard scrutiny or diagnostic workflow; however, it is envisioned as a consolidative device to be used in specific cases, potentially depicting the conclusive stage for enhancing cancer patients' treatment. Currently, AI is having a greater impact in this field, as evidenced by many approved instruments, in particular radiology and pathology. Cancer diagnosis typically characterizes the critical idea of beginning to plan appropriate treatment strategies and medical supervision. Furthermore, this specifies that the future emergence of AI technology should consider uncharted but critical horizons in this landscape, such as drug discovery, drug administration, and follow-up plans. According to us, to determine a conclusive development in cancer treatment, AI technology development must follow comprehensive and multifaceted designs. This demonstrates one of the most significant opportunities provided by AI. This will allow for precise connections and integration of cancer-related areas in a specific patient, conceivably interpreting the difficult purposes of the individualized drug. Specific types of cancer, such as lung cancer, breast cancer, and prostate cancer, are now benefiting more from AI-based devices in clinical practice. Because AI technology is based on the collection and analysis of large amounts of data, progress in the treatment of rare cancers will most likely be delayed. When all of this is considered, rare cancers are one of the most important classes in precision oncology [120].

As a result, even though the potential benefits appear far away, current approaches to AI progression cannot ignore this cancer cluster. The ability to assimilate multiple and compound data obtained from multiomics methods to cancer patients is the most talented anticipation for AI. AI-enabled devices may be the only devices capable of adjusting the large volume of data generated by various types of analysis [121]. However, assessing the precision of AI uses for medical decision-making remains hampered by a lack of real evidence obtained from protected clinical data sources. Overall, AI has an emerging impact on entire scientific branches, including cancer and its related fields, as emphasized in this review. The primary stages are represented by knowing it is past contextual and understanding its existing accomplishments for scheming novel progression approaches with real effects. As previously stated, AI has already entered the medical practice of oncology; however, ongoing and augmenting efforts must be justified for AI to realize its full potential [122]. In our opinion, the formation of multidisciplinary growing perspectives, the immediate understanding of the significance of entire cancers, including rare cancers, and continuous assistance for assuring their development are currently the most significant challenges for concluding the AI revolution in oncology.

6 Conclusion

To improve chemotherapy regimens, AI can manage the application of anticancer agents and predict chemotherapeutic agent tolerance. AI can assist physicians in making accurate treatment decisions, reducing unnecessary surgeries, and assisting oncologists in moving cancer patients' therapy plans forward. AI technology has made significant contributions to the development and treatment of chemotherapeutic drugs [123]. Humans have limited knowledge, which makes it difficult to provide the best possible care. According to this viewpoint, if physicians choose inappropriate therapy, patients will miss out on appropriate treatment. It can provide significant insights and indications that human recognition and individualized therapy for each cancer patient cannot [124]. While the various technologies suggested in the study have achieved significant prediction outcomes, the cancer mortality rate has not been reduced, possibly due to the numerous limitations of AI. As a result, a broader range of research is needed to meet the challenges in the field of cancer prediction. AI technology has the potential to accelerate the discovery of novel materials, which could significantly increase the spread of chemotherapeutic agents. AI technology is expected to soon become a major driving force in cancer research and treatment. We believe that AI technology will impact medical technology in the future.

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