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Artificial Intelligence for the Diagnosis and Management of Cancers: Potentials and Challenges

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ABSTRACT

Cancer continues to be one of the primary causes of death worldwide. Although there has been substantial progress in clinical cancer care, the outcomes for cancer patients still remain poor. The rapid advancements of artificial intelligence (AI) will revolutionize cancer management by addressing current obstacles in oncology research and practice, ultimately enhancing healthcare accuracy and patient outcomes. Increasing evidence demonstrates that AI-based models can improve the accuracy and efficiency of cancer diagnosis and treatment by leveraging multilayer data. Cancer patients could greatly benefit from AI's promising prospects, yet few AI models have been authorized for clinical use. A comprehensive understanding of AI's basic principles, applications, and potential impacts is essential to foster its clinical translation. In this review, we provide an overview of fundamental AI techniques, encompassing machine learning and deep learning. Moreover, we summarize recent studies on AI's transformative role in cancer diagnosis, classification, and personalized treatment planning. Furthermore, we discuss the current challenges that hinder the widespread use of AI, propose potential solutions, and outline future directions. Overall, through systematic analysis of existing preclinical and clinical evidence, this review highlights the substantial potential of AI technology and provides valuable guidance for future research in AI-driven oncology.

1 | Introduction

Cancer continues to be a leading cause of death worldwide, responsible for millions of deaths each year [1]. Despite significant advancements in treatment and understanding over the past few decades, several unmet needs persist, which impact patient outcomes, quality of life, and the efficiency of healthcare systems [2]. Specifically, cancer early detection remains crucial but elusive for many cancer types [3]. The lack of accurate biomarkers for early detection and inadequate access to cancer screening programs contribute to delayed diagnosis. Late-stage diagnosis often leads to higher treatment costs and poor prognosis. Chemotherapy, radiation, and immunotherapy are currently the standard curative treatments for cancer [4]. However, many patients experience severe side effects, such as cardiotoxicity and neuropathy, from treatments, and these issues are often not adequately managed in follow-up care [5]. Moreover, the high cost of cancer care poses a significant burden on both patients and healthcare systems [6]. Advanced treatments, such as immunotherapy and targeted therapy, are usually expensive, leading to issues of accessibility and equity in treatment options [7]. Furthermore, formulating individualized treatment plans remains challenging due to the heterogeneity of tumors, which causes significant variations in patients' responses to treatment, even for the same type of cancer [8]. Existing treatment measures usually fail to meet the needs of all patients. For instance, while immunotherapy has revolutionized treatment for some cancers, its effectiveness varies widely across different cancer types and individual patients [9]. In addition, there is an urgent need to improve tumor monitoring and follow-up methods. Conventional

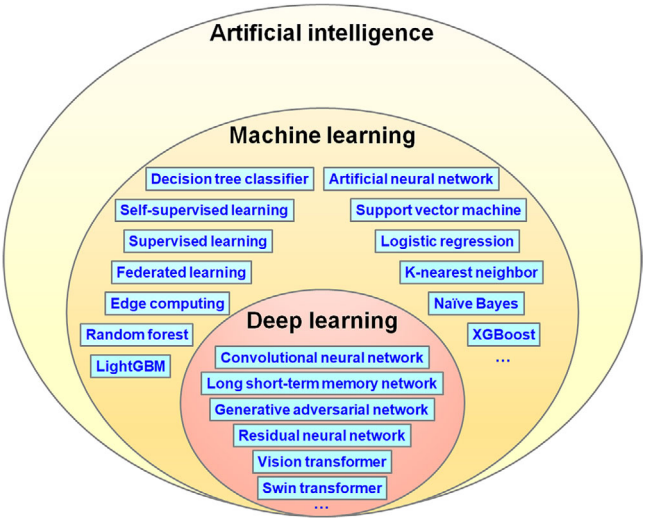

FIGURE 1 | Venn diagram showing the relationship among artificial intelligence, machine learning, deep learning, and commonly used algorithms.

imaging examinations and biomarker tests have limitations in terms of sensitivity and specificity and cannot promptly reflect the dynamic alterations of tumors [10, 11]. Altogether, persistent unmet needs in cancer practice underscore the imperative for ongoing research and comprehensive strategies to address the multifaceted challenges associated with this disease.

Integration of artificial intelligence (AI) technology into cancer medicine is emerging as a powerful approach to overcome many obstacles where medical experts fail to control and treat cancers in the clinical setting [12]. AI, also known as machine intelligence, represents a new technical subject that explores and develops theories, approaches, techniques, and application programs to imitate and broaden human intelligence in machines [13]. The technical architecture of AI primarily consists of four key modules: human–computer interaction, image recognition, machine learning, and natural language processing (NLP) [14, 15]. Machine learning, a specialized branch of the AI field, leverages statistical techniques to build intelligent systems (Figure 1) [16]. Representative machine learning algorithms include artificial neural network (ANN), deep learning (DL), decision tree, and enhancement algorithms [17]. In recent years, AI has received considerable attention owing to its exemplary advances in computer vision, such as object recognition and image classification [18]. AI is rapidly progressing in many aspects of cancer research and practice, offering transformative opportunities to improve cancer diagnosis, treatment, and prognosis [19]. In diagnostic imaging, AI algorithms can detect tumors with high precision, assisting radiologists and pathologists in interpreting radiological images and tissue samples more accurately and swiftly [20]. Beyond diagnostics, AI leverages patient data, including genetic profiles, medical history, and tumor characteristics, to recommend tailored treatment plans, hence personalizing cancer care [21]. AI systems facilitate matching patients to appropriate clinical trials based on their unique molecular and clinical profiles, accelerating access to cutting-edge treatments [22]. AI also plays a crucial role in optimizing treatment plans to minimize side effects while maximizing efficacy against cancer, improving the quality of life for patients [23]. Furthermore, AI-powered tools predict patient responses to various treatments, enabling oncologists to make real-time adjustments for better outcomes [24]. AI models monitor patients remotely posttreatment, detecting early signs of complications or tumor recurrence, which is essential for timely interventions and improved prognoses [25].

Although AI holds immense potential in cancer diagnosis and management, several challenges and misconceptions need to be addressed to fully realize its benefits. First, there is a common misconception that AI is a "magic bullet" capable of solving all challenges in cancer care. It is crucial to understand that AI programs are designed to augment human expertise, not replace it [26]. Medical professionals remain indispensable in making informed decisions and providing personalized care. Second, many AI models are still in the research phase and have not yet been validated in clinical settings [27]. The transition from theoretical efficacy to practical application warrants rigorous testing and verification to ensure their reliability when used on patients. The accuracy of AI systems is highly dependent on the quality of patient data [28]. High-quality, annotated datasets are essential for training these models, but accessing such data remains a significant bottleneck in developing efficient AI tools. Investment in better data collection and annotation processes is therefore critical. Third, the regulatory framework for AI in healthcare is still evolving [29]. Ensuring the safety, efficacy, and transparency of AI systems is crucial for building trust among patients and practitioners. Ethical concerns, particularly regarding patient privacy and consent, must be strictly addressed when utilizing AI to analyze sensitive health information [30]. Fourth, infrastructure and expertise pose another challenge. Many healthcare systems lack the necessary infrastructure and skilled personnel to effectively integrate and utilize AI tools [31]. This can lead to disparities in care, with only well-funded institutions having access to these advancements. In addition, clinicians may be hesitant to adopt AI systems due to a lack of understanding or trust in how these tools function [32]. Education and transparency regarding the decision-making processes of AI could help alleviate these concerns and foster greater acceptance among medical professionals [33]. Fifth, developing and deploying AI solutions can be quite expensive, which acts as a significant barrier [34]. Expensive development and implementation costs might limit access to AI technologies, potentially widening healthcare disparities between institutions with different financial resources. Last, there is a risk that overreliance on AI could cause medical professionals to overlook their own clinical expertise or patient-specific factors [35]. AI should be viewed as a decision-support tool, complementing human judgment rather than replacing it.

Over the past decade, with the ongoing investigation and development of AI, numerous reviews have been conducted [36–38]. However, there is a lack of systematic analyses on the applications of AI across different types of cancer. This comprehensive review delves into the latest advancements in biomedical application of AI in oncology across various cancer types, including breast, lung, gastric, liver, and prostate cancers. Multiomics, also referred to as integrated omics, involves combining two or more types of omics datasets to enhance data analysis, visualization, and interpretation [39]. By examining cutting-edge developments in diagnostic imaging, multiomics, and personalized treatment

planning, this review aims to illustrate how AI is transforming cancer care. Moreover, we delve into the current challenges and obstacles in implementing AI technology in clinical cancer settings. We also explore possible solutions and future directions. As AI becomes more integrated into medical settings and new AI-driven therapeutic options emerge, there is growing optimism that personalized cancer treatment for a broad spectrum of cancers will become a reality, accelerating progress in this field.

2 | AI Foundations for Oncology: Beyond Algorithms

AI technologies are revolutionizing modern medicine by driving breakthroughs in diagnostic accuracy, precision oncology, and predictive analytics [40]. By leveraging large-scale data analysis, AI enhances disease risk prediction and improves patient outcomes. Predictive analytics empowers effective patient care and optimizes healthcare resource allocation by providing insights into potential future scenarios [41]. Precision medicine tailors healthcare based on an individual's unique biological characteristics, instead of relying on generalized population data [42]. This can be achieved by collecting patient-specific physiological data, electronic medical records, and other health information, then applying advanced models to customize treatment strategies [43]. A thorough understanding of AI technology forms the essential foundation for healthcare practitioners to effectively integrate and utilize AI tools in clinical practice, significantly elevating their professional capabilities [44]. AI fundamentals cover essential concepts in machine learning, neural networks, and DL (Figure 1).

2.1 | Machine Learning Paradigms: Supervised versus Self-Supervised versus Reinforcement Learning

Machine learning is a branch of AI that addresses problems by employing self-improving models that learn from data rather than adhering to predefined rules [45]. Some key concepts form the foundation of machine learning. A dataset is a collection of data arranged in a clear, logical format. Measurable characteristics of the data are called features. A model, the output of a machine learning algorithm trained on datasets, can make predictions or decisions. Labels represent target variables or outputs that the model aims to predict. The loss function is responsible for calculating the disparity between the model's predictions and actual labels. Hyperparameters refer to predefined external configurations that control model training, such as learning rate, neural network hidden layers, and decision tree depth. Training data serve to teach the AI model, and test data are utilized to estimate model performance following training. Overfitting occurs when a model performs well on training data but poorly on new data. To solve this issue, a validation dataset is used to fine-tune hyperparameters and prevent overfitting. Machine learning is becoming increasingly valuable in clinical oncology, where it is applied to various crucial tasks [46]. These include disease diagnosis through the analysis of medical imaging data, prediction of patient outcomes based on multiple variables, and customization of treatment plans tailored to individual patients. Within machine learning, models are trained to make accurate predictions or classifications based on large datasets. This field encompasses several categories of conceptual models, primarily categorized into three major types of algorithms: supervised learning, unsupervised learning, and reinforcement learning [47]. Supervised learning is a subset of machine learning that relies on labeled input and output data for its learning process [48] (Figure 2A). In supervised learning, the model learns to associate variables from input data, known as features, with the desired output [47]. This process involves creating a labeled dataset, referred to as training data, which often requires manual annotation. The annotated data serve as the ground truth upon which the algorithms' predictive outcomes are based. There is a wide range of learning models, including basic logistic regression, random forest, neural network, and support vector machine (SVM) [49]. After being trained on associations between input features and an outcome of interest, trained models can precisely predict outcomes in new, unencountered cases. For instance, in the context of cancer imaging analysis, a substantial volume of labeled medical imaging data can be used to train DL models that are capable of automatically identifying the presence and type of cancers [50]. One of the key advantages of this approach is its high accuracy and reproducibility, which can markedly enhance the efficiency of cancer early diagnosis. However, a notable limitation of supervised learning is its heavy dependence on labeled data, and acquiring high-quality labeled data is often a time-consuming and costly process [51].

Self-supervised learning offers a new approach to address such challenge. This paradigm is a type of unsupervised learning that enhances the performance of multiple downstream computer vision tasks, including object detection, image understanding, and image segmentation [51]. By leveraging unstructured and unlabeled data, it enables the development of versatile AI systems at a low cost. Self-supervised learning acts as a bridge between supervised and unsupervised learning approaches. The self-supervised learning model trains on one portion of the input data to predict another part, a process known as predictive or pretext learning [52]. Self-supervised learning exhibits the ability to automatically generate labels for unlabeled data, effectively transforming an unsupervised model into a supervised one. Self-supervised learning does not rely on manual labeling and are divided into two types: pretext task and downstream target task [53] (Figure 2B). A pretext task utilizes supervised learning to learn representations, with labels generated directly from the data itself [54]. Once this learning is complete, the model utilizes the learned representations to the downstream task. Self-supervised learning presents an attractive solution to the challenges posed by the difficulties in curating large-scale annotations. Unlike supervised learning, self-supervised learning enables versatile models that can be fine-tuned for multiple downstream tasks without requiring extensive labeled datasets [55]. This strategy not only reduces the reliance on labeled data but also improves the generalization ability of the model. Self-supervised learning models have shown enhanced performance in diverse cancer classification and survival prognosis tasks when compared with conventional supervised learning models [56, 57].

As a machine learning paradigm, reinforcement learning trains an agent to make optimal decisions in uncertain environment to maximize cumulative rewards [58]. This paradigm involves agent learning via direct interaction with its environment, without rely-

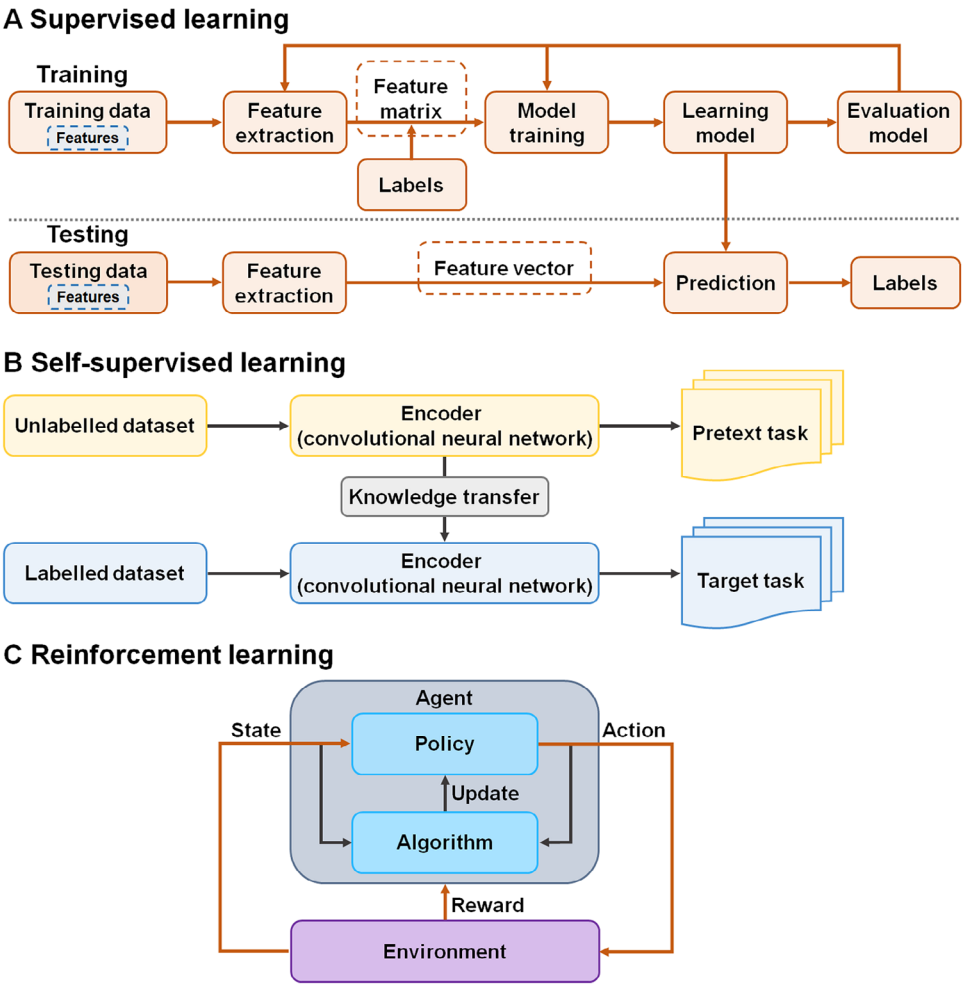

FIGURE 2 | Schematic representations of supervised, self-supervised, and reinforcement learning models. (A) Supervised learning structure. In this paradigm, the model is trained using labeled datasets, where the model learns to recognize various types of data. After completing the training process, the model is evaluated using a test database. Based on this evaluation, the model then predicts the output for new, unlabeled data. (B) Self-supervised learning structure. In this paradigm, a deep learning algorithm (e.g., CNN) is trained on unlabeled data using a proxy task. The obtained knowledge is transferred into a downstream task (target task). (C) Reinforcement learning structure. In reinforcement learning, data are not used as input but are accumulated through interactions with the environment. Instead of specifying optimal actions in advance, this system relies on a reward–penalty mechanism. The agent receives feedback immediately after each action, which allows it to learn iteratively. The agent aims to take the optimal action in a given state to maximize the total reward.

ing on labeled examples or fully predefined models (Figure 2C). Reinforcement learning stems from two foundational fields: psychology, which introduces trial-and-error learning principles, and optimal control, which contributes value functions and dynamic programming techniques [59]. Through trial-and-error, computational algorithms determine the best actions within a certain condition and optimize their performance. The computer receives positive or negative feedback based on its actions and learns how to complete a task. Reinforcement learning consists of several key elements, including an agent, an environment, an action, a reward, a state, and a value [60]. The agent refers to an algorithm that is trained to perform task within an environment. The agent explores and interacts with the environment. It comprises three main components: a policy that refers to the agent's way of behaving in the environment and which strategy is adopted to achieve the goal, a value function that defines the value of each state the agent reaches to evaluate state's effectiveness, and a model that refers to a prediction algorithm that forecasts the next state based on the next immediate reward [60]. The environment is real-world problems or simulated environment in which an agent operates or takes actions [61]. An action is the move taken by an agent within an environment that causes an alteration in the status. A reward is a feedback given to an agent in response to its action, which may be either positive or negative. Reinforcement learning uses a formal framework to model the interaction between an agent and its environment in terms of states, actions, and rewards [62]. This framework captures the key characteristics of AI-related issues, incorporating causality, uncertainty, nondeterminism, and explicitly defined goals. Without training datasets, the problem is solved by the agent's actions with input from the environment. Reinforcement learning performs well in unpredictable environments, making it ideal for real-world applications with uncertain or dynamic conditions. Reinforcement learning has been widely applied in robotics and rare disease diagnosis [63].

Overall, these machine learning algorithms possess their own unique advantages. Combing these approaches may yield a more effective solution for early cancer diagnosis and personalized treatment. Substantial efforts are required to explore the synergistic effects of these learning paradigms.

2.2 | DL Architectures: Applicability of CNNs, Transformers, and GANs to Oncology Data

DL has revolutionized the field of AI, achieving outstanding performance across various applications [64]. It has proven to be highly effective in handling large volumes of data and performing intricate computations. As a subset of machine learning, DL employs architectures consisting of multiple layers of nodes or neurons, with each layer designed to model increasingly complex patterns in the data [65]. In recent years, DL has demonstrated substantial potential in cancer diagnosis and management, particularly through the application of architectures such as convolutional neural network (CNN), transformer, and generative adversarial network (GAN). This section delves into the foundational architectures that have paved the way for modern DL and explores recent breakthroughs that are broadening the capabilities of neural networks.

2.2.1 | Convolutional Neural Network

CNN, a subtype of ANN, stands as a cornerstone architecture, transforming the manner in which neural networks extract knowledge from data [66]. CNN is characterized by architectures that incorporate multiple hidden layers to progressively extract higher-level features from raw input data. It plays a pivotal role in advancing computer vision tasks, including image classification, object detection, and image segmentation. By employing convolutional layers, CNN can automatically learn spatial hierarchies of features from input data, enabling the network to capture patterns such as edges, textures, and complex shapes [67]. A standard CNN architecture consists of several components: convolutional layers, pooling layers, and a fully connected layer, which collectively lead to an ultimate prediction [65] (Figure 3A). In a CNN, convolutional layers utilize a set of learnable filters or kernels to the input data, generating feature maps. Subsequently, pooling layers, commonly max-pooling, downsample these feature maps to reduce their dimensionality. This reduction not only helps prevent overfitting but also decreases computational complexity. Following several convolutional and pooling layers, the network incorporates a fully connected layer, similar to those in standard neural networks. These layers combine extracted features to make final predictions for classification or regression tasks [66]. Architectures such as AlexNet, LeNet, ResNet, and VGGNet have progressively enhanced CNN's ability to handle increasingly complex visual tasks. Notably, innovations like skip connections in ResNet facilitate efficient gradient flow through deeper networks, addressing issues such as vanishing gradients and enabling the training of exceptionally deep architectures [68]. Nevertheless, CNN is constrained by its reliance on large quantities of labeled data and high computational demands, which have spurred the development of more efficient and flexible architectures [69]. CNN has emerged as the primary tool for medical image analysis due to their excellent performance in image processing. It can effectively identify morphological and structural changes in tumors, thus enhancing the accuracy of cancer diagnosis [70].

2.2.2 | Transformer

The transformer architecture excels at processing sequential data and is particularly well suited for analyzing genomic data and clinical records [71]. Unlike conventional methods that depend on recurrent layers, the transformer model is built on an encoder–decoder architecture, with both components consisting of multiple layers that employ self-attention mechanisms and feed-forward neural networks [72] (Figure 3B). This design enables parallel processing of input data, making the model highly efficient and effective for tasks involving sequential data. This advancement not only boosts training efficiency but also improves model performance on large datasets. Its self-attention mechanism allows the model to focus on important parts of the input data, thereby capturing complex biological relationships [72]. This capability makes transformers highly valuable in the development of personalized treatment plans and cancer prognosis assessment. Furthermore, transformers are revolutionizing various fields, particularly in generative tasks and reinforcement learning, due to their ability to model intricate patterns and relationships within data [73]. Transformers have demonstrated remarkable effectiveness and scalability, paving the way for next-generation models that could provide deeper insights across various domains [74]. This underscores their substantial contribution to advancing both technology and DL methodologies.

2.2.3 | Generative Adversarial Network

GAN represents a pioneering category of DL models comprising two interlinked neural networks: the generator and the discriminator [75] (Figure 3C). These networks engage in an ongoing game-theoretic competition throughout their training phase. The generator's primary goal is to create data that closely resemble real-world data, effectively fooling the discriminator [76]. Meanwhile, the discriminator strives to differentiate between real data sourced from the dataset and fake data generated by the generator. These training processes occurs concurrently, with both networks competing to outperform the other. It is crucial to note that the generator does not have direct access to real images. Instead, it learns solely through its interaction with the discriminator. This discriminator has access to both synthetic samples produced by the generator and actual images from a dataset [77]. The discriminator is trained using ground truth labels indicating whether an image is real or synthetic. The error signal for the discriminator comes from these labels, allowing it to distinguish between real and fake images effectively. Importantly, this same error signal can be leveraged to train the generator. By receiving feedback from the discriminator about the quality of its generated samples, the generator can iteratively improve, aiming to produce more realistic forgeries. Altogether, the interplay between the generator and the discriminator, with the discriminator providing critical feedback, drives the generator to enhance the quality of its synthetic images [78]. GAN offers a

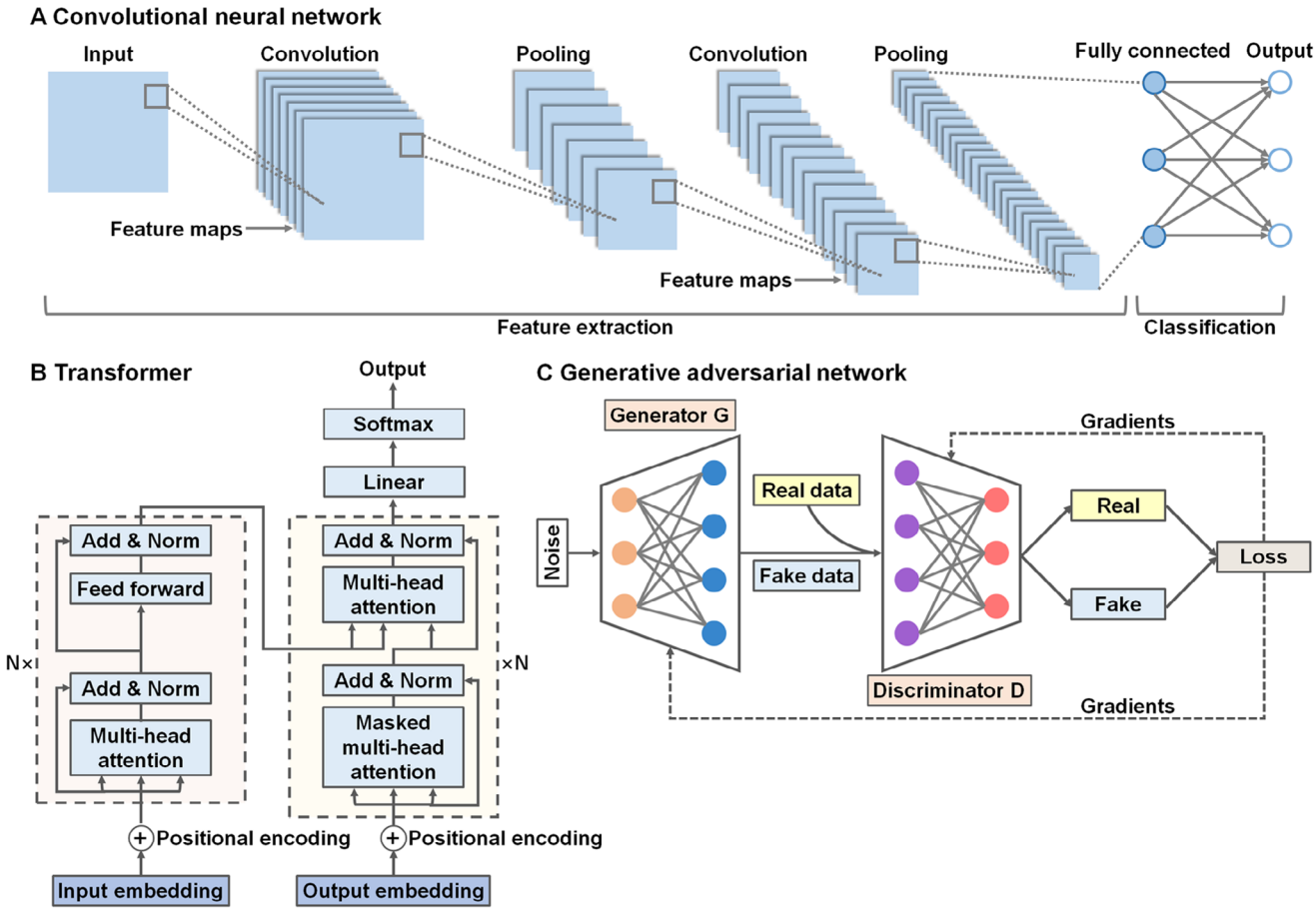

FIGURE 3 | Structure diagrams of different deep learning models. (A) Typical structure of a convolutional neural network. Convolutional neural network is primarily composed of convolution layers, pooling layers, and a fully connected layer. Convolution layers serve as the fundamental building block of convolutional neural network. They bear the main computational burden of the network. Pooling layers aim to decrease the dimensionality of the feature map. This is commonly achieved through average pooling or max pooling operations. The fully connected layer plays a crucial role in mapping the representation between the input and the output. (B) The architecture of a transformer model. The main component of a transformer model is the attention mechanism. The core function of the attention mechanism is to model interactions between different elements in a sequence, capturing dependencies among them regardless of their positions in the sequence. Besides the self-attention mechanism, another crucial component of the transformer architecture is the integration of positional encoding. Positional encoding incorporates information about the position of elements within the sequence. Adding positional encodings to the model allows it to utilize the sequence's order, which is significant for understanding structured data. (C) The basic architecture of a generative adversarial network. Generative adversarial network consists of two neural networks: a generator and a discriminator. The generator produces synthetic data (e.g., images, videos, or text) that closely resemble real-world data. The discriminator is responsible for assessing the data and differentiating between real and fake data.

way to perform advanced domain-specific data augmentation and provide solutions for tasks that necessitate a generative approach, such as image-to-image translation. In cancer research, GAN can be employed to generate imaging data of rare cancer types, helping researchers conduct more comprehensive model training [79]. In addition, GAN can be harnessed to create personalized treatment plans for patients, advancing the field of precision medicine.

While DL architectures have demonstrated substantial benefits in cancer diagnosis and management, they still encounter challenges such as data privacy, model interpretability, and transitioning to clinical applications [80]. Consequently, additional study is warranted to address these issues while enhancing model performance, thereby facilitating the broad adoption of AI in oncology research.

2.3 | Federated Learning and Edge Computing: Addressing Privacy and Real-Time Processing Constraints

Conventional AI algorithms frequently rely on a single, centralized dataset for training within a unified system. Although this approach seems straightforward for developing AI tools, it comes with substantial risks and vulnerabilities. Specifically, the necessity to centralize all data in one location and the potential for data exposure during transmission raise significant concerns. Federated learning steps in to address the growing privacy and security concerns associated with traditional AI models [81]. Federated learning enables multiple medical institutions to collaboratively train machine learning models without sharing patient data [82] (Figure 4A). This approach allows each institution to leverage the diversity of their local data to

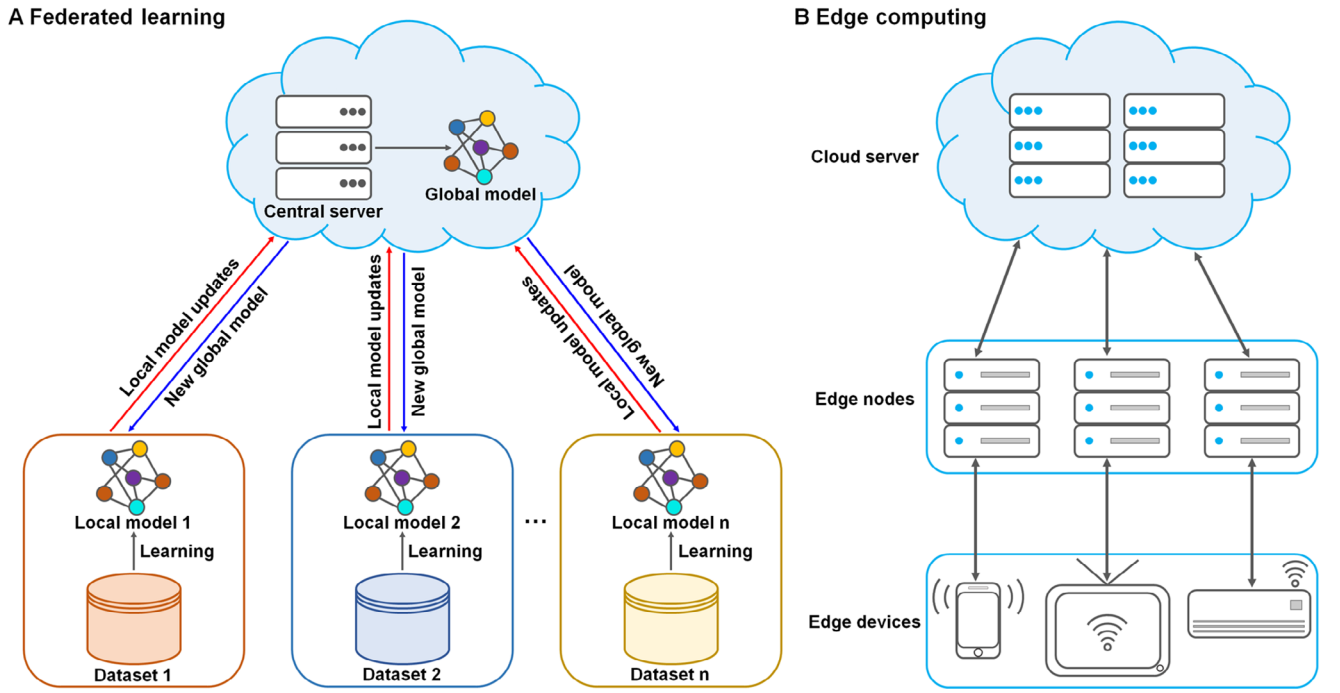

FIGURE 4 | Basic architectures of federated learning and edge computing. (A) A schematic architecture of a federated learning model. Federated learning is a machine learning technique that allows for the training of models on decentralized data, which is distributed across multiple devices. Federated learning functions by distributing computations to local devices or nodes. Each participating device trains the model locally using its private datasets and shares only the model updates with a central server. The central server then aggregates these updates to create a global model. (B) Edge computing architecture. A typical edge computing architecture is composed of three main layers: the cloud layer for secure storage and deep analysis, the edge layer for real-time data processing, and the device layer for data collection.

enhance the model's generalization ability while safeguarding patient privacy. By keeping data localized and exchanging only model updates through the communication network, federated learning ensures that sensitive information remains protected while still allowing for collective learning [81]. Federated learning can be categorized based on data distribution, specifically into vertical and horizontal federated learning [83]. Vertical federated learning is applicable when data are partitioned vertically according to the feature dimension [84]. In this scenario, data feature are distributed among multiple parties, and the goal is to collaboratively train a model using the combined dataset. In horizontal federated learning, similarities exist in the data features distributed across multiple nodes [82]. However, these data differ significantly in their sample spaces. Current federated learning algorithms are mainly designed for many applications involving internet of things (IoT) devices or smart devices [85].

As IoT continues to evolve and its applications become increasingly ubiquitous, cloud computing is encountering numerous limitations and challenges. For instance, processing and storing data from global terminal devices in centralized clouds lead to several issues: low throughput, high latency, bandwidth constraints, data privacy concerns, vulnerabilities associated with centralization, and increased costs (e.g., transmission, energy, storage, and computation expenses) [86]. In IoT applications, especially those involving the internet of vehicles, there is a critical need for high-speed data processing, analysis, and rapid result delivery [87]. Centralized cloud computing often cannot satisfy these requirements efficiently. To tackle these challenges posed by traditional cloud computing, a novel computing paradigm known as edge computing has emerged and garnered significant attention [88]. Edge computing aims to alleviate the workload on cloud servers by processing and preprocessing device data at the network edge [89]. This makes it well suited for big data analytics and scenarios requiring real-time responses or applications with time-critical constraints [90].

The general architecture of edge computing is composed of three layers: the device layer, the edge layer, and the cloud layer [91] (Figure 4B). The device layer serves two primary purposes [92]. First, it perceives the world by observing, obtaining, and digitizing information from the physical environment through various sensors. Second, it receives information or data from the edge or cloud and performs corresponding tasks based on that data. Devices in this layer typically have minimal computing and storage capabilities [93]. The edge layer, situated between the cloud and the end layers, contains computing, storage, and network resources, allowing it to undertake tasks that were traditionally handled by the cloud layer [94]. Its proximity to end devices reduces latency, making it advantageous for real-time applications. Generally, the edge layer consists of gateways, control units, storage units, and computing units. The cloud layer refers to the cloud servers widely used in practice [91]. Besides their robust computing and storage capabilities, cloud servers also have the ability to macro-manage the entire edge computing architecture [95]. Edge computing offers several advantages by offloading resources and tasks from the cloud to the edge. The proximity of the edge layer to end-users and data sources significantly reduces transmission distances, leading to decreased transmission times and improved response speeds for user requests. Additionally,

shorter transmission distances help mitigate costs associated with long-distance data transfer and address data security concerns [96]. From the cloud's perspective, processing large volumes of raw data at the edge layer allows for the filtering out of useless and erroneous data before uploading only essential information or important data to the cloud layer [97]. This approach notably reduces bandwidth pressure, transmission costs, and the risk of user privacy leakage. In the preprocessing phase of raw data within edge computing, confidential information unrelated to the final task can be obscured or deleted prior to sharing with external devices [98]. This approach mitigates the risk of leaks involving sensitive or confidential data. An indirect advantage of the edge computing paradigm is its facilitation of end device abstraction, particularly when dealing with heterogeneous devices that collect complementary information [99]. In such scenarios, an adaptation layer is necessary to standardize diverse data into a unified structure. Edge computing integrates this abstraction layer within each end device, ensuring that only relevant, transformed data are shared for the fusion process. This approach significantly reduces the computational burden on cloud servers that would otherwise be required to integrate raw, heterogeneous data.

2.4 | Data Cornerstones: Multimodal Data Fusion, Annotation Standards, and Data Governance

Multimodal data fusion has become a transformative approach in clinical oncology, systematically combining multiomics data, medical imaging, laboratory test results, electronic health records (EHRs), and outputs derived from wearable devices [100]. Each data type provides distinct clinical value, yet they may only present a partial perspective. Integrating these data sources enable a more systematic understanding of patient health status. Multimodal models that combine diverse modalities (clinical data and genomic analysis) can improve the timeliness and precision of cancer detection and diagnosis [101]. The synergistic integration of digitalized pathological images with multiomics data facilitate accurate tumor classification [102]. Moreover, multimodal features extracted from histopathological data, spatial, and single-cell transcriptomics can reveal the composition, spatial structure, and heterogeneity of tumor microenvironment [103]. Furthermore, integrated genomic analysis approaches can identify dysregulated biological functions and molecular pathways, offering novel opportunities for personalized therapy and patient monitoring [104]. The combination of biological information-driven multimodal imaging techniques allows for precise characterization of tumor heterogeneity and facilitate the selection of optimal treatment [105]. Integrating the features extracted from routine diagnostic approaches, pathology, clinical information, and genomics can enhance the prediction of immunotherapy response [106]. The multimodal approaches also achieve accurate prognostic predictions across diverse cancer types [107]. Although the significant potential of multimodal systems in healthcare, several critical challenges must be overcome to realize its full benefits. Data standardization and privacy protection remain significant issues requiring attention. There is a critical need to improve model interpretability to generate clinically actionable insights. To gain physician trust, it is essential to enhance the transparency of models' decision-making processes. Overall, the development of more advanced AI algorithms and data fusion technologies will significantly improve the analysis and interpretation of complex multimodal datasets, enabling more tailored solutions for clinical cancer care [108].

3 | AI-Powered Cancer Diagnosis and Molecular Profiling

The application of AI technology in cancer management has shown great promise, particularly in efficient diagnosis. Current diagnosis methods for cancer face several challenges [109]. Early cancer detection is often difficult due to the tumors' ability to conceal themselves, limitations in imaging technologies, and the difficulty in visualizing small or deeply situated tumors. Accurate differentiation among different tumor types remains challenging in clinical practice [110]. Some diagnostic procedures are invasive and come with associated risks. These approaches are also time consuming, have limited accessibility, and suffer from interpretation variability among experts. Clinicians mainly rely on their expertise and knowledge when evaluating a patient's signs and symptoms. However, given vast amounts of clinical data, it can be difficult for them to make quick and accurate diagnoses. Furthermore, there are challenges related to tumor heterogeneity, individual differences, atypical test results, and false negatives [111]. Heavy clinical workloads increase the risk of missed or incorrect diagnoses among clinicians. There is a clear need for advanced AI-based diagnostic methods to address these issues. AI possesses remarkable capabilities in efficiently processing large volumes of clinical data [112]. The diagnostic efficacy of AI approaches has been explored in imaging modalities and histopathologic examination [113]. AI is anticipated to advance tumor diagnostics by enhancing accuracy, expediting analytical process, enabling early detection, and improving differentiation between tumor types.

3.1 | Imaging Diagnostics Revolution

Oncological imaging methods provide a unique and unaltered view of the entire tumor. AI models hold the promise of significantly revolutionizing oncological imaging by leveraging machine learning and DL techniques [114]. Computed tomography (CT) scans are widely used for detecting the presence, size, and location of tumors, as well as whether they have spread to surrounding tissues or other organs. Early cancer diagnosis via nodule detection on CT scans remains crucial for improving patient survival rates. AI algorithms have shown significant potential in CT screening for breast cancer [115, 116], colorectal cancer (CRC) [117], esophageal cancer [118], lung cancer [119–144], gastric cancer [145], hepatocellular carcinoma (HCC) [146, 147], ovarian cancer [148], pancreatic ductal adenocarcinoma (PDAC) [149, 150], and pancreatic cancer [151–155] (Table 1). Magnetic resonance imaging (MRI) is a prevalent tool in cancer diagnosis, utilizing strong magnetic fields and radio waves to generate detailed internal body images without radiation exposure [156]. This makes it a safer option, especially for sensitive populations. MRI excels in imaging soft tissues like the brain, spinal cord, joints, and muscles [157]. It aids in detecting tumor size, location, and shape, which is essential for cancer staging and treatment planning. However, MRI scans generally require longer times and are more expensive than other imaging methods. DL methods could improve the detection of breast cancer

TABLE 1 | Summary of AI-based tools in different cancer diagnosis modalities.

Potential clinical application	Cancer type	AI algorithm	AI task	Algorithm performance	References
Oncological imaging	Breast cancer	Deep learning	Cancer screening using digital mammography and dedicated cone-beam breast CT	Interquartile range: 0.187; *p* value: 0.862	[115]
Oncological imaging	Breast cancer	Deep learning	Cancer diagnosis based on the Wisconsin Breast Cancer Dataset (WBC)	Recall rate: 98.7%; *F*1-score: 99.03%; accuracy rate: 99%	[116]
Oncological imaging	Colorectal cancer	Faster region-convolutional neural network	Cancer detection using CT colonography images	Sensitivities: 0.815 for lesions ≥ 6 mm, 0.738 for lesions = 6–10 mm, and 0.883 for lesions ≥ 10 mm	[117]
Oncological imaging	Esophageal cancer	Convolutional neural network	Cancer diagnosis using cancerous and noncancerous CT images	Accuracy rate: 84.2%; *F* value: 0.742; sensitivity: 71.7%; specificity: 90.0%	[118]
Oncological imaging	Lung cancer	3D convolutional neural network	Cancer screening using CT images	Reduce the risk of patient health information exposure	[119]
Oncological imaging	Lung cancer	Deep learning	Cancer early detection using 3D CT images	Accuracy: 0.959	[120]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using CT images and clinical data	AUC: 0.8021	[121]
Oncological imaging	Lung cancer	Transfer learning	Cancer detection using chest CT images	Accuracy rate: 91%; precision: 92%; recall: 91%; *F*1-score: 91.3%	[122]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using chest CT images	Effectively measure bone mineral density with an accuracy level comparable to manual measurements	[123]
Oncological imaging	Lung cancer	Densely connected convolutional neural network	Cancer detection using lung CT images	Accuracy rate: 98.17%; specificity: 97.32%; precision: 97.46%; recall: 97.89%	[124]
Oncological imaging	Lung cancer	Machine learning; deep learning	Cancer early screening using radiology, clinical and genomics data	AUC: 0.587–0.910	[125]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using lung imaging data and clinical metadata	AUC: 0.88	[126]

(Continues)

TABLE 1 | (Continued)

Potential clinical application	Cancer type	AI algorithm	AI task	Algorithm performance	References
Oncological imaging	Lung cancer	Multimodal integrated feature neural network	Cancer diagnosis using CT images and morphological characteristics of pulmonary nodules	Internal AUC: 0.890; external AUC: 0.843	[127]
Oncological imaging	Lung cancer	Three-dimensional convolutional neural networks	Cancer early detection using lung CT images	AUC values: 0.801 for 3D-CNN, 0.802 for MobileNet v2, 0.755 for EfficientNet-B0, 0.833 for SEResNet18	[128]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using CT images	AUC: 0.8719	[129]
Oncological imaging	Lung cancer	Deep learning	Cancer early detection using single low-dose CT images	AUC: 0.98	[130]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using low-dose CT images	AUC: 0.89 ± 0.02	[131]
Oncological imaging	Lung cancer	Machine learning	Cancer screening using modified CT index and serological indices	AUC values: 0.931 in the validation set, 0.99 in the test set; accuracies: 0.857 in the validation set, 0.955 in the test set	[132]
Oncological imaging	Lung cancer	Deep learning	Cancer early detection using low-dose CT images	AUC: 0.827 ± 0.028	[133]
Oncological imaging	Lung cancer	Deep neural network	Cancer early detection using lung nodule dataset	Accuracy rate: 98.2%	[134]
Oncological imaging	Lung cancer	Machine learning	Cancer early detection using lung CT images	Accuracy rate: 98.21%; precision: 98.71%; recall: 97.46%	[135]
Oncological imaging	Lung cancer	Convolutional neural network	Cancer early detection using CT images	Accuracy rate: 97.56%; specificity: 98.4%	[136]
Oncological imaging	Lung cancer	Deep learning	Cancer early detection using CT images	Accuracy rate: 93.4%; sensitivity: 90.2%; AUC: 94.1%	[137]
Oncological imaging	Lung cancer	Deep learning	Cancer diagnosis using CT images	AUC: 0.9711	[138]
Oncological imaging	Lung cancer	Deep learning; internet of things; convolutional neural network	Cancer early diagnosis using medical data (CT images and sensor information)	Accuracy rate: 98.85%	[139]

(Continues)

TABLE 1 | (Continued)

Potential clinical application	Cancer type	AI algorithm	AI task	Algorithm performance	References
Oncological imaging	Lung cancer	Convolutional neural network	Cancer diagnosis using CT images	Accuracy rate: 93.25%; sensitivity: 89.22%; specificity: 95.82%; precision: 92.46%; *F*1-score: 0.9114; AUC: 0.9629	[140]
Oncological imaging	Lung cancer	Deep learning	Cancer early detection using chest X-rays and chest CT images	Accuracy rate: 90%; sensitivity: 57.6%	[141]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using low-dose CT images	Remove noise from CT images and show good detail retention	[142]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using metadata and CT images	Effectively distinguish cancerous cases from benign cases using a combined slice thickness $\geq$ 2.5 mm	[143]
Oncological imaging	Lung cancer	Deep learning	Lung cancer detection using CT images and chest radiography	AUC: 0.92; sensitivity: 94%; specificity: 73%	[144]
Oncological imaging	Gastric cancer	Deep learning	Automated cancer screening using CT images	AUC: 0.98; accuracy: 0.93; sensitivity: 0.92; specificity: 0.92; *F*1-score: 0.93	[145]
Oncological imaging	Hepatocellular carcinoma	Deep learning	Cancer detection using solely noncontrast CT images	AUC values: 0.807 on the internal validation cohort, 0.789 on the external testing cohort	[146]
Oncological imaging	Hepatocellular carcinoma	Deep learning	Cancer detection using CT images	Precision: 0.97216; recall: 0.919; accuracy rate: 95.35%; specificity: 95.83%; sensitivity: 94.74%	[147]
Oncological imaging	Ovarian cancer	Deep learning	Automated cancer diagnosis	Accuracy rate: 98.43%	[148]
Oncological imaging	Pancreatic ductal adeno-carcinoma	Reinforcement learning; deep neural network	Early cancer diagnosis	Achieve method accuracies of 2.2, 4.9, and 2.6 mm measured in terms of the mean detection error, Hausdorff distance, and root mean squared error	[149]
Oncological imaging	Pancreatic ductal adeno-carcinoma	Generative adversarial network	Cancer diagnosis	AUC: 0.79; precision-recall AUC: 0.87; accuracy: 0.67	[150]

(Continues)

TABLE 1 | (Continued)

Potential clinical application	Cancer type	AI algorithm	AI task	Algorithm performance	References
Oncological imaging	Pancreatic cancer	Deep learning	Large-scale cancer detection	Accuracy: 0.907 ± 0.01; sensitivity: 0.905 ± 0.01; specificity: 0.908 ± 0.02; AUC: 0.903 ± 0.01	[151]
Oncological imaging	Pancreatic cancer	Deep learning	Early cancer detection	AUC: 0.98; sensitivity: 0.94	[152]
Oncological imaging	Pancreatic cancer	Convolutional neural network	Cancer detection	Sensitivity: 0.97; specificity: 1.00; AUC: 0.99	[153]
Oncological imaging	Pancreatic cancer	Convolutional neural network; vision transformer; K-nearest neighbor; support vector machine; random forest; XGBoost	Cancer diagnosis	Accuracy rate: 97.33%; *F*1-score: 96.25%	[154]
Oncological imaging	Pancreatic cancer	Convolutional neural network	Cancer diagnosis	Accuracy rate: 99.64%	[155]
Oncological imaging	Breast cancer	Faster region-convolutional neural network	Cancer detection using breast MRI	Accuracy rate: 94.46%	[158]
Oncological imaging	Breast cancer	Deep learning	Cancer detection using breast dynamic contrast enhanced-MRI images	Dice and Jaccard coefficients: 0.9468 and 0.8990	[159]
Oncological imaging	Glioma	Convolutional neural network	Cancer diagnosis using MRI images	Accuracy rate: 87%	[160]
Oncological imaging	Glioma	Convolutional neural network; vision transformer; explainable AI	Cancer detection using MRI images	Accuracy rates: 98.4% and 99.3% on two separate datasets	[161]
Oncological imaging	Intrahepatic cholangiocarci-noma	Deep learning	Cancer diagnosis using CT and MRI images	AUC values: 0.994 in the training cohort, 0.937 in the test cohort	[162]
Oncological imaging	Lung cancer	Deep learning	Cancer screening using pulmonary MRI images	Detection rates: ≥96.8%	[163]
Oncological imaging	Prostate cancer	Deep learning	Cancer detection using dense intraslice information and sparse interslice information of the anisotropic bi-parametric MRI images	AP score: 0.690; AUC: 0.909	[164]

(Continues)

TABLE 1 | (Continued)

Potential clinical application	Cancer type	AI algorithm	AI task	Algorithm performance	References
Oncological imaging	Prostate cancer	Support vector machine; XGBoost; deep learning	Cancer identification using bi-parametric MRI images and clinical variables	AUC values: 0.986 in the training set, 0.965 in the testing set	[165]
Oncological imaging	Prostate cancer	Deep learning	Cancer detection using noncontrast MRI sequences	Simulated contrast-enhanced MRI images show high similarities (0.69, 0.71, and 0.82) with excellent reader agreement of PI-RADS scores	[166]
Oncological imaging	Prostate cancer	Deep learning	Cancer detection using clinical information (e.g., prostate MRI)	Positive predictive value: 58% (94 out of 163); specificity: 44% (48 of 108); sensitivity: 96% (93 out of 97); AUC: 0.79	[167]
Oncological imaging	Prostate cancer	Machine learning (XGBoost, random forest, neural network, logistic regression)	Cancer early detection using MRI images and clinical data	Specificities: 0.640, 0.638, 0.634, 0.620	[168]
Oncological imaging	Lymphoma	Deep learning	Cancer diagnosis using PET images	Improve the quality of lymphoma PET with a twofold acceleration	[170]
Oncological imaging	T-cell lymphoma	Logistic regression	Cancer screening using ^{18}F-FDG PET/CT images	Accuracy: 0.779; AUC: 0.863	[171]
Oncological imaging	Lung cancer	Fully convolutional network	Cancer diagnosis using PET images	Have good performance and time cost	[172]
Oncological imaging	Lung cancer	Adaptive dilated convolution neural network, hybrid attention-based deep networks	Cancer detection using PET and CT lung images	Demonstrate enhanced effectiveness over traditional detection approaches	[173]
Oncological imaging	Follicular lymphoma	Deep learning, machine learning	Cancer identification using radiomic features extracted from PET/CT images	AUC: 0.820	[174]
Pathology	Breast cancer	Paige Breast Suite	Cancer detection using histopathological images	Undetermined	[175]
Pathology	Breast cancer	Ibex Galen Breast HER2	Cancer detection using breast biopsies	AUC: 0.997	[176]
Pathology	Breast cancer	Mindpeak Breast	Cancer detection using breast biopsies	AUC values: 0.99 for invasive carcinoma, 0.98 for ductal carcinoma in situ	[177]

(Continues)

TABLE 1 | (Continued)

Potential clinical application	Cancer type	AI algorithm	AI task	Algorithm performance	References
Pathology	Breast cancer	PathAI: AIM-HER2	Cancer detection using histopathological images	Enhance diagnostic precision and streamline workflow efficiency	[178]
Pathology	Breast cancer	Visiopharm	Cancer metastasis diagnosis using histopathological images	Sensitivity: 100%; specificity: 41.5%; positive predictive value: 29.5%	[179]
Pathology	Prostate cancer	Paige prostate	Cancer diagnosis using prostatic biopsies	Maintain high diagnostic accuracy; lead to a significant decrease in immunochemistry studies, second opinion requests, and time for reporting	[180]
Pathology	Gastric cancer	Convolutional neural network algorithms	Cancer diagnosis using gastrointestinal endoscopic images	Improve the accuracy and efficiency of current diagnostic methods	[181]
Pathology	Skin cancer	DermAI	Early cancer detection using dermatoscopic images	Mean accuracy rate: 99.60%	[182]

[158, 159], glioblastoma multiforme [160], glioma [161], intrahepatic cholangiocarcinoma [162], lung cancer [163], and prostate cancer [164–168] based on conventional MRI. Positron emission tomography (PET) imaging offers detailed images of metabolic processes within the body [169]. This noninvasive technique facilitates early cancer detection and identifies cancers often missed by other methods. AI models enhanced the efficiency of PET screening for lymphoma [170, 171], lung cancer [172, 173], and transformed follicular lymphoma [174].

3.2 | Digital Pathology Breakthroughs

Pathology is essential for confirming the presence of cancer, identifying its type, and assessing its grade [183]. Digital pathology is a groundbreaking development in the field of pathology, involving the scanning of glass slides to create high-resolution digital slides for analysis [184]. The integration of AI can assist in the rapid and accurate analysis of pathology slides, helping to identify patterns and anomalies that might be missed by human eyes [185]. In recent years, AI tools designed to aid in tumor detection have emerged and are being integrated into routine clinical practice, particularly in the diagnosis of breast and prostate cancers. For instance, several AI-based tools have been developed and evaluated for accurate diagnosis in breast cancer pathology, such as Paige Breast Suite, Ibex Galen Breast, Mindpeak Breast, PathAI: AIM-HER2, and Visiopharm (Table 1). Paige Breast Suite assisted pathologists in identifying breast cancer, thus enhancing diagnostic accuracy and effectiveness [175]. Ibex Galen Breast HER2 [176], Mindpeak Breast [177], and PathAI: AIM-HER2 [178] improved the identification and categorization of various subtypes of breast cancer by accurately analyzing histopathological images. Visiopharm facilitated the precise quantification of ER, PR, HER2, and Ki-67 biomarkers for breast cancer diagnosis in a digital pathology workflow [179]. Paige Prostate, a clinically validated AI tool, categorized prostate core biopsy whole-slide images as either “suspicious” or “not suspicious” for prostate cancer [180]. The implementation of Paige Prostate notably reduced reporting time and resource consumption, including IHC studies and second opinion requests. AI tools are also being developed and applied to improve the diagnosis for other cancer types. AI-aided endoscopic lesion detection systems were able to detect and characterize lesions in the gastrointestinal tract through real-time image analysis [181]. This enhancement increased diagnostic accuracy and minimized the risk of overlooking lesions. In addition, DermAI served as a useful AI platform for diagnosing skin cancers based on image input [182]. These AI applications provide a comprehensive tumor landscape, facilitating better-informed decision-making.

3.3 | Integrated Multiomics Diagnostics

Multimodal data fusion is a process of combining various data sources and types, such as medical images, pathological, genomic, transcriptomic, proteomic, and clinical data, to gain

TABLE 2 | Summary of AI-based multimodal models for cancer diagnosis.

Cancer type	AI algorithm	AI task	Algorithm performance	References
Breast cancer	Transformer	Cancer diagnosis using MRI images, lesion characteristics, and clinical information	AUC: 0.928 ± 0.027	[188]
Breast cancer	Vision transformer	Cancer malignancy classification using imaging histopathological features and clinical parameters	AUC values: 0.942 and 0.945 for two independent testing cohorts; *F*1-scores: 0.872 and 0.857 for the two testing cohorts	[189]
Breast cancer	Convolutional neural network	Cancer segmentation and classification using multimodal ultrasound images	Dice score: 78.23%; intersection over union: 68.60%; precision: 82.21%; recall: 80.58%; accuracy rate: 98.46%	[190]
Glioma	Convolutional neural network, transformer, LightGBM, random forest	Cancer diagnosis using histopathology images and clinical data	Accuracy: 0.936; AUC: 0967	[191]
Lung cancer	Convolutional neural network, ResNet, transformer	Cancer diagnosis using multimodal spectral data and text features	Accuracy rates: 95.83, 97.92, and 100% for three test sets	[192]
Oral squamous cell carcinoma	Convolutional neural network	Cancer detection using histopathological images and complex cancerous patterns	Accuracy rates: 90.98 and 98.24% for two testing datasets; dice similarity coefficients: 86.14 and 94.09% for two testing datasets; mean intersection over unions: 77.10 and 88.84% for two testing datasets	[193]
Hepatocellular carcinoma	XGBoost	Cancer detection using clinical, radiological, and peripheral immunological features	AUC values: 0.985 and 0.915 for the internal and external validation cohorts	[194]
Bladder cancer	Logistic regression, random forest, support vector machine, decision tree	Cancer detection using clinical and biological information	AUC values: 0.82 on the training set, 0.83 on the test set	[195]

a thorough understanding of disease complexity [186, 187]. By leveraging the synergies among varied data types, medical professionals can make more informed decisions, improving diagnostic accuracy and enabling the selection of personalized treatment options for better patient care. DL-based multimodal networks achieve good performance in the detection of breast cancer [188–190], glioma [191], lung cancer [192], and oral cancer [193] (Table 2). Machine learning-driven multimodal feature models improved the detection of HCC [194] and bladder cancer [195]. These studies also demonstrated that multimodal fusion modeling of biomedical data achieve better performance than single-modality approaches. Accordingly, multimodal fusion methods hold great promise for cancer management by providing comprehensive and accurate insights [196]. To fully harness the potential of multimodal fusion approaches, several key improvements are imperative, including resolution of data heterogeneity issues, refinement of feature fusion strategies, and optimization of network architectures.

3.4 | Classification and Molecular Subtyping

Recent advancements in AI techniques have the potential to improve tumor characterization, grading, classification, and molecular subtyping, ultimately leading to more accurate and reliable diagnosis and management [197]. A machine learning classifier, known as the "Heidelberg brain tumor classifier," was developed to achieve accurate, affordable, and fast classification of brain tumors based on genome-wide DNA methylation profiles [198, 199] (Table 3). The random forest algorithm-based NEP100 model improved the subtyping of neuroendocrine prostate cancer through multiomics analysis [200]. DL models, such as UNet and CCN, demonstrated high accuracy in the automated segmentation of oral carcinoma [201], brain tumors [202–211], breast cancer [212], lung cancer [213, 214], prostate cancer [215], renal tumors [216], and thyroid cancer [217] due to their ability to learn complex patterns from medical images . DL algorithms also show promising performance in cancer classification and molecular subtyping using single- or multiomics data (e.g., epigenomics, proteomics, radiomics, and single-cell omics) [218–224].

Accurate tumor classification is essential for reliably and reproducibly tracking tumor size and volume over time. AI-assisted automated cancer segmentation can be integrated into clinical oncological imaging workflows, overcoming the time constraints associated with manual size comparisons [313, 314]. AI techniques help identify new imaging biomarkers that serve as indicators for cancer subtypes and disease progression [315]. Furthermore, AI models can incorporate multimodal data to enhance cancer classification and subtyping [316].

4 | AI-Driven Precision Therapy and Dynamic Management

4.1 | Therapeutic Decision Optimization

AI has the ability to optimize the decision-making process. For instance, optimal policy trees, an interpretable AI-based method, could identify patients with gastrointestinal stromal tumor who should receive adjuvant imatinib, determine the optimal treatment duration, and assess the benefits of this treatment [225]. Machine learning-based autophagy-related prognostic signature was correlated with decreased sensitivity to immunotherapy in breast cancer and thus represented a practical tool to optimize decision-making [226]. ChatGPT-generated treatment recommendations showed strong concordance (72.5%) with those posed by traditional multidisciplinary team in CRC [227]. The clinical decision support system (CDSS) utilizes AI-driven data integration to deliver evidence-based, real-time clinical recommendations in oncology [317]. A machine learning-based CDSS showed outstanding performance in identifying patients with renal cell carcinoma (RCC) who were at high risk of late recurrence, thus emphasizing the need for long-term follow-up and the development of patient-specific treatment strategies [228]. RCC-Supporter, another machine learning-driven CDSS system, recommended individualized therapy for RCC patients, taking into account their diverse clinical statuses [229]. SVM algorithm-based CDSS (CureMate) demonstrated high accuracy and effectiveness in selecting the optimal first treatment strategy in breast cancer [230]. A machine learning-based HCC-CDSS model demonstrated promising performance in recommending initial treatment options and predicting overall survival in HCC patients [231]. A CDSS based on ANN was developed to support clinical decisions in non-small cell lung cancer (NSCLC) patients by distinguishing the efficacy of EGFR-TKI therapy [232]. Valdes et al. [233] developed a CDSS system that helped clinicians efficiently match new patients with historically approved treatment plans, facilitating the selection of radiotherapy in lung and oropharyngeal cancers.

4.2 | Dynamic Treatment Monitoring

AI has become an important tool for longitudinal tracking of tumor progression following treatment. A multitask AI system was developed to predict residual cancer burden scores in breast cancer, thereby supporting clinical decision-making during neoadjuvant chemotherapy [234]. A CNN-based DL model that integrated MRI data showed good performance in assessing changes in tumor load in breast cancer after neoadjuvant chemotherapy treatment [235]. A machine learning-based detection platform monitored tumor burden in advanced melanoma and lung cancer following neoadjuvant immunotherapy by tracking changing dynamics of circulating tumor DNAs [236]. Explainable AI (XAI) methods, such as Guided Backpropagation and DeepLIFT, could assess the reliability of a DL-based tumor tracking model for lung cancer patients during radiation delivery [237]. AI helps identify changes in tumor size, volume, or growth, allowing clinicians to define whether the tumor shrinks due to treatment efficacy or develops because of treatment resistance.

Accurate prediction of tumor response to therapeutic regimens enables personalized treatment for cancer. With numerous radiomics/radiopathomics data, AI algorithms, such as XGBoost, boosted decision tree, Vision Transformer, and 3D-ResNet, showed potential in predicting pathological complete response to neoadjuvant chemotherapy in breast cancer [238–240] and esophageal squamous cell carcinoma (ESCC) [241]. AI techniques showed favorable performance for predicting pathological complete response to chemoradiotherapy in rectal cancer [242–244], esophageal cancer [245], and cervical cancer [246]. Image-based machine learning could efficiently predict radiotherapy response in oligometastatic gynecologic cancer [247] and prostate cancer [248]. DL models were used to predict clinical response to checkpoint blockade immunotherapy in advanced melanoma [249], gastric cancer [250, 251], HCC [252], and NSCLC [253]. AI-based algorithms hold significant promise for real-time monitoring of treatment response, leading to improved clinical outcomes in cancer patients.

4.3 | Overcoming Treatment Resistance

Increasing evidence indicates that AI can analyze genetic mutations, drug metabolism, and drug sensitivity to identify patients at risk of developing resistance to specific treatments, facilitating timely and effective interventions [254–257]. Moreover, AI techniques can decipher the mechanisms responsible for treatment resistance in cancer patients. For instance, AI algorithms (e.g., transformer, SVM, and random forest) identified key genes/proteins associated with treatment resistance in

TABLE 3 | Summary of recent studies exploring the potential of artificial intelligence techniques in cancer classification, treatment, and prognostic prediction.

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Cancer classification	Central nervous system tumor	Genome-wide DNA methylation profiles	Random forest	AUC: 0.99; sensitivity: 0.989; specificity: 0.999	[198]
Cancer classification	Brain cancer	Genome-wide DNA methylation profiles	Random forest	Accurately classify cancer	[199]
Cancer classification	Neuroendocrine prostate cancer	Multiomics data (transcriptomics, single-cell transcriptomics, and spatial transcriptomics)	Random forest	AUC values: 0.924, 0.986, 0.989, 0.994, 0.995, and 1.000 for validation sets	[200]
Cancer classification	Oral carcinoma	Medical images	Convolutional bidirectional long short-term memory network	Accuracy rate: 98.47%	[201]
Cancer classification	Brain tumor	MRI images	UNet, Bayesian	Accuracy rate: 97.75%	[202]
Cancer classification	Brain tumor	MRI images	Convolutional neural network	Accuracy rate: 99.16%	[203]
Cancer classification	Brain tumor	Medical images	Convolutional neural network	Accuracy rate: 98.47%; mean intersection over union: 0.8185; average dice coefficient: 0.7; average Hausdorff 95 score: 1.66; precision: 98.55%; sensitivity: 98.40%; specificity: 99.52%	[204]
Cancer classification	Brain tumor	MRI images	Convolutional neural network	Negative predictive value: 89.91%; true negative rate: 92.26%; true positive rate: 93.78%; positive predictive value: 93.60%	[205]
Cancer classification	Brain tumor	MRI images	Convolutional neural network	Accuracy: 0.962; *F*1-score: 0.965; precision: 0.965; recall: 0.965	[206]
Cancer classification	Brain tumor	MRI images	Convolutional neural network	Accuracy rate: 98.5%	[207]
Cancer classification	Brain tumor	MRI images	Residual neural network; convolutional neural network	Accuracy rate: 98.4%; AUC: 0.999	[208]
Cancer classification	Brain tumor	MRI images	Convolutional neural network	Accuracy rate: 96.01%	[209]
Cancer classification	Brain tumor	MRI images	Deep neural network	Segment and categorize brain tumors more accurately than the existing state-of-the-art mechanisms	[210]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Cancer classification	Glioma	MRI images	Deep learning	Sensitivity: 98.58%; specificity: 99.09%; accuracy rate: 99.1%; dice similarity coefficient: 98.96%	[211]
Cancer classification	Breast cancer	Whole mount slide images, microscopic biopsy images	Convolutional neural network, long short-term memory	Accuracy rates: 99.17 and 99.90% on the respective datasets	[212]
Cancer classification	Lung cancer	Chest CT images	Convolutional neural network	Accuracy rate: 97.7%; sensitivity: 98.1%; specificity: 97.4%	[213]
Cancer classification	Non-small-cell lung cancer	Liquid-based cytology images	Convolutional neural network	Sensitivity: 0.73; specificity: 0.82; accuracy: 0.78	[214]
Cancer classification	Prostate cancer	MRI images	Deep learning	Accuracy rate: 99.31%; sensitivity: 98.24%; specificity: 98.46%	[215]
Cancer classification	Renal tumor	Contrast-enhanced CT images	Convolutional neural network	Dice similarity coefficients: 0.83 for tumors larger than 4 cm, 0.65 for tumors smaller than 4 cm; accuracies: 0.77 for tumors larger than 4 cm and 0.68 for tumors smaller than 4 cm	[216]
Cancer classification	Thyroid cancer	Pathological tissue slide images, genetic and protein data	Convolutional neural network, recurrent neural network	Accuracy rate: ~90%	[217]
Cancer classification	Breast cancer	Epigenomic data	Deep learning	Accuracy rate: 95.85%; recall: 95.96%; precision: 95.85%; *F*1-score: 95.90%; false positive rate: 1.03%; false negative rate: 4.12%	[218]
Cancer classification	Stomach cancer	Multilayer omics data (Exon, mRNA, mRNA expression data, and DNA methylation profiling)	Recurrent neural network	AUC values: 0.990 for TCGA-Stomach Adenocarcinoma project, 0.994 for TCGA-Liver Hepatocellular Carcinoma project	[219]
Cancer classification	Brain tumor	MRI images, radiomics features	Convolutional neural network	Accuracy rate: 95.0%; AUC: 0.92; sensitivity: 88%; specificity: 90%	[220]
Cancer classification	Glioma	Radiomics and clinical features	Deep learning	AUC: 0.98 in an externally validated cohort	[221]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Cancer classification	Brain tumor, leukemia, lung cancer	Gene microarray data	Generative adversarial network	Accuracies: 0.9519 and 0.9644 for brain tumor datasets; 0.9896 and 0.9867 for leukemia datasets; 0.9524 for the lung cancer dataset	[222]
Cancer classification	Clear cell renal cell carcinoma	Radiomics features	Deep learning, support vector machine, K-nearest neighbor, neural network classifiers	Accuracy rate: 90.9%	[223]
Cancer classification	Lung adenocarcinoma	Radiomics data, MRI images	Convolutional neural networks	AUC: 0.880	[224]
Therapeutic decision optimization	Gastrointestinal stromal tumor	Clinical characteristics	Random forest	Determine the patients who should receive treatment, the optimal duration and treatment outcomes with an AUC of 0.77	[225]
Therapeutic decision optimization	Bladder cancer	Transcriptomic data	Machine learning	Efficiently optimize risk stratification and decision-making	[226]
Therapeutic decision optimization	Colorectal cancer	Demographic data and staging examination results	ChatGPT	Show high concordance (72.5%) with recommendations posed by traditional multidisciplinary team	[227]
Therapeutic decision optimization	Renal cell carcinoma	Clinicopathological data	Machine learning	Predict the probability of a late recurrence 5 years after surgery with a sensitivity of 0.673, a specificity of 0.807, an accuracy of 0.799, an AUC of 0.740 and a *F*1-score of 0.609	[228]
Therapeutic decision optimization	Renal cell carcinoma	Clinical data	Gradient boosting machine	Recommend personalized treatment for various clinical situations with an accuracy score of 95%	[229]
Therapeutic decision optimization	Breast cancer	Demographic data, anato-mopathological data, and MRI images	Support vector machine	Improve decision-making processes with a test accuracy of 0.933	[230]
Therapeutic decision optimization	Hepatocellular carcinoma	Pretreatment demographic, clinical, and imaging variables	Random forest	Show good performance in treatment decision with 81% of accuracy for radiofrequency ablation or resection versus not, 88.4% for radiofrequency ablation versus resection, and 76.8% for transarterial chemoembolization or not	[231]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Therapeutic decision optimization	Non-small cell lung cancer	Clinical characteristics, next-generation sequencing data	Artificial neural network	Assess the efficacy of first-line EGFR-TKI treatment with an accuracy of 0.82 and an AUC of 0.82	[232]
Therapeutic decision optimization	Lung cancer, oropharyngeal cancer	Anatomical information, medical records	Machine learning	Have the potential to guide therapy and reduce the time needed to reach an acceptable plan	[233]
Dynamic treatment monitoring	Breast cancer	MRI images	Deep learning	Achieve AUC values of 0.975 and 0.976 for classifying residual cancer burden scores in the primary cohort and AUC values of 0.923 and 0.910 in external validation cohorts	[234]
Dynamic treatment monitoring	Breast cancer	MRI images	Convolutional neural network	Assess changes in tumor load with an AUC of 0.76	[235]
Dynamic treatment monitoring	Melanoma, lung cancer	Plasma whole genomic data	Support vector machine	Monitor cancer progression following immunotherapy with an AUC of 0.998	[236]
Dynamic treatment monitoring	Lung cancer	Clinical data	Explainable artificial intelligence, convolutional neural network	Efficiently track tumor progression following radiotherapy	[237]
Dynamic treatment monitoring	Breast cancer	Longitudinal MRI spatial habitat radiomics, transcriptomics, single-cell transcriptomics	XGBoost	Predict pathological complete response to immunotherapy with a specificity of 88% and a positive predictive value of 93%	[238]
Dynamic treatment monitoring	Breast cancer	Clinical and imaging data	Vision transformer	Monitor pathological complete response to chemotherapy with an AUC of 0.813	[239]
Dynamic treatment monitoring	Breast cancer	MRI images, radiomics data	XGBoost	Predict pathological complete response to chemotherapy with an AUC of 0.89	[240]
Dynamic treatment monitoring	Esophageal squamous cell carcinoma	CT images, radiomics data	Transformer	Predict pathological complete response to immunotherapy combined with chemotherapy with accuracies of 0.83–0.91 and AUC values of 0.83–0.92	[241]
Dynamic treatment monitoring	Rectal cancer	Radiology images	Deep learning	Predict pathological complete response to chemoradiotherapy with an AUC of 0.90	[242]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Dynamic treatment monitoring	Rectal cancer	MRI images	Gradient boosting machine	Identify complete response to radiation with a sensitivity of 90% and a specificity of 86%	[243]
Dynamic treatment monitoring	Rectal cancer	Laboratory data	Machine learning	Predict pathological complete response to chemoradiotherapy with AUC values of 0.86 and 0.83 in the internal and external validations set	[244]
Dynamic treatment monitoring	Esophageal cancer	CT radiomics, dosimetric characteristics	XGBoost	Predict the response to chemoradiation with an accuracy of 0.708 and an AUC of 0.541	[245]
Dynamic treatment monitoring	Cervical cancer	Multimodal data	Support vector machine	Predict chemoradiotherapy response with an AUC value of 0.86	[246]
Dynamic treatment monitoring	Gynecologic cancer	Multimodal data	Machine learning	Predict complete response to radiotherapy	[247]
Dynamic treatment monitoring	Prostate cancer	MRI images	Random forest, decision tree, support vector machine	Predict radiotherapy response with AUC values of 0.722, 0.685, and 0.5	[248]
Dynamic treatment monitoring	Melanoma	Histology data, clinicodemographic characteristics	Machine learning	Predict immunotherapy response with AUC values of 0.800 and 0.805	[249]
Dynamic treatment monitoring	Gastric cancer	Radiomics, clinicopathological, and imaging data	Convolutional neural network	Predict immunotherapy response with an AUC of 0.783	[250]
Dynamic treatment monitoring	Gastric cancer	Transcriptomic and digital pathology data	ResNet	Predict immunotherapy response	[251]
Dynamic treatment monitoring	Hepatocellular carcinoma	CT images, radiomics, clinical data	ResNet, convolutional neural network	Predict immunotherapy response with AUC values of 0.96 and 0.88	[252]
Dynamic treatment monitoring	Non-small cell lung cancer	Radiology text reports	Deep learning	Predict immunotherapy response	[253]
Overcoming treatment resistance	Brain cancer, colon cancer, ovarian cancer, breast cancer	Gene expression profiles	Machine learning	Identify drug resistance signatures	[254]
Overcoming treatment resistance	Breast cancer	Drug response data	Artificial neural network	Identify genetic mutations associated with drug resistance	[255]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Overcoming treatment resistance	Bladder cancer	Multiomics data	Machine learning	Identify drug resistance signatures	[256]
Overcoming treatment resistance	Lung cancer	CT images	Convolutional neural network	Predict *EGFR* mutation relevant to drug resistance	[257]
Overcoming treatment resistance	Nasopharyngeal carcinoma	Radiomics, plasma metabolomics profiles	XGBoost	Reveal the relationship between dysregulation of plasma lipoprotein and chemotherapy resistance	[258]
Overcoming treatment resistance	Breast cancer	Gene expression profiles	Transformer	Identify key genes (*SNHG25* and *SNCG*) associated with chemotherapy resistance	[259]
Overcoming treatment resistance	Colorectal cancer	Gene expression profiles	Machine learning	Identify the key gene (*EIF5A*) associated with radioresistance	[260]
Overcoming treatment resistance	Gastric cancer	Gene expression data	Machine learning	Identify key genes (*CDH6*, *EGFLAM*, and *RASGRF2*) associated with immunotherapy resistance	[261]
Overcoming treatment resistance	Esophageal squamous cell carcinoma	Proteomic data	Support vector machine, random forest	Identify critical spatial protein features linked to immunotherapy resistance	[262]
Overcoming treatment resistance	Breast cancer	Transcriptomic data	K-nearest neighbor	Identify the association between RTK and ER oncogenic pathways and endocrine resistance	[263]
Overcoming treatment resistance	Melanoma	Transcriptomic data	Machine learning	Identify the involvement of chemotaxis-associated ligand–receptor interactions in immunotherapy resistance	[264]
Overcoming treatment resistance	Gastric cancer	Multiomics data	Machine learning	Unveil the specific cellular interplay (TGFB1–HSPB1 and LTF–S100A14) underlying chemotherapy resistance	[265]
Overcoming treatment resistance	Ovarian cancer	Histopathological data	Machine learning	Reveal the relationship between intratumor heterogeneity and chemotherapy resistance	[266]
Overcoming treatment resistance	Gastric cancer	Transcriptomic data	Support vector machine, random forest, neural network, XGBoost, decision tree, K-nearest neighbor	Reveal the relationship between tumor microenvironment cellular heterogeneity and chemotherapy resistance	[267]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Overcoming treatment resistance	Hepatocellular carcinoma	Transcriptomic data	Graph neural network	Identify potential therapeutic candidates	[268]
Overcoming treatment resistance	Melanoma, lung cancer	Genomic and transcriptomic data	Machine learning	Identify immune inhibitory receptors as potential therapeutic targets	[269]
Overcoming treatment resistance	Lung adenocarcinoma	Transcriptomic data	Deep neural network	Identify ABCC2 as a promising therapeutic target	[270]
Overcoming treatment resistance	Colorectal cancer	Metabolomics data	Machine learning	Identify hexokinase as a promising therapeutic target	[271]
Overcoming treatment resistance	Acute myeloid leukemia	Transcriptomics data, single-agent response profiles	XGBoost	Identify personalized regimens to overcome treatment resistance	[272]
Overcoming treatment resistance	Gastric cancer	Multiomics data	Transformer	Accurately predict treatment response	[273]
Toxicity management and survivorship	Different types of cancer	Clinical, laboratory, and echocardiographic data	Machine learning	Predict chemotherapy-induced cardiotoxicity	[274]
Toxicity management and survivorship	Breast cancer	Clinical and demographic data	Cox regression, XGBoost	Predict chemotherapy-induced toxicity	[275]
Toxicity management and survivorship	Renal cell carcinoma, colorectal cancer, gastrointestinal stromal tumor, thyroid cancer, soft tissue sarcoma	Clinical data	ResNet, XGBoost	Predict chemotherapy-induced hand-foot skin reaction	[276]
Toxicity management and survivorship	Colorectal cancer	Clinical data	Random forest	Predict chemotherapy-induced toxicity	[277]
Toxicity management and survivorship	Lung cancer, liver cancer	Medical records	XGBoost	Predict immunotherapy-induced hypothyroidism	[278]
Toxicity management and survivorship	Melanoma, lung cancer, genitourinary cancer	CT images	Convolutional neural network, transformer	Predict immunotherapy-induced pneumonitis	[279]
Toxicity management and survivorship	Lung cancer	CT and radiation dose images	ResNet	Predict radiation pneumonitis	[280]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Toxicity management and survivorship	Nasopharyngeal carcinoma	Clinical data	Machine learning	Predict radiation-induced oral mucositis	[281]
Toxicity management and survivorship	Breast cancer	Clinical data	Neural network, random forest, XGBoost, logistic regression	Predict radiation dermatitis	[282]
Toxicity management and survivorship	Rectal cancer	MRI images	Vision transformer, convolutional neural network	Predict overall survival with a concordance index of 0.82 and a hazard ratio of 2.3 in the external test set	[283]
Toxicity management and survivorship	Colorectal cancer	Histopathology images	Convolutional neural network	Predict 5-year survival with AUCs of 0.70 and 0.69 for two validation datasets	[284]
Toxicity management and survivorship	Colorectal cancer	Histopathology images	Long short-term memory	Achieve a hazard ratio of 2.3 and an AUC of 0.69 for outcome prediction	[285]
Toxicity management and survivorship	Head and neck cancer, colorectal cancer	Histopathology images	Graph neural network	Show high accuracy in predicting patient outcome	[286]
Toxicity management and survivorship	Colorectal cancer	Immune cell patterns	Deep learning	Show high prognostic capabilities	[287]
Toxicity management and survivorship	Ocular cancer, rectal cancer	Electronic health records	Explainable artificial intelligence	Determine the prognostic contribution of clinical markers	[288]
Toxicity management and survivorship	Breast cancer	Clinicopathological and MRI characteristics	XGBoost	Achieve AUC values of 0.805, 0.803, and 0.818 for prognostic prediction in three cohorts	[289]
Toxicity management and survivorship	Breast cancer	Mitochondrial and lysosomal gene expression data	Coxboost, support vector machine	Achieve AUC values exceeding 0.647 for prognostic prediction in various datasets	[290]
Toxicity management and survivorship	Breast cancer	TCGA, METABRIC and GEO datasets	Machine learning (random survival forest, elastic network, CoxBoost, and support vector machine)	Reach an average concordance index of 0.79 for prognostic prediction	[291]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Toxicity management and survivorship	Melanoma	Single cell transcriptome data and medical variables	Machine learning (LightGBM, CatBoost, random forest, and ensemble learning)	Achieve AUC values of 0.9957, 0.9939, 0.9681, and 0.9975 for outcome prediction in the testing cohort	[292]
Toxicity management and survivorship	Lung adenocarcinoma	CT and histopathology images	Support vector machine	Achieve concordance indices of 0.744, 0.719, and 0.711 for the prediction of disease-free survival in one training dataset and two testing datasets	[293]
Toxicity management and survivorship	Lung cancer	Radiomics data and clinical parameters	Machine learning	Demonstrate superior performance in overall survival prediction, with time-dependent AUC values above 0.75 and concordance indices of 0.87 and 0.76 for the training and testing sets	[294]
Toxicity management and survivorship	Hepatocellular carcinoma	Demographic, clinical, pathological, and laboratory data	Machine learning (K-nearest neighbor and support vector machine)	Reach accuracy rates above 87% for 3-year overall survival prediction	[295]
Toxicity management and survivorship	Pancreatic ductal adenocarcinoma	Serum biomarker data and prognosis information	Deep learning	Excel in prognosis prediction with concordance indices of 0.738 and 0.724 on training and validation sets	[296]
Toxicity management and survivorship	Bladder cancer	Clinical and histopathology data	LightGBM	Show good performance in predicting 5-year cancer-specific mortality with concordance indices of 0.723 and 0.791 in internal and external validation sets	[297]
Toxicity management and survivorship	Bladder cancer	Clinical data	Random survival forest, elastic network	Achieve concordance indices of 0.683, 0.688, and 0.666 for prognostic prediction in training, internal and external test sets	[298]
Toxicity management and survivorship	Breast cancer	Pathomics data	Weakly supervised learning	Achieve a concordance index of 0.710 for survival prediction	[299]
Toxicity management and survivorship	Hepatocellular carcinoma	Contrast-enhanced MRI and pathologic images	Convolutional neural network, densely connected convolutional network, vision transformer, swin transformer	Achieve time-dependent AUC values of 0.83, 0.81, and 0.78 for 3-year progression-free survival in training, internal, and external test sets	[300]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Toxicity management and survivorship	Papillary thyroid carcinoma	Preoperative ultrasound images	Deep learning	Efficiently predict disease-free survival with a hazard ratio of 16.49	[301]
Toxicity management and survivorship	Castration-resistant prostate cancer	Digital histopathological images and clinical parameters	Deep learning	Achieve significant correlations between AI-based risk score and shorter metastasis-free survival (hazard ratio, 1.72; $p < 0.005$) and overall survival (hazard ratio, 1.41; $p = 0.02$)	[302]
Toxicity management and survivorship	Prostate cancer	Digitized histopathology images and clinical variables	Multimodal artificial intelligence	Achieve a hazard ratio of 6.46 and a 95% confidence interval of 1.44–28.9 for overall survival prediction	[303]
Toxicity management and survivorship	Breast cancer	Gene expression and survival data, RNA-binding protein information	Machine learning	Show better prognostic performance than 106 established signatures	[304]
Toxicity management and survivorship	Esophageal cancer	Transcriptome data	Machine learning	Exhibit good prognostic performance with AUC values exceeding 0.7 in two external validation sets	[305]
Toxicity management and survivorship	Colorectal cancer	Single cell RNA sequencing data, spatial transcriptome data	Machine learning (LASSO regression and random survival forest)	Exhibit good prognostic performance with an average concordance index of 0.729	[306]
Toxicity management and survivorship	Colorectal cancer	Gene expression data	Machine learning	Achieve AUC values exceeding 0.6132 in predicting 1-, 2-, and 3-year survival	[307]
Toxicity management and survivorship	Gastric cancer	Transcriptomic and clinical characteristic data	Machine learning	Show good prognostic performance with a hazard ratio of 1.145	[308]
Toxicity management and survivorship	Hepatocellular carcinoma	Transcriptomic and clinical data	Machine learning	Outperform 22 existing models in predicting patient outcomes	[309]
Toxicity management and survivorship	Pancreatic cancer	Gene expression data	Machine learning	Achieve AUC values exceeding 0.566 in predicting 1-, 3-, and 5-year survival	[310]
Toxicity management and survivorship	Ovarian cancer	Transcriptomic and clinical data	Machine learning	Exhibit reliable predictive potential in predicting 1- (AUC = 0.702), 3- (AUC = 0.640), and 5-year survival (AUC = 0.618)	[311]

(Continues)

TABLE 3 | (Continued)

Potential application	Cancer type	Data used for analysis	AI algorithm	Algorithm performance	References
Toxicity management and survivorship	Prostate cancer	mRNA microarray data	Machine learning	Exhibit excellent predictive performance in predicting 1- (AUC = 0.754), 3- (AUC = 0.776), and 5-year overall survival (AUC = 0.706)	[312]

nasopharyngeal carcinoma (NPC) [258], breast cancer [259], CRC [260], gastric cancer [261], and ESCC [262]. Machine learning algorithms provided new insights into cell pathways underlying treatment resistance in breast cancer [263], melanoma [264], and gastric cancer [265]. The correlation between tumor heterogeneity and cancer treatment resistance was also explored through employment of machine learning-based platforms [266, 267]. Furthermore, AI techniques have the potential to discover novel therapeutic targets to overcome treatment resistance. Graph neural network was used to predict the interactions between genes and chemotherapeutic agents and identify potential therapeutic candidates for HCC intervention [268]. A machine learning-based bioinformatics pipeline identified immune inhibitory receptors as prospective therapeutic targets for cancer immunotherapy [269]. Integrating transcriptomics data with machine learning identified the ferroptosis regulator ABCC2 as a potential therapeutic target to overcome cisplatin resistance in lung adenocarcinoma [270]. A machine learning-based metabolic modeling approach screened hexokinase as a contributing factor to drug resistance in CRC and as a promising target [271]. In addition, AI offers a rational means to customize appropriate regimens to reduce treatment resistance. A machine learning-based computation model identified personalized drug combination strategies that effectively targeted treatment-resistant cancer cells in patients with acute myeloid leukemia [272]. A transformer-based DL model that incorporated multimodal data was likely to improve the management of patients with HER2-positive gastric cancer by assessing treatment response [273]. Collectively, AI techniques are expected to revolutionize cancer drug resistance research through prediction of resistance patterns, interpretation of underlying molecular mechanisms, discovery of novel therapeutic targets, and optimization of anticancer treatment strategies.

4.4 | Toxicity Management and Survivorship

AI technology is advancing toxicity assessments in anticancer therapies. Machine learning algorithms predicted chemotherapy-induced toxicity, such as cardiotoxicity and hand-foot skin reaction, and guided treatment decisions for cancer patients [274–277]. AI algorithms, including XGBoost and CNN, predicted the likelihood of immune checkpoint inhibitor-induced hypothyroidism and pneumonitis in cancer patients, providing guidance for risk management and individualized therapy [278, 279]. AI techniques could also predict the occurrence of radiation-induced oral mucositis, pneumonitis, and dermatitis in cancer patients [280–282]. AI-powered timely identification of patients experiencing adverse events enables clinicians to customize treatment strategies and reduce the risk of toxicity.

AI can assess and interpret "multifactor" data from patient evaluations, offering more accurate insights into patient survival and prognosis [318]. Prognostic AI models for cancer have been developed across multiple data modalities, encompassing multiplex imaging, histopathology, and clinical characteristics [283–287]. XAI decoded the outcome of solid cancer patients based on clinical markers derived from multimodal real-word data including clinical records, image-derived body composition, and mutational tumor profiles [288]. XAI determined the prognostic contribution of each marker at the patient level and revealed prognostic interactions between markers. Machine learning platforms, including XGBoost, survival-SVM, random survival forest, and CoxBoost, have shown prognostic potential for patients with breast cancer [289–291], melanoma [292], lung cancer [293, 294], HCC [295], and PDAC [296]. Particularly, two machine learning models (LightGBM and RSF+Enet[alpha = 0.8] model) integrating clinical data exhibited superior performance in prognostic prediction compared with existing models in bladder cancer [297, 298]. DL models incorporating radiomics/radiopathomics could effectively forecast patient outcomes in breast cancer [299], HCC [300], papillary thyroid carcinoma (PTC) [301], and prostate cancer [302, 303], enabling data-driven postoperative treatment planning. Further work is necessary to assess the clinical utility of these AI-assisted prognostic models. The features used by AI models to infer clinical outcomes should be clearly interpreted.

In addition to directly predicting prognosis, many studies have explored AI's ability to identify predictive biomarkers for patient outcomes. Reportedly, machine learning-assisted prognostic models integrating cancer-associated genes/noncoding RNAs were established for outcome prediction in breast cancer [304], esophageal cancer [305], CRC [306, 307], gastric cancer [308], HCC [309], pancreatic cancer [310], ovarian cancer [311], and prostate cancer [312]. Collectively, AI may be a promising option for improving the prognosis and quality of life of cancer patients. Integration of AI techniques into cancer prognosis would contribute to more effective cancer treatments. However, clinical trials comparing AI programs with standard prognostic models are imperative to assess their real-world value in cancer care.

5 | Translational Evidence: From Bench to Real-World Impact

AI approaches are transforming the integration and interpretation of real-world oncological data and are starting to influence various aspects of clinical cancer management [319]. Image-based AI frameworks facilitated the early diagnosis of breast cancer in the mammography screening [320], brain tumors using MRI images [321], skin cancer using dermoscopy [322], and colon cancer through histopathological images [323]. Notably, AI-based diagnostic tools assist in alleviating the workload of screen-reading without increasing the number of false positives. Previous studies demonstrated the high accuracy of AI prediction models in automated cancer classification in the real-world context [324, 325]. Importantly, AI tools could improve decision-making processes and symptom management for cancer patients [326, 327]. They also showed outstanding performance in predicting treatment response and prognosis in cancer patients by leveraging digital histopathological data [328–331]. In the aforementioned studies, ChatGPT, CNN, and ensemble models were used for data analysis. ChatGPT can streamline the detection workflows, reduce errors, and improve consistency in pathology assessments [332]. However, its ability to handle images and other nontext data are limited. Since images and sound data are critical inputs in clinical settings, GhatGPT cannot directly process these medical data to generate diagnostic recommendations. CNN shows human-level performance in computer vision tasks; however, it cannot encode spatial information in the inputs, such as orientation, position, and size [65]. Moreover, CNN requires large training data and exhibits low performance in overlapped images. Ensemble machine learning methods leverage computational functions to combine diverse learning models, which mitigates the limitations of individual algorithms [333]. The drawbacks of ensemble models include high computational costs, high bias, vulnerability to overfitting, and difficulty in model interpretability.

AI has the potential to revolutionize the way by which cancer diagnoses and treatment recommendations are delivered to patients. Nevertheless, implementing AI in clinical oncology faces numerous challenges [334]. It is uncertain whether patients prefer AI-based diagnoses to those from doctors. In automated diagnostic settings, it remains unclear whether patients seek comfort and clarification from nonexpert operators. Developing oncological AI platforms requires accessing patient data, which raises questions about data security and privacy protection. Furthermore, patients may lack trust in AI systems to handle their diagnosis and treatment information appropriately. All these issues should be resolved before the widespread application of AI in clinical oncology.

5.1 | Key Preclinical Validation Studies

It is well established that successful clinical trials are built upon thorough preclinical validation studies. The efficacy and reliability of AI algorithms in cancer care are evaluated in preclinical studies that involve large-scale biomedical datasets, medical imaging, and clinical information. For instance, AIEgenDeep, a DL algorithm-driven model, showed significant accuracy in identifying cancer cell morphology and differentiating between healthy cells and cancer cells [335]. This tool might facilitate early cancer diagnosis and improve clinical outcomes in cancer patients. DL-based semantic segmentation models could detected head and neck tumor from the multimodal data with high sensitivity and specificity in a preclinical study [336]. A novel semi-automatic machine learning approach accurately detected brain metastatic lesions and quantified metastatic burden in preclinical models [337]. Machine learning algorithms (e.g., SVM and mRMR) were efficient in assessing breast cancer progression through photoacoustic spectroscopy in a mouse model [338]. A transcriptome-based tool (Pancreas-View) was developed using preclinical models and random forest approach [339]. This tool could accurately predict patient sensitivity to adjuvant chemotherapy in PDAC patients. Machine learning algorithms, including ANN, SVM, and random forest, efficiently evaluated the predictive potential of circulating biomarkers for metastatic outcomes in breast cancer animal models following neoadjuvant treatment [340]. These preclinical models may help identify treatment failures that should be avoided in clinical practice.

Preclinical AI studies not only pave the way for subsequent clinical trials but also foster the effective integration of AI into clinical oncology workflows. It should be noted that preclinical studies confront many challenges. The quality and integrity of data remarkably affect the performance of AI models. The availability of high-quality datasets are essential to maximize data value. Moreover, the inherent "black-box" nature of AI algorithms makes their decision-making process opaque, raising concerns about reliability in clinical settings. Consequently, it is necessary to gain a better understanding of the decision-making basis of AI models and increase clinicians' trust in AI tools. By overcoming current challenges, AI is expected to play an increasingly significant role in the field of clinical cancer.

5.2 | Landmark Clinical Trials

Clinical trials serve to assess the efficacy of AI technologies in cancer detection and explore their potential integration into clinical decision-making processes (Table 4). In randomized controlled trials, endoscopy-guided AI detection systems (e.g., CADe, CADopt, EW10-EC02, LCA, and CNN) improved the diagnosis of adenoma [341–346] and esophageal cancer [347, 348]. AI-powered image analysis tools efficiently detected glioma [349], breast cancer [350], and prostate cancer [351, 352] using MRI data. An AI-based clinical decision support tool achieved high diagnostic accuracy in detecting cutaneous melanoma through dermoscopic image analysis, assisting physicians in detecting skin lesions for melanoma [353]. Although many AI tools show promising utility, most of them remain insufficiently developed for clinical use. Notably, several AI systems did not result in improved cancer detection [354–356]. Therefore, AI-driven clinical tools must undergo thorough training and rigorous validation of their universality and robustness before being adopted into patient clinical care.

The clinical utility of AI algorithms in monitoring cancer progression has been explored. For example, PCMM-Net was a DL framework that integrated prior clinic and radiological features of accurate lymphovascular invasion (LVI) prediction in breast cancer [357]. In a study involving 341 breast cancer

TABLE 4 | Summary of clinical trials evaluating the effect and performance of artificial intelligence technologies in oncology.

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Single-center pragmatic randomized controlled trial	NCT05963724	Not applicable	Completed	Colorectal cancer	1100	Evaluate the sensitivity of computer-aided detection compared to standard colonoscopy in detecting colon polyps	Cancer detection using histopathologic findings	CADe	Have a higher adenoma detection rate (42.5%) than the traditional colonoscopy (34.4%)	[341]
Randomized controlled trial	NCT05236790	Phase 2	Completed	Colorectal cancer	467	Assess the performance of the AI system for detection and classification of polyp histology	Cancer detection using histopathologic findings	CADe	Have a higher adenoma detection rate (49.3%) than the standard colonoscopy (38.2%)	[342]
Three-arm prospective randomized colonoscopy study	NCT05133544	Not applicable	Completed	Colorectal cancer	682	Compare the adenoma detection rates among endocuff-AI-assisted colonoscopy, AI-assisted colonscopy, and conventional colonoscopy	Cancer detection using histopathologic findings	Endocuff-AI	Have a higher adenoma detection rate (58.7%) than AI alone (53.8%)	[343]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Multicenter, prospective randomized trial	NCT04979962	Not applicable	Completed	Colorectal cancer	1031	Investigate the superiority of colorectal polyp detection using computer-assisted colonoscopy compared to conventional colonoscopy	Cancer detection using histopathologic findings	CAD-EYE	Lead to a higher adenoma per colonoscopy (0.99) compared with conventional colonoscopy (0.85)	[344]
Multicenter, randomized, noninferiority tandem study	NCT05323279	Not applicable	Completed	Colorectal cancer	685	Assess the effects of an AI system on colonoscopy quality of novice endoscopists	Cancer detection using histopathologic findings	AI-assisted system	Have a lower adenoma miss rate (18.82%) than the control novice group (43.69%)	[345]
Randomized trial	Not applicable	Not applicable	Completed	Colorectal cancer	800	Compare adenoma detection rate between linked-color imaging (LCI) with AI and LCI alone	Cancer detection using histopathologic findings	LCA	Show a higher adenoma detection rate (58.8%) than the linked-color imaging method (43.5%)	[346]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Multicenter, tandem, double-blind, randomized controlled trial	ChiCTR2100052116	Not applicable	Completed	Oesophageal squamous cell carcinoma	5934	Assess the auxiliary diagnostic performance of the AI system in a real clinical setting	Cancer detection using histopathologic findings	AI-assisted endoscopy	Show a lower per-patient miss rate (1.9%) than the routine method using a computerized random number generator	[347]
Prospective, randomized controlled trial	ChiCTR2100044126	Not applicable	Completed	Esophageal squamous cell carcinoma	3117	Assess the efficacy of CNN-based system in improving cancer detection rate in clinical practice	Cancer detection using histopathologic findings	CNN-assisted endoscopy	Have a higher cancer detection rate (1.8%) than unassisted endoscopy (0.9%)	[348]
Randomized controlled trial	Not applicable	Not applicable	Completed	Glioma	146	Investigate the application of machine learning-based MRI radiomics in predicting lower-grade glioma	Cancer detection using MRI radiomics	Machine learning	Show an excellent performance with an AUC value of 0.925 and accuracy of 0.882 in the training cohort and an AUC value of 0.886 and accuracy of 0.864 in the testing cohort	[349]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Randomized controlled trial	NCT04832594	Not applicable	Completed	Breast cancer	559	Determine the ability of an AI pipeline to identify patients who would benefit from supplemental MRI	Cancer detection using MRI images	AISmart-Density	Show higher efficiency in terms of cancers detected per 1,000 MRI examinations compared with traditional breast density measures (64 versus 16.5)	[350]
International, paired, non-inferiority, confirmatory study	NCT05489341	Not applicable	Completed	Prostate cancer	9,129	Investigate the performance of the AI system at detecting clinically significant prostate cancer on MRI in comparison with radiologists	Cancer detection using MRI images	PI-CAI	Show better predictive performance (AUC=0.91) than the pool of 62 radiologists (AUC=0.86)	[351]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Randomized controlled trial	NCT06362291	Not applicable	Completed	Prostate cancer	380	Compare the cancer detection rates of AI-cTB and routine cTB	Cancer detection using MRI images	AI-cTB	Have a higher cancer detection rate (58.64%) than the cognitive fusion MRI-guided targeted biopsy (46.56%)	[352]
Prospective real-life clinical trial	NCT05172232	Not applicable	Completed	Cutaneous melanoma	228	Determine the diagnostic performance of an AI-based clinical decision support tool for cutaneous melanoma detection	Cancer detection using histopathologic findings	AI-based clinical decision support tool	Achieve an AUC of 0.960, a sensitivity of 95.2% and a specificity of 84.5%	[353]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
International, multicenter, randomized controlled trial	NCT04909671	Not applicable	Completed	Colorectal cancer	456	Evaluate the performance of AI-assisted colonoscopy in cancer detection	Cancer detection using histopathologic findings	CADe	Achieve comparable efficiency to white light endoscopy	[354]
Prospective, single-center, exploratory, and randomized controlled trial	Not applicable	Not applicable	Completed	Esophageal squamous cell carcinoma	320	Determine the ability of AI in improving cancer detection in a clinical setting	Cancer detection using histopathologic findings	AI diagnostic support system	Achieve a cancer detection rate (47%) comparable to that of endoscopists (45%)	[355]
Prospective, randomized controlled trial	NCT05178095	Not applicable	Completed	Colorectal cancer	286	Evaluate adenoma and polyp detection rate of AI-aided colonoscopy	Cancer detection using histopathologic findings	AI-C	Achieve a cancer detection rate (41%) comparable to that of conventional colonoscopy (42%)	[356]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Randomized controlled trial	Not applicable	Not applicable	Completed	Breast cancer	341	Assess the performance of a deep learning framework in predicting lymphovascular invasion	Cancer progression prediction using MRI images and histopathologic findings	MM-Net, PCMM-Net	Achieve AUC values of 0.774 and 0.843	[357]
Non-randomized, single-center clinical trial	14323711	Not applicable	Completed	Breast cancer	190	Assess the efficacy of an AI-assisted workflow for detecting cancer metastases in sentinel lymph nodes	Cancer progression prediction using histopathologic findings	Visiopharm	Lead to cost and time savings and up to 30% improved sensitivity in the detection of cancer metastases	[358]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Multi-center, randomized crossover, multi-reader evaluation study	Not applicable	Not applicable	Completed	Breast cancer, lung cancer, melanoma, colorectal cancer	50	Evaluate the performance of an AI system for brain metastasis segmentation	Cancer progression prediction using MRI images	BMSS	Yield a median Dice similarity coefficient of 0.91 in brain metastasis delineation	[359]
Randomized controlled trial	Not applicable	Not applicable	Completed	Lung cancer	141	Assess the efficacy of a machine learning model in differentiating between bone metastases and benign bone lesions	Cancer progression prediction using SPECT/CT images	LASSO regression, support vector machine	Achieve AUC values of 0.939 and 0.925 in differentiating between bone metastases and benign bone lesions for the training and testing set	[360]
Randomized controlled trial	Not applicable	Not applicable	Completed	Prostate cancer	211	Evaluate the efficacy of a deep learning-based model in early diagnosis of bone metastasis	Cancer progression prediction using MRI images and pathological features	Deep transfer learning	Yield AUC values of 0.89 and 0.85 in predicting the risk of bone metastases for the training and validation sets	[361]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Prospective multicenter study	ChiCTR1900025592	Not applicable	Completed	Papillary thyroid carcinoma	488	Determine the performance of an AI-assisted method for predicting cervical lymph node metastasis	Cancer progression prediction using ultrasound videos	MMD-DL	Achieve AUC values of 0.85 and 0.81 in the test and validation cohorts; improve the average diagnostic accuracy and sensitivity in predicting cervical lymph node metastasis	[362]
Randomized controlled trial	Not applicable	Not applicable	Completed	Ovarian cancer	849	Assess the accuracy of a deep learning radiomics nomogram for predicting the malignant risk of cancer	Cancer progression prediction using ultrasound imaging	DLR_ Nomogram	Show superior performance in predicting the risk of cancer malignancy, with AUC values of 0.985 and 0.928 for the training and testing sets	[363]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Randomized controlled trial	Not applicable	Not applicable	Completed	Nasopharyngeal carcinoma	219	Assess the performance of a machine learning approach in predicting radiation-induced hypothyroidism	Treatment response prediction using clinical features, dose-volume histograms, radiomics, and dosiomics features	LASSO regression, XGBoost	Achieve an AUC value of 0.842 in the test cohort; have superior clinical utility within the threshold probability range of 1% to 79%	[364]
Phase 2 clinical trial	Not applicable	Not applicable	Completed	Non-small cell lung cancer	45	Evaluate the effectiveness of a deep learning model in predicting therapeutic response to neoadjuvant immunotherapy	Treatment response prediction using CT images	Deep learning	Show superior predictive performance with an AUC value of 0.820	[365]

(Continues)

TABLE 4 | (Continued)

Type of study	Clinical trial ID	Phase	Status	Cancer type	Number of subjects	Objectives	AI task	AI method	Preliminary findings	Reference
Randomized controlled trial	Not applicable	Not applicable	Completed	Hepatocellular carcinoma	114	Explore the performance of deep learning (convolutional neural networks) in predicting overall survival	Survival outcome prediction using CT images and clinical parameters	Clinical cox-regression model	Show excellent performance in overall survival prediction with a concordance index of 0.74	[366]
TPExtreme clinical trial	NCT02268695	Phase 2	Completed	Head and neck squamous cell carcinoma	526	Compare the predictive power of machine learning models versus conventional survival models	Survival outcome prediction using on-treatment tumor kinetics and clinical parameters	Random survival forest	Exhibit superior predictive capability with a concordance index of 0.63	[367]

patients, this approach improved the accuracy of LVI prediction. Nonrandomized clinical trials showed the efficiency of DL-aided workflows for detecting breast cancer metastases by analyzing digital pathological images [358] and contrast-enhanced MRI [359]. Radiomics-based AI tools could accurately predict the malignant risk of ovarian tumors [363], and identify bone metastases in lung cancer [360] and prostate cancer [361]. AI trained using thyroid ultrasound (US) offered precise and reproducible predictions of cervical lymph node metastasis in PTC patients, potentially serving as a valuable assisting tool to improve the diagnostic performance of US radiologists [362]. Moreover, AI-based models have also been applied to evaluate the efficacy of anticancer treatments and predict the prognosis of cancer patients. A machine learning-based predictive model that integrated clinical features, dose-volume histograms, radiomics, and dosiomics features was developed to predict radiation-induced hypothyroidism (RIHT) in NPC patients undergoing tomotherapy [364]. As a result, the combined model showed superior performance in identifying potential RIHT patients and could aid in implementing preventative measures. An integrated model that combined CT-based DL scores, blood-based tumor mutational burden, and clinical parameters had the potential to predict tumor response to neoadjuvant chemoimmunotherapy in NSCLC patients, thus helping modify therapeutic regimens for patients [365]. CNN algorithms demonstrated greater prognostic potential for predicting overall survival in HCC patients compared with conventional radiomics approaches [366]. A machine learning model leveraging tumor kinetics demonstrated superior performance in predicting overall survival for patients with head and neck squamous cell carcinoma [367]. AI-based systems have the potential to improve the evaluation of cancer treatment effectiveness.

Collectively, these trials not only verify the accuracy of AI-assisted diagnosis but also demonstrate its impact on patient management, including treatment plan selection, prognosis assessment, and follow-up strategies. Compared with conventional diagnostic methods, AI provides superior efficiency, reduced misdiagnosis rates, and improved treatment strategies. Nevertheless, despite the considerable potential of AI in cancer management, clinical trials still face many challenges, including data privacy concerns, algorithm interpretability, and clinician trust barriers in AI-assisted decision-making. Therefore, further study should strike a balance between advancing AI clinical applications and safeguarding patient data.

5.3 | Real-World Evidence: Effectiveness Validation in EHRs/Registry Databases

Real-world evidence (RWE) studies mainly focus on gathering and analyzing observational data, providing insights into cancer treatment outcomes in routine practice. RWE resources include EHRs and patient registries. EHRs compile a wide array of real clinical data from patients, covering medical histories and treatment workflows. AI techniques, such as NLP and machine learning, have been applied to identify and retrieve important information from unstructured EHR data for scalable and efficient generation of RWE [368]. Based on unstructured EHR data, NLP-based oncological frameworks identified treatment-associated adverse events [369], optimized patient clinical management [370, 371], predicted treatment outcomes [372–374], and classified cancer recurrence status in clinical practice [375]. Machine learning models evaluated optimal treatment regimens and classified postoperative status in patients with lung cancer by analyzing real-world patient data [376, 377]. Patient registry databases collected from various institutions become a value resource for generating RWE. Machine learning-based models, including Bayesian and XGBoost, accurately predicted the effects of different treatments on patient survival outcomes [378], identified typical treatment sequences [379], and assessed the effects of pre-existing chronic conditions on cancer-directed treatments based on cancer registry databases [380]. RWE provides a robust foundation for advancing cancer care and guiding population-level decision making. High-quality clinical data are critical for generating credible RWE. AI techniques have the ability to handle large-scale, heterogeneous real-world data. To ensure generalizability and avoid overfitting, cross-database validation and longitudinal assessments are urgently needed [381]. With increasing use of RWE in clinical decision-making, cross-sector collaboration is essential to establish data quality standards, address ethical issues, and ensure the long-term efficiency of AI models.

5.4 | Health Economic Evaluation: Cost Effectiveness of AI in Reducing Misdiagnosis/Diagnostic Delays

The employment of AI technology not only improves the efficiency of clinical decision-making but may also significantly impact health economic evaluations [382]. AI systems can provide more accurate diagnoses and personalized treatment plans by analyzing a large amount of medical data, thereby reducing misdiagnosis rates and treatment costs. By detecting cancer rapidly, AI can facilitate early-stage treatment for patients, thereby improving survival rates and reducing the economic burden associated with more advanced treatments [383]. However, the widespread application of AI in cancer care also faces some economic challenges. The development and implementation of AI technology necessitate substantial investment, including hardware facilities, software development, and the training of relevant personnel [384]. These initial investments may put pressure on the financial situation of medical institutions, especially in resource-limited areas. The effectiveness and safety of AI systems need to be verified through strict clinical trials to ensure their reliability in actual applications, and this process requires a great deal of time and money.

In addition, the widespread adoption of AI in healthcare could result in the redistribution of medical resources and affect the economic model of traditional medical services. Medical insurance policies should be adjusted to adapt to the new challenges and opportunities presented by AI technology. To ensure the sustainability and effectiveness of AI technology in cancer management, it is necessary to comprehensively evaluate its cost effectiveness, long-term economic impact, and its ability to improve patient health outcomes.

6 | Clinical Implementation: Roadblocks and Pathways

6.1 | Technical Limitations

The application of AI in clinical oncology faces two major technical limitations: data scarcity and algorithmic bias [385]. The data scarcity issue is primarily manifested by the insufficiency of high-quality labeled data. The diversity and complexity of cancer pose significant challenges in obtaining sufficient clinical data, especially for rare cancer types [386]. The insufficient sample size not only hampers the training efficacy of AI models but may also lead to inadequate generalization in practical applications, thereby compromising the accuracy of cancer diagnosis and the effectiveness of cancer management. Algorithmic bias occurs when AI models are affected by inherent biases present in the training data during the learning process [387]. These biases can originate from various sources, including data collection methods, sample selection bias, or inadequate feature selection. For instance, if the training data mainly originate from a specific population, the performance of AI algorithms may significantly deteriorate when applied to other populations [388]. Moreover, the design and selection of the AI algorithm itself may also introduce bias, causing an over-reliance on or neglect of certain features, which in turn affects the final decision-making outcome [389]. Hence, addressing the issues of data scarcity and algorithmic bias is the key to enhancing the effectiveness of AI in cancer diagnosis and management. Future research should concentrate on building more comprehensive and diverse datasets, along with developing more robust algorithms to minimize the impact of bias on model performance. Through these endeavors, the full potential of AI technology can be better realized.

6.2 | Clinical Integration Barriers

The gradual integration of AI technology into clinical cancer management faces numerous obstacles. Among these, workflow integration and physicians' acceptance being particularly crucial [390]. The successful implementation of AI systems in healthcare requires their smooth integration into current medical workflows. Many hospitals and clinics have established multidepartmental workflows that involve collaboration and information sharing. Introducing AI technology may need significant adjustments to existing workflows. This involves not only technical integration but also considerations such as personal training and system compatibility. If effective integration is not achieved, it will be challenging to fully harness the potential of AI, and it may even lead to a decline in medical efficiency. Physicians' acceptance of AI technology directly affects its clinical application [27]. While AI excels in data analysis and decision-support, many physicians remain skeptical about its reliability and accuracy, especially regarding diagnostic accuracy and the potential to overlook nuanced patient symptoms. Some physicians are concerned that the growing dependence on AI could undermine their professional judgment, resulting in a reduced sense of professional security as their role in patient care evolves [35]. Some, on the other hand, see AI as a valuable tool that can augment human capabilities and lead to better patient outcomes. Education and training programs could help address these concerns by emphasizing the complementary roles of AI and human physicians. Additionally, physicians' limited familiarity with AI technology hinders its practical application [391]. To overcome this, it is essential to enhance their awareness, build trust, and provide comprehensive training, thereby boosting their confidence in AI. In summary, addressing the challenges of workflow integration and gaining physicians' acceptance are crucial steps in AI-driven oncology. Through collaborative efforts from all stakeholders, we can ensure that AI technology fulfills its intended role in clinical practice.

6.3 | Ethical and Regulatory Quandaries

In the era of rapid AI technology advancement, cancer diagnosis and management are experiencing unprecedented opportunities, yet a series of ethical and regulatory issues have also been triggered. First, the transparency and interpretability of AI platforms present significant challenges [392]. Many DL models are considered "black boxes" due to their complex internal mechanisms [393]. These models operate as an ambiguous system where their internal workings are not easily accessible or interpretable. They make predictions according to input data, but the systems cannot offer any suitable explanations involved behind their decision-making processes. The lack of transparency may lead to decreased trust from physicians and patients in AI-generated recommendations. Therefore, improving the interpretability of AI models is crucial for physicians to comprehend and validate their diagnostic outcomes, addressing an urgent need in the field. XAI has emerged as a solution to enhance the transparency of AI models. XAI can provide clinicians with clear insights into how AI models arrive at their predictions by clarifying AI decision-making processes [394]. This bridges the gap between complex, opaque algorithms, and human comprehension, thus fostering greater trust in AI-assisted clinical decisions. The widespread application of XAI faces multiple challenges, with expanding XAI technology and adapting to everchanging regulations being key obstacles to overcome. Generative pretrained transformers (GPTs) can also be used to demystify black-box AI models. By training GPTs on extensive explanations of diverse problems and models, they can explain the fundamental algorithms, techniques, inputs and outputs of AI models, as well as how they are employed in decision making [395]. These explanations can shed light on the inner workings of black-box models and provide insight into how they make predictions. The quality and accuracy of the training data, as well as the complexity and feature of black-box models, may affect the precision of GPT-generated explanations [396]. Combining GPT-produced explanations with other techniques, including model-specific interpretability techniques and model-agnostic approaches, may further improve the interpretation of black-box AI models. Second, ensuring data privacy and security is a critical ethical consideration in the application of AI for cancer patients [397]. Patients' medical data often contain sensitive information, and maintaining their privacy during data collection and usage is a substantial challenge. With its clinical application in big data analysis, AI is expected to transform the future of oncology from diagnosis to treatment. However, it is necessary to address the ethical concerns regarding patient data usage. Furthermore, issues of data diversity and representativeness must be settled [398]. Biases in training data can lead to poor performance of AI in certain populations, thereby exacerbating health inequalities [399]. Last, the issues of liability

attribution is equally intricate [400]. In the context of AI-assisted diagnosis, determining liability in cases of misdiagnosis or missed diagnosis is a complex issue [401]. It is imperative to clarify who should be held accountable. Whether it is the company that develops the AI system, the medical institution that utilizes the system, or the physicians themselves. Real-time feedback systems should be implemented to offer clinicians positive or negative feedback on AI-assisted diagnostic decisions. This may enable clinicians to quickly make new and accurate diagnoses. Although AI holds great promise for cancer care, it is critically important to address its regulatory and ethical challenges thoroughly. This ensures the safe, effective, and fair application of AI technology in clinical oncology, thereby protecting patients' rights and interests within the legal and ethical framework.

7 | Future Frontiers: Next-Generation AI Oncology

7.1 | Technological Breakthroughs

In the realm of clinical oncology, causal inference and XAI have emerged as prominent research areas [402, 403]. Unlike correlation-based approaches, causal inference aims to uncover direct relationships between variables, which facilitates the understanding of cancer initiation and progression [404]. By developing causal models, researchers can identify potential biomarkers and therapeutic targets, thereby paving the way for personalized medicine. For example, causal inference methods can be used to evaluate the effects of different treatment strategies on patient outcomes, assisting physicians in devising more effective treatment plans. Concurrently, XAI provides clinicians with more transparent decision-support tools [405]. XAI technologies provide visualizations and explanations of the model's internal workings, thereby boosting physicians' trust in AI systems [406]. This is particularly important in the context of early cancer diagnosis and treatment planning, where swift and accurate decisions are imperative in complex clinical settings. Nevertheless, implementing causal inference and XAI comes with its own set of challenges. Causal inference heavily depends on large amounts of high-quality data, which can be difficult to acquire and integrate in cancer research [407]. Moreover, while XAI improves model transparency, striking a balance between model complexity and interpretability remains a pressing concern [408]. Therefore, these obstacles must be overcome to enable wider AI application in cancer care.

7.2 | Clinical Translation Accelerators

For AI technology, establishing a global cooperation framework is of great significance [409]. With the rapid advancement of AI technology, international collaboration in cancer research and management has become increasingly necessary. By sharing data, technology, and best practices, international cooperation can accelerate the application of AI in cancer, improving diagnostic accuracy and treatment effectiveness [410]. First, establishing transnational research networks can facilitate data integration and sharing [409]. Cancer patients in different regions exhibit significant differences in genetic backgrounds, environmental factors, and lifestyles. Global data sharing contributes to training AI algorithms, enabling them to have stronger generalization abilities [411]. Moreover, international cooperation can facilitate multicenter clinical trials to validate the applicability and efficacy of AI technology across diverse populations. Second, the global cooperation framework plays a pivotal role in fostering the standardization and regularization of AI technologies in cancer management [410]. Currently, there exists a spectrum of differences among nations regarding the application standards, ethical norms, and regulatory policies for AI technology. These disparities can lead to inconsistencies in the safety and efficacy of AI applications across borders, which may hinder the seamless integration and adoption of these technologies in healthcare systems worldwide [412]. Through coordinated efforts by international organizations, it is possible to formulate unified standards that ensure the safe and effectiveness of AI technology. Such standardized approaches not only enhance public trust in AI but also provide researchers with clear guidance, facilitating rapid development and wide acceptance of innovative solutions. Moreover, establishing standardized ethical norms is essential for addressing concerns related to data privacy, algorithmic bias, and the responsible use of AI in healthcare [389]. By promoting consensus on these issues, international cooperation can build a robust framework that safeguards both patients and researchers. Therefore, harmonizing AI standards through global collaboration is essential for advancing clinical cancer care. Finally, global cooperation can facilitate the widespread adoption of education and training in AI for cancer management [413]. Organizing international conferences, offering online courses, and establishing exchange programs facilitate knowledge sharing and learning among researchers and clinicians from various countries [414]. This exchange enhances their understanding and application of AI technology, which in turn strengthens the foundation for advancements in global cancer management.

7.3 | Policy and Equitable Implementation

Ensuring the equitable implementation of AI technology in oncology practice is of utmost importance [415]. To achieve this, policymakers must prioritize the accessibility of AI technology, especially in areas with limited resources. By investing in essential infrastructure and offering technical support, it can be ensured that all patients, regardless of their economic status, can benefit from AI-driven medical services [416]. Moreover, governments and medical institutions need to enhance their oversight of AI technology to guarantee its transparency and fairness in clinical settings [417]. This is crucial to prevent diagnostic disparities arising from algorithmic biases. Education and training are also key to achieving equitable implementation [418]. Medical professionals must be trained in AI technology to effectively collaborate with these tools, understand their limitations, and recognize potential risks. Simultaneously, public education plays a vital role in raising awareness about the role of AI in cancer management and fostering patients' trust in these new technologies [419]. Furthermore, policy recommendations should encompass financial support for research and development in AI technology, with a particular focus on ethnic minorities and low-income groups [420]. This will facilitate the development of AI algorithms that are diverse and representative, thereby improving their applicability across different

populations. By comprehensively considering the aforementioned factors, policymakers can promote the equitable implementation of AI technology in cancer management, ultimately leading to higher-quality medical services and better patient outcomes.

8 | Conclusions

AI has the potential to revolutionize cancer care by enhancing the accuracy of early detection, optimizing personalized treatment plans, and improving patient outcomes. However, the clinical application of AI still faces several challenges. The quality and diversity of data are pivotal factors affecting AI model performance. Insufficient high-quality labeled data can lead to inadequate generalization of AI models. The transparency and interpretability of AI systems need urgent attention. Understanding the decision-making process of AI by physicians and patients directly affects its clinical application. Moreover, ethical and privacy issues cannot be ignored, and achieving a balance between data utilization and patient privacy protection is crucial for future research. Collectively, further efforts should concentrate on refining algorithms, strengthening data-sharing mechanisms, and establishing appropriate ethical frameworks to promote the deep integration of AI technology into clinical oncology.

Author Contributions

Man Wang: conceptualization, supervision, investigation, writing—original draft preparation, and funding acquisition. Wenguang Chang: investigation and visualization. Yuan Zhang: writing—reviewing and editing. All authors have read and approved the final manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Ethics Statement

The authors have nothing to report.

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