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Artificial Intelligence in Early Cancer Detection: Advances, Challenges, and Future Perspectives

Ziyue Gao

School of Life Sciences, Tianjin University, Tianjin, China
gzy3023207135@tju.edu.cn

Abstract. Cancer remains a major global public health challenge due to its high mortality rate. Early detection and diagnosis are critical for reducing cancer-related deaths, yet conventional screening methods, such as medical imaging and tissue biopsy, have limitations in accuracy, efficiency, and objectivity. Recent advances in Artificial Intelligence (AI), particularly deep learning, have shown strong potential in improving early cancer detection. This review summarizes recent progress and clinical applications of AI in this field. Key developments in deep learning architectures, including Convolutional Neural Networks (CNNs) and Transformer-based models, have enabled improved analysis of medical images, nanosensor signals, and multi-omics data. AI has been increasingly applied in the early detection of common cancers, including lung cancer (CT screening), breast cancer (mammography, ultrasound, and MRI), and colorectal cancer (endoscopy, fecal testing, and circulating tumor DNA analysis). However, challenges such as data heterogeneity, limited interpretability, and regulatory barriers remain. Future advances in multimodal data integration and Explainable AI (XAI) are expected to further enhance diagnostic performance. Overall, AI is likely to serve as an important assistive tool to support more accurate and personalized cancer diagnosis.

Keywords: artificial intelligence, early cancer detection, deep learning, medical image analysis, multi-modal fusion

1. Introduction

1.1. The importance of early cancer detection

Data from the World Health Organization (WHO) and the International Agency for Research on Cancer (IARC) shows that the incidence and mortality of cancer have remained high for years, imposing a heavy economic burden on society and patients alike [1]. Clinical evidence indicates that early cancer detection is a crucial link in improving patient prognosis; intervention before tumors develop local invasion or metastasis can greatly raise the cure rate, cut down treatment costs and alleviate patients' suffering at the same time.

To achieve early cancer detection, the medical community has developed and widely applied a variety of technical methods. Firstly, population-based screening programs serve as an important means for early identification of asymptomatic precancerous lesions or early-stage cancer. Secondly,

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imaging examinations are core methods for localizing and characterizing suspicious lesions. Thirdly, molecular diagnostic technologies represented by liquid biopsy provide a revolutionary tool for non-invasive and dynamic early warning and monitoring. Nevertheless, the existing technical system still faces numerous challenges, such as the difficulty in balancing sensitivity and specificity, over-reliance on physicians' experience, low efficiency in interpreting massive data, and poor patient compliance due to invasive examinations. All these issues are in urgent need of empowerment from innovative methods.

1.2. The development of Artificial Intelligence technology and its application prospects in healthcare

The development of AI has evolved from rule-based expert systems to data-driven deep learning models. In particular, the groundbreaking achievements of deep Convolutional Neural Networks (CNNs) in image recognition tasks have provided a powerful tool for processing highly complex medical imaging data. Its core value lies in the ability to mine potential and complex patterns and correlations from massive, high-dimensional medical data with far superior speed and consistency compared with humans [2]. Early cancer detection faces several fundamental challenges. One major difficulty is the identification of small lesions within large volumes of normal tissue. Another key challenge is the accurate differentiation between benign and malignant abnormalities. Artificial Intelligence (AI) has shown potential in addressing these issues. It can improve the sensitivity and efficiency of image interpretation. In addition, AI enables the integration and analysis of molecular biomarkers. Furthermore, multimodal data fusion may support the development of more accurate risk prediction models. Therefore, exploring and systematically summarizing the latest progress, specific applications, existing challenges and future directions of AI technology in early cancer detection is of great theoretical and practical significance for accelerating the translation of this field from research to clinical practice and ultimately advancing the frontiers of cancer prevention and control.

2. Current progress of AI-based cancer detection technologies

2.1. Nanostructured sensors for cancer biomarker detection

Early cancer detection is the key to improving patient survival rate and prognosis. Traditional detection methods such as tissue biopsy and imaging examinations are often limited by high invasiveness, insufficient sensitivity, or the inability to identify tumors until they develop to a certain stage. In recent years, non-invasive or minimally invasive detection technologies based on liquid biopsy (blood, saliva, exhaled breath, etc.) have developed rapidly, bringing revolutionary hope for early cancer screening. At the forefront of this field, the integration of nanomaterial-based sensors with AI-driven signal analysis is forging a highly promising paradigm for high-sensitivity and high-specificity detection.

Nanomaterials-based sensors take advantage of the unique physicochemical properties of nanomaterials (e.g., gold nanoparticles, carbon nanotubes, quantum dots and graphene)—such as high specific surface area, tunable surface chemical properties and enhanced local field effects—to efficiently capture and amplify the signals of trace cancer-related biomarkers in body fluids, including Circulating Tumor DNA (ctDNA), exosomes, specific proteins and Volatile Organic Compounds (VOCs) [3]. However, the signals generated by these sensors are often complex, multi-dimensional and accompanied by noise, making it difficult for traditional analytical methods to

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extract stable and reliable features. AI technologies, especially machine learning and deep learning, rely on their powerful pattern recognition and complex data analysis capabilities to mine subtle patterns imperceptible to the human eye from massive, high-dimensional sensor data, thus achieving accurate identification and classification of early cancer signals [2]. The combination of the two essentially integrates the "ultra-sensitive sensing" capability of nanomaterials with the "super-strong cognitive" capability of AI, jointly driving the development of early cancer detection towards greater precision and convenience.

2.2. Deep learning methods in cancer diagnosis

As an important branch of machine learning, deep learning can automatically learn hierarchical feature representations from raw data by constructing neural network models with multi-layer nonlinear transformations. Its rise in the field of cancer diagnosis mainly benefits from the evolution of three core architectures: convolutional neural networks, recurrent neural networks and Transformer architectures, each of which excels at processing different types of medical data.

2.2.1. Convolutional Neural Networks (CNNs)

CNNs serve as the fundamental architecture for processing data with grid-like topological structures (e.g., images) [4]. Their core idea is to automatically extract local spatial features (e.g., edges and textures) through convolutional layers, achieve feature dimensionality reduction and translation invariance by using pooling layers, and finally perform classification or regression through fully connected layers. In medical image analysis, CNNs can directly learn the mapping from pixels to diagnostic results, avoiding the complex manual feature extraction process that relies on experts' experience in traditional methods [2]. Variants such as U-Net, ResNet and DenseNet have further improved the model's ability to identify subtle lesions in medical images and enhanced training stability through mechanisms such as skip connections and deep residual learning [5].

2.2.2. Recurrent Neural Networks (RNNs) and their variants

RNNs are specially designed for processing sequential data, with a network structure featuring recurrent connections that can retain historical information to process current inputs. As improved versions of RNNs, Long Short-Term Memory and Gated Recurrent Unit effectively alleviate the problem of gradient vanishing/explosion in the training of original RNNs by introducing gating mechanisms, enabling them to learn long-distance dependencies. In cancer diagnosis, RNN series models are mainly used to analyze time-series data and one-dimensional signal data [2].

2.2.3. Transformer architecture

Originally designed for natural language processing tasks, the Transformer takes the self-attention mechanism as its core. This mechanism can dynamically calculate the correlation weight between any two elements in the input sequence, thus directly modeling global contextual information and overcoming the bottlenecks of limited receptive field in CNNs and sequential computation in RNNs. The success of Vision Transformer (ViT) has extended the application of Transformer to the field of computer vision, which processes images by dividing them into sequences of image patches. In the healthcare field, relying on its powerful global feature integration capability, Transformer shows great potential in tasks that require understanding the global structure of images or the semantics of long texts [6].

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2.3. Automated visual assessment and imaging-based cancer detection

2.3.1. Limitations of traditional imaging assessment

Traditional medical imaging assessment inherently relies on qualitative human interpretation, exposing the diagnostic process to significant subjectivity and inter-observer variability, particularly when evaluating atypical lesions with blurred boundaries. This reliance on visual perception makes diagnosticians highly susceptible to fatigue-induced sensitivity degradation during extended shifts, increasing the risk of omitting micro-lesions [5]. Furthermore, human observers lack the capacity to precisely quantify critical imaging biomarkers—such as morphological irregularity and spatial heterogeneity—which are essential for differentiating benign from malignant tissues. These perceptual limitations are further compounded by the severe inefficiencies and error susceptibility associated with the manual integration of longitudinal and multi-modal data. Collectively, these intrinsic constraints underscore the urgent clinical demand for automated, imaging-based assessment systems capable of providing objective, consistent, and high-throughput diagnostic support.

2.3.2. Applications of automated visual assessment in imaging-based cancer detection

Automated visual assessment overcomes the limitations of traditional manual image interpretation directly by using deep learning technology, realizing objective and high-throughput medical image analysis. Firstly, Computer-aided Detection (CADe) systems automatically scan CT, MRI or whole-slide pathological images to accurately locate and segment suspicious lesions. Unaffected by visual fatigue, this process significantly reduces the missed diagnosis rate of tiny cancer foci. Secondly, radiomics has greatly expanded the boundaries of visual assessment. Algorithms extract thousands of quantitative features imperceptible to the human eye (e.g., texture complexity, morphological irregularity and spatial heterogeneity) from conventional images, and build prediction models based on these features to achieve accurate differentiation of benign and malignant tumors. In addition, automated visual systems optimize the overall clinical workflow. They can quickly conduct intelligent preliminary screening and triage of massive screening images, and mark high-risk cases for radiologists' review first, thus greatly improving the efficiency of medical resource allocation and the speed of early diagnosis.

2.4. AI-driven genomic analysis and large-scale sequencing data interpretation

With the popularization of high-throughput sequencing technology and the significant reduction in costs, multi-omics data such as genomics, transcriptomics, epigenomics and proteomics have grown exponentially. A single human whole-genome sequencing can generate more than 100 GB of raw data, and large-scale projects such as The Cancer Genome Atlas (TCGA) and UK Biobank have accumulated petabyte-level multi-omics data. This data explosion has brought three core challenges: high costs of data storage and management, a significant increase in computational complexity (e.g., genome-wide association studies need to process millions of variant loci), and difficulties in the integration of multi-dimensional biological signals (how to effectively correlate and biologically interpret heterogeneous data from different levels such as genomics, epigenomics and transcriptomics) [7]. Traditional statistical methods and computing tools have limitations in efficiency, accuracy and scalability when dealing with data of such scale and complexity.

AI algorithms play a key role in big data and bioinformatics analysis: they can efficiently process the massiveness and high dimensionality of sequencing data, identify disease-related genetic

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variations and regulatory patterns by mining hidden correlations in the data, and reduce the interference of background noise on analysis results. Looking ahead, AI has great potential in multi-omics integration and precise tumor diagnosis. By fusing multi-omics data with phenotypic data such as clinical and imaging data, AI can construct a comprehensive molecular portrait of tumors, realize precise subtyping of cancer, predict tumor progression and treatment response, and provide a more solid theoretical and technical foundation for the implementation of precision oncology.

3. Specific clinical applications of AI in the early diagnosis of different cancers

3.1. Applications of AI in early lung cancer detection

Lung cancer is the leading cause of cancer-related deaths worldwide, and early diagnosis is the key to improving patient survival rate. Low-dose Computed Tomography (LDCT) screening has been proven to effectively reduce the mortality rate of high-risk groups, but it also detects a large number of pulmonary nodules, the vast majority of which are benign. This brings a huge burden of image interpretation and diagnostic uncertainty to radiologists, and there is an urgent need for more efficient and accurate auxiliary analysis tools.

3.1.1. AI-based CT imaging screening and auxiliary diagnosis

Artificial intelligence, especially deep learning, shows great potential in the automatic analysis of chest CT images. Models such as convolutional neural networks (CNNs) can perform end-to-end analysis of CT images, completing a series of tasks such as lung parenchyma segmentation, automatic nodule detection, segmentation and feature extraction. Studies have shown that AI systems can process the entire CT sequence in a few seconds, with nodule detection sensitivity comparable to that of senior radiologists, and even can detect tiny nodules that are easily overlooked by the human eye [8]. This greatly improves screening efficiency and reduces the risk of missed diagnosis.

3.1.2. Progress of AI in the differentiation of benign and malignant pulmonary nodules

In addition to detection, AI has more prominent value in nodule characterization. By analyzing the morphological features (e.g., lobulation, spiculation), texture features and growth rate in dynamic contrast-enhanced CT of nodules, AI models can comprehensively calculate the malignant probability of nodules. For example, some deep learning models trained on large-scale multi-center datasets can predict the malignant risk of indeterminate pulmonary nodules found in screening through baseline CT images, with diagnostic performance superior to traditional clinical prediction models and some radiologists [9]. This not only helps reduce unnecessary invasive biopsy or surgery, but also assists physicians in formulating more personalized follow-up and intervention strategies.

3.2. Applications of AI in early breast cancer detection

Mammography is the cornerstone of breast cancer screening, but its sensitivity is greatly affected by breast density, with a high false negative rate in women with dense breast tissue, and there is a certain false positive recall rate, which brings psychological pressure to patients and leads to unnecessary examinations. The introduction of AI technology aims to optimize this situation.

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3.2.1. AI-assisted mammographic image interpretation

AI algorithms are mainly applied in two aspects in mammographic image analysis: first, acting as an independent "image reader" for preliminary screening and marking suspicious areas; second, serving as an auxiliary tool for radiologists, prioritizing the display of high-risk cases or prompting subtle lesions (e.g., architectural distortion) that may be overlooked. A number of retrospective studies have shown that AI systems can independently reach or even exceed the screening and diagnostic level of human experts. Especially in the double-reading mode, the combination of AI and one radiologist can achieve or even surpass the effect of traditional double-reading by two physicians, which is expected to become a solution to improve efficiency [10].

3.2.2. Applications of AI in ultrasound and MRI image analysis

For women with dense breast tissue or high-risk groups, ultrasound and Magnetic Resonance Imaging (MRI) are important supplementary screening methods. AI performs excellently in the automatic segmentation of breast and lesions, quantitative analysis of Dynamic Contrast-enhanced MRI (DCE-MRI) kinetic curves, and differentiation of benign and malignant lesions. In ultrasound examinations, AI can assist in the standardization of BI-RADS (Breast Imaging-Reporting and Data System) classification and reduce operator dependence; in MRI examinations, AI can efficiently process massive imaging data, accurately evaluate the scope and multifocality of lesions, and provide key information for the formulation of treatment plans [11]. These applications make up for the deficiencies of traditional screening and build a more three-dimensional AI-assisted detection system for early breast cancer.

3.3. Applications of AI in early colorectal cancer detection

The early detection and resection of adenomatous polyps, the precancerous lesions of colorectal cancer, can effectively prevent the occurrence of cancer. Colonoscopy is the "gold standard" for screening and diagnosis, but its effect is highly dependent on the operator's skills and attention, with a certain missed diagnosis rate (especially for tiny and flat polyps), and it is an invasive examination.

3.3.1. AI-assisted endoscopic polyp detection and classification

Real-time AI-assisted detection systems run deep learning models on endoscopic video streams, and can remind endoscopists through visual prompts (e.g., bounding boxes) the moment polyps appear. A number of randomized controlled trials have confirmed that this real-time assistance can improve the polyp detection rate, especially the Adenoma Detection Rate (ADR), a key indicator for measuring the quality of colonoscopy, with an increase of about 10%-15% [12]. In addition, the latest AI systems can not only "detect" polyps, but also perform optical biopsy on them in real-time endoscopic images, that is, predict their pathological properties (e.g., whether they are neoplastic polyps), with an accuracy rate of more than 90%. This helps to decide whether to resect immediately during the examination and optimize the diagnosis and treatment process.

3.3.2. Potential applications of AI in fecal testing and circulating tumor DNA analysis

Non-invasive screening methods such as Fecal Immunochemical Test (FIT) and the emerging circulating tumor DNA (ctDNA) liquid biopsy are important directions to improve screening

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compliance. AI can enhance the efficacy of these methods: in FIT, the ability to identify early bleeding signals can be improved by analyzing the microscopic images or chemical composition patterns of fecal samples; in ctDNA analysis, faced with massive, low-frequency mutation data generated by ultra-deep sequencing, AI models can more accurately distinguish real tumor-derived signals from background sequencing noise, and can combine multi-dimensional features such as methylation and fragmentomics to achieve earlier and more accurate early warning and traceability of canceration [13]

4. Future directions and prospects of AI in cancer detection

4.1. Advantages of AI in early cancer detection

Traditional cancer screening is often limited by the physical bottlenecks of human resources and the cognitive threshold of human visual perception. The introduction of artificial intelligence is not merely a replacement for individual diagnostic tools. It represents a fundamental transformation of the early screening paradigm. Its core advantages are mainly reflected in three dimensions: breaking the bottleneck of statistical efficiency, crossing the limit of human perception, and reshaping the medical economics model.

4.1.1. Improving diagnostic sensitivity and specificity

Traditional diagnostic methods often face the dilemma of being difficult to balance sensitivity and specificity. AI models, especially systems based on deep learning, can optimize these two key indicators at the same time by learning massive annotated data. For example, in mammography and colonoscopy, AI systems have been repeatedly proven to significantly improve the detection rate of tiny cancer foci and precancerous lesions (e.g., increasing the adenoma detection rate) without increasing the false positive rate [10,12]. This improved balance is directly translated into more reliable screening results, reducing missed diagnosis and over-treatment.

4.1.2. Identifying subtle lesions beyond human perception

Human observers have inherent limitations of attention and cognitive bias in image interpretation. AI can quantitatively analyze microscopic and submicroscopic features that are difficult to perceive or define by the human eye, such as subtle texture heterogeneity of pulmonary nodules in CT images, tiny abnormalities in the morphology and spatial arrangement of cell nuclei in pathological sections, or hidden changes in mucosal vascular patterns in endoscopic images. These "radiomics" or "digital pathology" features beyond human visual perception provide a new way to identify early or even very early malignant transformation [9].

4.1.3. Realizing large-scale and cost-effective screening

AI features a high degree of automation and replicability, can work 24 hours a day, and process standardized data at an extremely fast speed. This advantage makes it an ideal tool to meet the needs of large-scale population screening, which is expected to significantly reduce the per capita screening cost, alleviate the shortage of professional medical personnel (e.g., radiologists and pathologists), and improve the accessibility of cancer screening in areas with insufficient medical resources [8].

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4.2. Challenges and limitations of AI in early cancer detection

In summary, although artificial intelligence has shown disruptive early screening efficacy in theoretical and retrospective studies, it still faces numerous obstacles in crossing the translational chasm from "laboratory algorithms" to "routine clinical tools". The island effect and heterogeneity at the data level fundamentally limit the generalization ability of models; the "black box" attribute at the algorithm level inevitably triggers a crisis of trust among clinicians and patients; and the relative lag of clinical verification and regulatory systems directly lengthens the cycle of technology landing. These multi-dimensional limitations clearly indicate that solving the dilemma of AI clinical application has long gone beyond the scope of a single computer science, and there is an urgent need for in-depth collaboration between the medical community, engineering community, ethics community and government regulatory agencies. Facing up to and systematically overcoming these barriers is not only the pain point of current research, but also the only way to spawn a next-generation AI diagnostic ecosystem that is safer, more transparent and more clinically applicable.

4.2.1. Issues of data availability, quality and standardization

High-quality, large-scale, and well-annotated datasets are essential for training robust AI models with strong generalization ability. However, several challenges remain. Data sharing is often limited by patient privacy concerns, resulting in fragmented datasets across institutions that are difficult to integrate. In addition, obtaining gold-standard annotations, such as pathological confirmation, is costly and may be subject to inter-observer variability among experts. Furthermore, data heterogeneity across different hospitals and equipment, including variations in CT scanning parameters and staining protocols, lead to reduced model performance in cross-center validation [14].

4.2.2. Model interpretability and the "black box" problem

The complex internal working mechanism of deep learning models makes their decision-making process a "black box", and physicians find it difficult to understand the reasons for the model's specific judgments. In life-critical medical decision-making, the lack of interpretability will seriously hinder clinicians' trust and adoption of AI, and it is difficult to trace the reasons and make corrections when the model makes mistakes.

4.2.3. Challenges in clinical validation and regulatory approval

The real integration of AI tools from laboratory performance verification to clinical workflow requires rigorous prospective, multi-center clinical trials to prove that they can improve the final patient outcomes (e.g., reducing mortality), rather than just improving intermediate indicators (e.g., detection rate). In addition, the regulatory pathways (e.g., approval by the US FDA and China NMPA) are still being explored and improved, and how to conduct continuous and effective supervision on the constantly self-updating AI algorithms is still an unsolved problem [15].

4.3. Future development trends of AI in early cancer diagnosis

To break the above barriers of data silos, algorithm black boxes and regulatory lag, and fully release the clinical efficacy of artificial intelligence in early cancer detection, the evolution of this field is at a critical turning point from "single-point technological breakthroughs" to "whole-chain ecological

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reconstruction". The focus of future research and development has gradually bid farewell to the extreme competition for single model performance indicators, and shifted to higher-dimensional systematic innovation—namely, how to make AI more comprehensively analyze the complexity of tumor biology, more transparently integrate into the clinical decision-making of human physicians, and more intelligently adapt to the dynamically changing clinical environment. Specifically, the following core technical trends will lead this paradigm shift and provide a substantive strategic path for truly crossing the current "translational chasm".

4.3.1. Multi-modal data fusion and integrated analysis

Future AI systems will no longer be limited to analyzing a single type of data (e.g., imaging). By fusing genomics, transcriptomics, proteomics, radiomics, digital pathology information, electronic health records and even lifestyle data to build a multi-dimensional "digital twin" of patients, AI can conduct more comprehensive risk assessment, more accurate early diagnosis and more personalized prognosis prediction. For example, a model combining CT imaging and blood ctDNA information may identify lung cancer risks at an early stage more effectively than a single modality [13].

4.3.2. Progress in explainable Artificial Intelligence

Explainable Artificial Intelligence (XAI) aims to make the decision-making process of AI transparent to humans. Related technologies include generating attention maps (highlighting the most critical areas for diagnosis in images), using inherently interpretable model architectures, and providing case-based reasoning. These technologies can not only enhance clinical trust, but also help researchers discover new and understandable disease biomarkers.

4.3.3. Continuous learning and model adaptation

Static AI models will become obsolete due to the evolution of medical practice, equipment updates and changes in disease spectrum. Future systems need to have continuous learning capabilities, and on the premise of protecting patient privacy (e.g., through federated learning technology), safely use new data generated in clinical practice to continuously update and optimize themselves, adapt to the characteristics of different populations and institutions, and realize lifelong learning and personalized adaptation of models [15].

4.3.4. Integration of AI with robotics, digital pathology and telemedicine

AI is expected to be increasingly integrated with other cutting-edge technologies. Its combination with surgical and diagnostic robotics may enable more accurate biopsy navigation and real-time microscopic assessment. Integration with whole-slide imaging technologies is likely to facilitate the digitalization of pathological workflows and support quantitative, objective, and reproducible analysis. In addition, the incorporation of AI into telemedicine platforms may extend advanced diagnostic capabilities to primary healthcare settings, enabling remote screening and consultation while promoting a more balanced distribution of high-quality medical resources.

5. Conclusion

The integrated development of artificial intelligence in the field of early cancer detection marks that tumor diagnosis is moving from the traditional model relying on individual physicians' experience

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and single-modal data to a new era of intelligent and precise diagnosis characterized by data-driven, algorithm-empowered and multi-dimensional integration. This paper systematically reviews the key applications, core advantages, existing challenges and future trends of AI technology in this field, and reveals a clear path for its evolution from an auxiliary tool to a transformative force.

Key progress and fundamental breakthroughs are reflected in multiple dimensions. At the technical level, deep learning, especially convolutional neural networks, has been proven to have higher sensitivity than human experts in analyzing medical images (e.g., low-dose CT, mammograms, endoscopic images and pathological sections), and can stably and efficiently identify tiny lesions and subtle feature patterns. At the application level, the value of AI has expanded from a single auxiliary image interpretation to the intelligent interpretation of multi-omics data such as circulating tumor DNA, the fusion analysis of multi-modal information, and even risk stratification and prognosis prediction, initially building an early detection closed loop covering "screening-diagnosis-risk assessment". Its core value lies in that by processing massive, high-dimensional data, AI can reveal potential and complex biological correlations, and significantly advance the "window period" of early diagnosis.

However, the road to its widespread clinical popularization is still full of challenges and limitations. Firstly, the robustness and generalization ability of models are limited by the scarcity of high-quality, standardized and finely annotated multi-center datasets, with prominent problems of data silos and heterogeneity. Secondly, the lack of model interpretability caused by the "black box" decision-making mechanism seriously hinders clinicians' trust and in-depth adoption of AI. Finally, the translational path from technical verification to clinical utility proof is long and complex, involving rigorous prospective randomized controlled trials, seamless integration with existing workflows, clear economic evaluation and the construction of a regulatory framework adapted to the characteristics of AI. These challenges are not purely technical problems, but systematic projects that require cross-disciplinary collaboration between medicine, computer science, ethics, health policy and other fields to solve.

Looking to the future, the development of artificial intelligence in early cancer detection will present the following prospective trends. In the short term, the focus will be on promoting the practical application of explainable artificial intelligence (XAI) technology, developing reliable tools that can be seamlessly embedded into the existing clinical workflow, and building a larger-scale collaborative training network on the premise of ensuring data security through privacy computing technologies such as federated learning. In the medium and long term, technology fusion and ecological integration will become the mainstream: AI will be deeply integrated with robot-assisted technology, wearable devices and continuous dynamic monitoring technology, driving the development of cancer screening and monitoring towards real-time, non-invasive and home-based; at the same time, going beyond diagnosis itself, AI-driven multi-omics integration analysis will be more closely combined with prevention, intervention and personalized treatment, ultimately providing a core driving force for realizing the ultimate vision from "passive treatment of advanced diseases" to "active management of health risks". In the final analysis, the success of AI does not lie in replacing physicians, but in empowering humans to jointly build a more efficient, inclusive and precise early cancer prevention and control system.

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