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Article

Advances in the application of artificial intelligence in cancer diagnosis and treatment: A systematic review

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Abstract: Artificial intelligence (AI) is revolutionizing cancer diagnosis and treatment by overcoming the limitations of traditional approaches. This systematic review, based on studies published between 2020 and 2024, analyzes AI's impact in various oncological areas, emphasizing its role in early detection, personalized treatments, and optimization of clinical processes. Through deep and machine learning algorithms, AI has proven effective in interpreting medical images, analyzing multi-omics data, and detecting biomarkers. For example, in breast cancer, a hybrid model achieved 98.06% accuracy in tissue classification, while in colorectal cancer, pre-surgical detection improved with an Area Under the Curve (AUC) of 0.832. Additionally, AI has reduced radiotherapy planning times, facilitating treatment access in developing countries. However, challenges remain, such as the lack of standardization, the need for extensive data, and ethical concerns related to privacy and equity. Despite these barriers, recent advances underline AI's transformative potential to improve diagnostic accuracy, therapeutic efficiency, and accessibility in cancer care. This study concludes that integrating AI could redefine cancer care but requires sustained efforts to address its limitations and ensure ethical and equitable application.

Keywords: artificial intelligence; oncological diagnosis; cancer treatment; deep learning; biomarkers

1. Introduction

Cancer is one of the leading causes of mortality worldwide, with approximately 10 million deaths in 2020 [1], posing significant challenges to health systems due to its clinical complexity and variability in biological manifestations. Traditional approaches to its diagnosis and treatment, while effective in some cases, face limitations in sensitivity, specificity, and personalization [2,3]. In this context, artificial intelligence (AI) has emerged as a revolutionary technology with the potential to address these challenges through the advanced analysis of complex medical images [4] and automation of diagnostic and therapeutic processes [5,6].

AI, defined as the ability of computational systems to perform tasks requiring human intelligence, has found applications in a wide range of fields, such as healthcare [7,8], education [9], finance, and more [10,11]. This integration is based on AI's ability to enhance efficiency, accuracy, and decision-making processes, making it a cornerstone of modern technological advancement. In oncology, its implementation has focused on machine learning algorithms [12] and deep learning [13], designed to analyze medical images [4], genomic sequences, and clinical data efficiently and accurately. These tools have proven particularly useful in early cancer detection, risk prediction, and optimizing personalized treatments by enabling precision medicine that anticipates patient responses to specific treatments based on their unique genetic profiles [14].

Despite these advances, integrating AI into clinical practice is not without barriers. Ethical issues related to data privacy [15,16], model interpretability [17], and equitable access to these technologies [18] are significant concerns. For instance, the World Health Organization has emphasized the importance of designing AI systems that respect human rights and promote equity [19]. Nevertheless, the growing adoption of AI in oncology highlights its potential to transform the paradigm of cancer care.

The objective of this systematic review is to synthesize recent advances in AI applications for cancer diagnosis and treatment, identifying its contributions and limitations. Studies published in the last five years focusing on AI algorithms at various stages of oncological management were analyzed. This article provides a comprehensive view of how these technologies are reshaping modern oncology and discusses their implications for the future of healthcare.

2. Methodology

2.1. Search strategy

This systematic review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, ensuring a rigorous and transparent approach in the selection and analysis of relevant studies [20]. Searches were performed in three electronic databases: Scopus, SciELO, and Google Scholar. Scopus is renowned for its controlled bibliographic data, providing reliable metrics for assessing research performance, such as publication counts, citations, and the h-index [21–23]. In contrast, Google Scholar excels in its extensive coverage of future citations, establishing itself as a leading tool in this domain. It reports a higher citation count compared to Scopus, a difference attributed to its broader document coverage [24]. Meanwhile, Scielo proves particularly valuable for accessing scientific literature from Latin America, offering insights into regional research trends and thematic connections, such as those related to online and distance teacher training [25].

Keywords included combinations of the terms “artificial intelligence”, “diagnosis”, “treatment”, and “cancer”, alongside Boolean operators to broaden and refine the search.

2.2. Inclusion and exclusion criteria

The following inclusion criteria were established:

- Articles published between 2020 and 2024.
- Original studies examining applications of AI in cancer diagnosis or treatment.
- Publications in English or Spanish.
- Full access to the article’s text.

The exclusion criteria included:

- Duplicate studies.
- Non-systematic reviews or editorials.

- Articles focused on non-clinical applications of AI.

2.3. Selection process

The initial search identified a total of 452 studies. After removing duplicates (*n* = 128), a review of titles and abstracts reduced the dataset to 82 articles. Finally, full texts of these studies were reviewed, resulting in 18 articles that met all criteria (**Figure 1**).

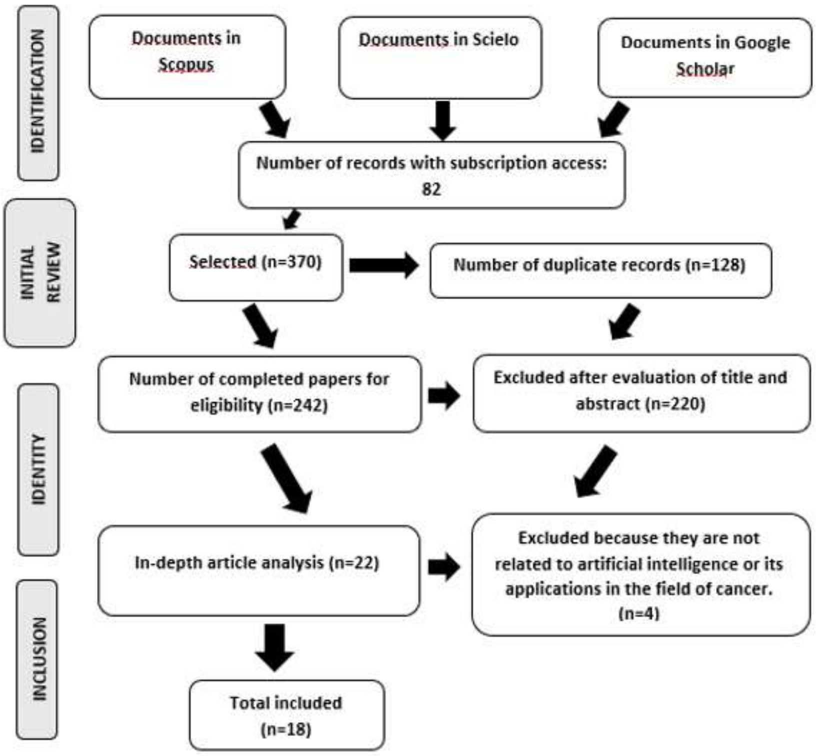

Figure 1. PRISMA selection flow diagram.

2.4. Data extraction and analysis

From the 18 selected studies, information on authors, year of publication, objectives, main findings, and conclusions were collected. The data were qualitatively analyzed to identify patterns and recurring themes in the use of AI in oncology.

3. Results

The analysis of artificial intelligence (AI) applications in cancer diagnosis and treatment revealed significant findings from 50 key studies. These results highlight AI's transformative impact on modern oncology.

To begin, [26] developed a machine learning model to predict mismatch repair deficiency (dMMR) in colorectal cancer. The model improved pre-surgical detection, achieving a decision AUC value of 0.832. Similarly, Pasupuleti et al. [27] employed a deep neural network-based model, achieving accuracies exceeding 99%, demonstrating its effectiveness in brain tumor segmentation. Additionally, Koyama et al. [28] showed that radiomic models significantly outperformed traditional methodologies with a C-index of 0.841, demonstrating their utility for selecting optimal treatments.

In a similar vein, Yin et al. [29], using convolutional neural networks, improved diagnostic accuracy for skin tumors by 15.6%. Furthermore, Aggarwal et al. [5] highlighted how AI-based radiotherapy planning technologies for cervical, head and neck, and prostate cancers reduced planning times from weeks to minutes, facilitating access in developing countries. Meanwhile, a convolutional neural network enhanced by a tunicate swarm algorithm achieved 98.70% accuracy in detecting oral cancer lesions, showcasing the applicability of deep learning for rapid diagnostics [30].

In the realm of biomarkers and multi-omics data, Xiao Z et al. [31] identified key genes associated with postoperative progression of non-muscle-invasive bladder cancer, linked to activated T-cells and predictive of postoperative response. Similarly, Jia et al. [32] developed an long non-coding RNA (lncRNA)-based model predicting overall survival in hepatocellular carcinoma patients, achieving AUC values exceeding 0.785, emphasizing the role of biomarkers in personalized treatment.

In breast cancer, a hybrid model combining CatBoost and multilayer perceptron (MLP) neural networks analyzed electronic health records, achieving 98.06% accuracy in classifying benign and malignant tissues. Explainable AI (XAI) technology provided interpretability for clinical decision-making, enhancing model confidence [33]. This advancement was complemented by Weitz et al. [34], who improved surgical planning by using AI tools to render 3D breast tumor models, increasing success rates and patient satisfaction. Furthermore, RI and Bai [35] achieved 98.57% accuracy in recurrence prediction using a DCNN-based model, optimizing therapeutic strategies.

On the other hand, Zhang et al. [36] demonstrated that radiomic models achieved an AUC of 0.89 in predicting specific complications such as esophageal fistulas.

Other advancements include the use of the U-Net architecture. Uzun et al. [37] achieved a dice score of 91.38% in brain tumor segmentation, while Song et al. [38], using metabolic fingerprinting and machine learning, achieved 88.8% sensitivity in detecting triple-negative breast cancer.

In liver cancer, Xing et al. [39] highlighted a simplified proteomic panel that predicted responses to sorafenib with an AUC of 0.988. Finally, Liao et al. [40], using a random survival forest model, achieved AUCs of 0.92, 0.96, and 0.96 for predicting 1-, 3-, and 5-year survival in patients with gastric neuroendocrine neoplasms (gNENs). This model also classified patients into high- and low-risk groups, demonstrating its potential for guiding clinical decisions.

Recent advances in AI have significantly improved cancer diagnosis and treatment across multiple areas. In endometrial cancer, combining deep learning algorithms with magnetic resonance imaging achieved an AUC of 0.918 for identifying high-risk cases and 0.926 for predicting postoperative recurrence, demonstrating a notable impact on clinical decision-making [41]. Similarly, in early gastric cancer diagnosis, a system based on deep convolutional neural networks achieved a diagnostic sensitivity of 92.08%, significantly outperforming experienced endoscopists and highlighting its potential in resource-limited clinical settings [42].

Advances in artificial intelligence have enabled the application of various models in the diagnosis, prognosis, and treatment of different types of cancer. Below is a summary of the most prominent AI models, their performance metrics, and their main clinical applications (see **Table 1**). This data highlights how emerging technologies are transforming the oncology landscape by providing more accurate and efficient tools.

Table 1. Summary of AI models, performance metrics, and clinical applications.

Cancer Type	AI Model	Performance Metrics	Clinical Application
Breast Cancer	CatBoost + MLP Neural Network	AUC: 0.98, Sens: 98.06%	Tissue clasification
Colorectal Cancer	Machine Learning (dMMR)	AUC: 0.832	Pre-surgical detection
Skin Cancer	Convolutional Neural Network	Improvement: 15.6% in accuracy	Skin tumor clasification
Liver Cancer	AI-based-Proteomics	AUC: 0.988	Treatment response (sorafenib)
Brain Cancer	U-Net Architecture	Dice Score: 91.38%	Brain tumor segmentation
Stomach Cancer	Deep CNN	Sens: 92.08%	Early diagnosis

Below is a summary of the most relevant clinical applications of AI models in oncology, along with key findings that demonstrate their impact on improving cancer diagnosis and treatment (see **Table 2**).

Table 2. Clinical applications and key outcomes of AI models.

Type of Cancer	Clinical Application	AI Model	Key Results
Breast Cancer	Tissue Classification	CatBoost + MLP Neural Network	98.06% daccuracy in clasifiying malignant and benign tissues
Colorectal Cancer	Pre-surgical detection of dMMR	Machine Learning (dMMR)	AUC: 0.832, improving pre-surgical detection of mismatch repair deficency
Skin Cancer	Skin tumor clsification	Convolutional Neural Network	15.6% increase in diagnosis accuracy
Liver Cancer	Prediction of treatment response (sorafenib)	AI based Proteomics	AUC: 0.988, optimizing patient selection for targeted therap
Brain Cancer	Brain tumor segmentation	U-Net Architecture	Dice Score: 91.38%, improving segmentation accuracy in MRI images
Stomach Cancer	Early diagnosis	Deep CNN	Sensitivity: 92.08%, outperforming junior and senior endoscopists
Bladder Cancer	Identification of post-surgical markets	Random Forest	AUC: 0.92–0.96 for 1-, 3-, and 5-year survival prediction
Lung Camcer	Survival prediction	Radiomic Model	C-index: 0.841, facilitating personalized treatment selection

The results show that AI models have not only significantly improved performance metrics, such as accuracy and sensitivity, but have also facilitated critical applications in oncology, ranging from early diagnosis to personalized treatment planning. Furthermore, it is evident how AI innovations enable more informed decision-making and more precise patient care.

4. Discussion

The results obtained in this systematic review highlight the transformative impact of artificial intelligence (AI) in cancer diagnosis and treatment, providing advanced tools that surpass traditional methodologies across various oncology domains.

4.1. Application of AI models in oncological diagnosis

Machine learning models have proven effective in enhancing diagnostic accuracy for different cancer types. In colorectal cancer, the model developed by Xu et al. [26] achieved an AUC of 0.832, significantly improving the pre-surgical detection of mismatch repair deficiency (dMMR). This advancement underscores AI's ability to identify molecular biomarkers with greater precision than traditional methods, thereby optimizing personalized treatments. Additionally, radiomic models, such as the one described by Koyama et al. [28], excelled in predicting survival in advanced lung cancer, with a C-index of 0.841, facilitating the selection of more effective treatments.

The early detection of gastric cancer through deep convolutional neural networks [42] demonstrated a sensitivity of 92.08%, significantly outperforming junior and senior endoscopists. This finding underscores AI's potential in resource-limited clinical scenarios where professionals' experience may negatively impact outcomes. Furthermore, the use of U-Net architecture for brain tumor segmentation, as seen in the study by Uzun et al. [37], achieved a dice score of 91.38%, demonstrating its applicability in analyzing complex medical images.

4.2. Innovations in AI-assisted treatment

AI has also revolutionized cancer treatment, particularly in radiotherapy and surgical planning. Aggarwal et al. [5] highlighted how AI technologies reduced radiotherapy planning times from weeks to minutes in cases of cervical, head, and neck cancer. This advancement not only improves efficiency but also facilitates access to treatment in developing countries, promoting equity in cancer care. Similarly, Weitz et al. [34] demonstrated that AI tools for rendering 3D tumors significantly improved surgical success rates and patient satisfaction in breast cancer cases.

In immunotherapy and biomarker research, recent advancements have enabled the identification of key genetic markers associated with cancer progression. For example, Xiao Z et al. [31] identified genes linked to the postoperative progression of non-muscle-invasive bladder cancer, while Jia et al. [32] developed an lncRNA-based model with AUC values exceeding 0.785 to predict overall survival in hepatocellular carcinoma patients. These findings underscore the importance of integrating AI into multi-omics analyses to personalize treatments and improve prognoses.

4.3. Impact of AI on specific cancers

In breast cancer, hybrid models based on CatBoost and multilayer perceptron (MLP) neural networks, such as those described by Srinivasu et al. [33], achieved 98.06% accuracy, providing interpretability in clinical decision-making through explainable AI (XAI). This advancement was complemented by Weitz et al. [34], who improved surgical planning through AI tools, enhancing success rates for breast cancer patients. Additionally, RI and Bai [35] achieved 98.57% accuracy in recurrence prediction using a DCNN-based model, optimizing therapeutic strategies.

For other cancer types, Song et al. [38] used metabolic fingerprinting to detect triple-negative breast cancer, achieving 88.8% sensitivity. This advancement highlights AI's capacity to identify unique metabolic characteristics in specific cancer subtypes. Similarly, in liver cancer, Xing et al. [39] developed a proteomic panel with an AUC of 0.988 to predict treatment responses, reflecting AI's impact on optimizing pharmacological treatments.

The results show that AI models have not only significantly improved performance metrics, such as accuracy and sensitivity, but have also facilitated critical applications in oncology, ranging from early diagnosis to personalized treatment planning. Furthermore, it is evident how AI innovations enable more informed decision-making and more precise patient care.

5. Limitations

While the findings of this review are significant, they face several limitations. First, many of the analyzed studies are based on retrospective cohorts, which may introduce selection biases and limit the applicability of the results in prospective clinical settings. Additionally, most AI models evaluated require large, well-curated datasets to achieve optimal performance, which is not always available in resource-limited settings. This limitation may restrict the implementation of these technologies in regions with less developed healthcare infrastructures.

Moreover, one of the main challenges in integrating artificial intelligence (AI) into oncology is the heterogeneity of available models and the differences in the datasets used. Variability in algorithms, model architectures, and evaluation criteria complicates direct comparisons between studies and limits the generalization of findings. For example, deep learning models that require large volumes of homogeneous data may not be applicable in contexts where data is scarce or inconsistent due to differences in clinical protocols or data capture standards.

Moreover, resource-limited settings face additional barriers to implementing these technologies. The lack of technological infrastructure, such as specialized hardware (e.g., Graphics Processing Units (GPUs) for model training) and high-speed internet access, hampers the adoption of advanced models. Similarly, the absence of well-curated and annotated local datasets makes training and validating models in these contexts challenging. This can exacerbate global inequities in access to advanced healthcare technologies.

To overcome these limitations, it is necessary to develop more robust and adaptable AI models that can effectively operate with heterogeneous data. Additionally, fostering international collaborations to share knowledge, infrastructure, and data is crucial to ensure technological advancements are accessible to resource-limited countries. Implementing "explainable AI" (XAI) strategies and transfer learning models could also provide viable solutions, as these approaches require less domain-specific data and can be applied in contexts with underdeveloped infrastructures.

5.1. Data quality and standardization as key challenges

Data quality and standardization are critical issues that directly impact the accuracy and applicability of AI models in oncology. Medical data, such as diagnostic images, electronic health records, and omics data, often originate from heterogeneous sources with significant variations in collection protocols, formats, and quality. This lack of uniformity makes it difficult to compare studies and develop generalizable models applicable in diverse clinical contexts.

Additionally, the absence of global standards for data collection and labeling creates issues related to model interoperability and reproducibility. For example, differences in the resolution of medical images, the types of annotations used in imaging studies, and protocols for handling omics data can introduce biases into models, limiting their ability to generalize across diverse populations.

Data quality is further affected by errors in manual annotation and the lack of representative data from specific populations, such as those in developing countries. This not only reduces model effectiveness but also exacerbates inequities in access to advanced healthcare technologies.

5.2. Ethical challenges in applying AI in oncology

The implementation of AI in oncology raises numerous ethical challenges that must be addressed to ensure its safe, transparent, and equitable use. Key issues include:

5.2.1. Data privacy

AI models in oncology rely on large volumes of patient data, including sensitive information such as medical images, genetic data, and clinical records. While these data are essential for training accurate algorithms, their collection and storage pose significant privacy risks. Breaches in health databases can expose personal information, undermining patient trust and willingness to participate in future research. To mitigate these risks, approaches such as data anonymization, blockchain technologies to ensure data integrity, and strict compliance with regulations like the General Data Protection Regulation (GDPR) in Europe are needed.

5.2.2. Bias in AI models

AI models are inherently influenced by the data on which they are trained. When datasets are not representative of diverse populations, algorithms may perpetuate or exacerbate existing healthcare inequalities. For example, models trained predominantly on data from urban populations or developed countries may not perform effectively in rural settings or resource-limited countries. Additionally, differences in gender, ethnicity, and access to healthcare can lead to biased predictions and clinical decisions. Implementing techniques to identify and mitigate these biases, such as regular model audits, designing more inclusive datasets, and adopting explainable AI (XAI) approaches, is crucial to allow healthcare professionals to understand and question algorithmic decisions.

5.3. Practical recommendations

- Transparency: Ensure that AI models are interpretable and auditable by healthcare professionals. This not only enhances trust in predictions but also enables real-time identification of potential errors or biases.

- International collaboration: Promote global regulations to ensure equitable access to AI-based technologies and foster the creation of shared ethical frameworks.
- Education and training: Equip healthcare professionals with the necessary skills to understand how AI models are developed and applied, ensuring their ethical and effective use.
- Establishment of global standards: Develop international standards for medical data collection, labeling, and storage to significantly improve data quality and interoperability.
- Data curation and validation: Implement automated curation processes and regular audits to ensure that datasets are consistent and free from annotation errors.
- Encouraging international consortia: Support the creation of international consortia to share standardized data and protocols, enabling the development of more robust and generalizable AI models.
- Data augmentation techniques: Use data augmentation and synthetic data generation techniques, such as generative adversarial networks (GANs), to address the lack of representative data in underrepresented populations.

6. Conclusions

Advances in artificial intelligence (AI) in oncology, while promising, are accompanied by significant ethical challenges that must be prioritized to ensure its responsible and equitable adoption. As discussed in the findings, the key ethical issues include data privacy, biases in models, and transparency in algorithms. Data privacy is fundamental to preserving patient trust and the willingness of medical institutions to share information. On the other hand, biases inherent in models can exacerbate inequalities in access to effective treatments, particularly in underrepresented populations.

To address these challenges, it is essential to implement robust international regulations governing data management and promoting equity in the design and application of AI models. Furthermore, future research should focus on developing explainable artificial intelligence (XAI) tools that enable healthcare professionals to understand and audit algorithmic decisions, ensuring they are fair and transparent. These measures would not only mitigate ethical concerns but also strengthen the acceptance of these technologies among healthcare professionals and patients, amplifying their positive impact on modern oncology.

6.1. Opportunities for future research

The advancement of artificial intelligence (AI) in oncology offers fertile ground for exploring its integration with emerging technologies, potentially amplifying its impact on cancer diagnosis and treatment. Key areas deserving attention in future research include:

6.1.1. Integration with nanotechnology

Nanotechnology enables the development of targeted drug delivery systems and molecular sensors for early tumor detection. Combining AI with this technology could optimize personalized treatments through algorithms that analyze real-time patient responses to nanodrugs.

6.1.2. Use of blockchain for data management

Blockchain provides a secure and decentralized approach to storing and sharing clinical data, ensuring privacy and transparency. Integrating AI with blockchain could facilitate training models on large datasets while preserving patient confidentiality and fostering global collaboration among medical institutions.

6.1.3. Combination with advanced omics

Omics technologies (genomics, transcriptomics, proteomics, metabolomics) generate massive amounts of data that AI algorithms can analyze to identify complex biological patterns. Integrating AI with these technologies could accelerate the development of predictive biomarkers and enhance precision medicine.

6.1.4. Applications in augmented reality (AR) and virtual reality (VR)

In the surgical domain, combining AI with AR and VR could improve the planning and execution of complex surgeries by providing 3D visualizations of tissues and tumors. This would enable surgeons to make more informed and precise decisions during procedures.

6.1.5. Adoption of quantum algorithms

Quantum computing promises to solve optimization and big data analysis problems at unprecedented speeds. Combining AI with quantum computing could revolutionize medical image analysis, treatment prediction, and modeling of biological interactions.

6.1.6. Development of multi-modal models

Future research could focus on creating models that integrate multiple data sources, such as medical images, omics data, and clinical records, to provide more robust and accurate predictions for cancer management.

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