

MINI-REVIEW

Artificial intelligence for early detection and diagnosis of colorectal cancer: Current evidence and future directions

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Abstract

Colorectal cancer (CRC) is one of the most prevalent and deadly malignancies globally. Early detection and accurate diagnosis are crucial for improving survival rates and treatment outcomes. Research in oncology and medical informatics has made significant progress. However, conventional screening approaches, such as colonoscopies, fecal occult blood tests, and imaging modalities, have limitations in terms of sensitivity, specificity, and patient adherence. Thus, a literature review was conducted to identify contemporary evidence relevant to the study objectives. Searches were conducted across major scientific databases, including PubMed, EBSCO, and Scopus. The search strategy targeted peer-reviewed publications encompassing original research articles, systematic reviews, and expert commentaries published within the past 5 years. High-impact journals, such as The New England Journal of Medicine and Nature were manually screened to ensure the inclusion of seminal and authoritative works. Notably, advances in artificial intelligence (AI), software detection tools, models, and algorithms have enabled improved screening, rapid detection, risk prediction, and more accurate and consistent diagnosis. Real-time AI-assisted endoscopy has improved detection rates for colorectal neoplasia. The review indicated that the adenoma detection rate during colonoscopy was 54.8% in the computer-aided polyp detection group compared to 40.4% in the control group. The incorporation of AI in the early detection and diagnosis of CRC presents considerable potential. While the use of these tools has potential benefits, challenges remain. Ongoing efforts are focused on overcoming barriers to clinical integration and improving clinical outcomes, ensuring that AI technologies are safe, effective, and accessible.

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1. Introduction

Artificial intelligence (AI), a rapidly evolving branch of computer science that mimics the brain's thought process, learning ability, and handling of information, offers promising applications in public health and clinical oncology. AI has contributed to enhancing the early detection and diagnosis of colorectal cancer (CRC).¹ As one of the most common and fatal malignancies worldwide, CRC accounts for 1.9 million new cases and 930,000 deaths annually. At present, low- to middle-income countries are experiencing a rise in

CRC rates, primarily attributed to urbanization. Although CRC is a global disease, there are significant regional differences in both incidence and mortality, with the highest incidence in the Pacific (Australia/New Zealand) and European regions, with the highest incidence rates observed in Australia/New Zealand and Europe (40.6 per 100,000 males), while the lowest were recorded in several African regions and Southern Asia (4.4 per 100,000 females).²

Early detection and accurate diagnosis are crucial for improving survival rates and treatment outcomes. Traditional screening methods, including colonoscopies, fecal occult blood tests, and imaging techniques, have limitations in terms of sensitivity, specificity, and patient compliance, with various unmet clinical needs. Many patients are diagnosed at advanced stages due to low participation in screening programs or missed lesions during colonoscopy. Moreover, pathologic grading and imaging interpretation are subjective and time-consuming, resulting in variability among pathologists and radiologists, which can lead to inconsistent diagnoses. Colonoscopy-based screening is further hindered by discomfort, cost, and resource availability, especially in low-resource settings. Although factors, such as genetics, lifestyle, microbiota, and imaging/histology characteristics all affect the risk of CRC, current screening guidelines still rely on a largely “universal” approach. Clinicians are overburdened with large volumes of radiological images, pathology slides, and colonoscopy recordings, which are labor-intensive and prone to errors related to fatigue. These challenges are exacerbated in settings with shortages of endoscopy specialists and pathology infrastructure. Against this backdrop, AI offers promising advancements for the earlier, more accurate, and more accessible detection and diagnosis of CRC, particularly when integrated with emerging imaging technologies, such as narrow-band imaging and high-definition colonoscopy.³

2. AI in CRC screening

Nomogram models that integrate deep learning-based pathomics, radiomics, and Immunoscore have been successfully developed to predict the post-operative outcome of metastatic CRC, including overall survival (OS) and disease-free survival (DFS). These models utilize comprehensive analyses of structural alterations in tissues, employing a support vector machine classifier to identify radiomics features and the density of CD3⁺ and CD8⁺ cells at the invasive margin, and outperform approaches relying on Immunoscore or clinicopathological features alone.⁴ Radiomics features include intensity, shape, texture, and wavelength, whereas pathomics features

include cellular morphology, glandular architecture, texture, and stroma. When integrated with measures of functional immune response, the feature set generates a multi-scale biomarker signature with strong prognostic value. In a study of 103 CRC patients with metastases, the composite nomogram performed exceptionally well in predicting DFS (area under the curve [AUC] = 0.875) and OS (AUC = 0.860), thereby proving the nomogram’s clinical utility. In addition, algorithms trained on large datasets of traditionally stained slides (e.g., hematoxylin and eosin) to identify patterns suggestive of CRC have shown superior prognostic performance. These algorithms outperform traditional morphological prognostic markers, yielding consistent results across tumor and nodal stages.^{5,6} Other common models, including convolutional neural networks (CNNs), are particularly effective in analyzing medical images for the prediction of mutational, microsatellite, and chromosomal instability status. An analysis of samples comprising 67 slides labeled as high mutation density and 363 labeled as low mutation density achieved a mean cross-validated area under the receiver operating characteristic curve of 0.81 (standard deviation 0.03), an improvement over previously reported values of 0.71.⁷ Given that deep learning models, such as artificial neural networks and CNNs, can solve complex mathematical problems with straightforward computational methods, they are well-suited for a wide range of problems involving polyps and tumors. Several reviews offer insights into the clinical implementation of these models, highlighting their rapid detection, prediction, and prognostic capabilities.⁸

Polyp detection and real-time analysis demonstrate the impact of AI systems in image analysis and colonoscopy. Timely and accurate diagnosis is essential to save patients’ lives. Clinical trials have shown the impact of computer-aided polyp detection (CADe) as applied during routine colonoscopy screening for CRC. The rate of missed adenomas was significantly lower in the computer-aided group compared with standard colonoscopy. Furthermore, CNNs and trained imaging tools have demonstrated effective classification and accuracy in polyp identification, showing significant advantages compared to manual inspections performed by trained professionals, which are prone to numerous errors.⁹ In general, adenoma detection rates (ADRs) are higher with greater accuracy; the number of adenomas detected per colonoscopy was significantly higher in the CADe group. In a study involving 1,624 patients, the adenoma miss rate was considerably lower in the CADe-assisted group (15.9%) compared to the routine colonoscopy group (35.9%).^{10,11} Among the AI systems approved by the FDA for pathology, radiology, and

Table 1. Food and Drug Administration-approved artificial intelligence tools in digital pathology and oncology

AI tool/model	Developer	Dataset/training source	Performance (accuracy/AUC)	Clinical applicability
Paige prostate	Paige.AI; FDA 2021	>32,000 prostate biopsy slides (MSKCC)	AUC=0.98	Assists pathologists in detecting prostate cancer on digitized slides
Ibex Galen™ Prostate/Breast	Ibex Medical Analytics, CE-IVD; FDA pending	6,000+ WSI (Israel, UK datasets)	AUC=0.99; sensitivity >95%	Detects cancer and grading in prostate/breast biopsies
PathAI platform	PathAI/LabCorp; ongoing FDA collaborations	TCGA, partner labs	Accuracy >95%	AI-assisted biomarker scoring and tumor grading
Paige Breast Lymph Node	Paige.AI; FDA 2023	>10,000 WSI (multicenter)	AUC=0.96	Detects lymph node metastases in breast cancer
Proscia Concentriq® Dx	Proscia Inc.; FDA 510(k) 2023	12,000+ slides (US/Europe)	N/A	AI-assisted digital pathology review platform
Viz LVO, oncology imaging	Viz.ai; FDA-cleared (radiology)	NIH ChestX-ray14, TCIA	AUC=0.95	Workflow AI for oncology and stroke imaging
Paige Colon (Research)	Paige.AI; research use only	7,500+ colon biopsy WSIs	AUC=0.97	Prototype for colorectal cancer screening and staging

Abbreviations: AI: Artificial intelligence; AUC: Area under the curve; FDA: Food and Drug Administration; IVD: *In vitro* diagnostic; LVO: Large vessel occlusion; MSKCC: Memorial Sloan Kettering Cancer Center; TCGA: The Cancer Genome Atlas; UK: United Kingdom; US: United States; WSI: Whole slide imaging.

cancer screening are GI Genius, for real-time polyp detection during colonoscopies, as well as Discovery AI and Endobrain-EYE (Table 1).¹² AI systems can provide endoscopists with immediate feedback, flagging questionable lesions and possibly lowering the miss rate. A multicenter RCT found that novice endoscopists using AI-assisted colonoscopy had a significantly lower adenoma miss rate compared to non-AI novices and performed at a level non-inferior to expert endoscopists.¹³ In parallel, AI-assisted reporting tools can automatically provide structured summaries, while automated pre-screening and triage systems flag abnormal findings for priority inspection. By reducing labor for clinicians and enabling faster interpretation of diagnostic data, these enhancements help mitigate human-factor limitations, such as fatigue and oversights.

2.1. Tissue detection and immune profiling

Algorithms can automate histopathological slide analysis and grading of tumor samples. With the growing demand for targeted therapies, there is an increasing need for diagnostic precision and a reduction in the turnaround time between diagnosis and the reporting of prognostic information. The integration of digital pathological slide analysis and AI-based solutions can facilitate seamless workflows while maintaining accuracy, reproducibility, and scalability.¹⁴ Some AI and digital pathology applications utilize whole slide images and image-based biomarkers derived from the tumor microenvironment.^{14,15} Whole slide images may provide scans at 20 to $\times 40$ magnification, with a resolution of 0.5 μm to 0.25 μm per pixel, enabling a detailed examination of cellular and nuclear

characteristics. Discrepancies in scale and resolution may lead to misleading or inaccurate inferences.¹⁶ A particular study assessed several magnifications ($\times 40$, $\times 100$, $\times 200$, $\times 400$ equivalents) for CNN tasks and discovered that performance differed by assessment, with mid-to-high magnifications frequently surpassing low magnification for cellular assessments. Recommendations suggest that $\times 20$ (0.4 $\mu\text{m}/\text{px}$) is sufficient for many histologic architecture assessments, whereas $\times 40$ (0.2 $\mu\text{m}/\text{px}$) is preferred when nuclear detail is required.¹⁷ The ability of predictive software models to detect activation of immune and inflammatory gene markers directly from histopathological samples further enhances early diagnosis while limiting errors. The development of a clinical-grade AI tool for quantitative tissue analysis of colorectal biopsy and tumor specimens shows a high level of specificity with a composite multiclass Dice score of up to 0.895 and pixel-wise tumor detection specificity and sensitivity of up to 0.958 and 0.987, respectively, for tumor detection and precision in classifying tissue samples based on tumor TNM staging.¹⁸⁻²⁰ The prognostic accuracy of CRC assessment depends on the distribution and interaction of immune cells. In addition to these predictive models, deep learning and CNNs can determine the spatial distribution of CD3⁺ and CD8⁺ T cells within the tumor microenvironment, thereby enhancing the reliability of prognosis at the time of screening.²¹ AI models, including HoVer-Net, ResNet-50, Inception-v3, and Vision Transformers, can automate tumor grading, providing more objective evaluations for diagnosis and prognosis. Although AI models are capable of identifying subtle patterns that are imperceptible to humans, newer explainable AI approaches are needed to

make these model decisions visible and understandable to human specialists.

3. Artificial intelligence in non-invasive screening methods

3.1. Fecal tests and biomarkers

In addition to traditional screening methods, such as colonoscopies, fecal occult blood tests, and imaging techniques, the composition of stool-sampled gut microbiota can be analyzed using machine learning models to identify patterns associated with CRC. As the mortality burden of cancers, such as CRC remains substantial, new techniques are being developed using machine learning algorithms and AI to evaluate the contribution of the gut microbiome to the development of dysplastic luminal cells. According to large cohort and cross-cohort studies, stool microbiota profiles can distinguish CRC cases from controls when analyzed using machine learning classifiers or multivariable predictive models. These datasets demonstrate the predictive power of combined signatures, with an AUC of approximately 0.91 for adenoma and approximately 0.99 for CRC.^{22,23} Several studies using machine learning techniques, such as logistic regression, naïve Bayes, and Shapley method additive explanations, demonstrate a strong association between gut microbiota composition and the development of CRC.^{24,25} Shapley method additive explanations, in particular, is an interpretability algorithm that explains the prediction of a machine learning model by assigning each feature a Shapley value, indicating how strongly—and in which direction (positive or negative)—that feature contributes to the final prediction. AI enables the interpretation of complicated datasets from liquid biopsies, including circulating tumor DNA and other biomarkers, to identify early indications of CRC. Microsatellite instability and DNA repair mismatches are hallmark features of CRC pathogenesis. The real-time use of AI in clinical settings not only helps rule out the possibility of CRC but also reduces the cost and time associated with molecular profiling and analysis.^{26,27} AI accelerates and improves each of these processes by prioritizing patients for colonoscopies, decreasing false positives and negatives, automating pattern identification in complicated biological data, minimizing manual effort in feature extraction and interpretation, and enabling quick risk assessment. Examples include solutions from Exact Sciences and partners, Google DeepMind's AI colonography project (2023), and the FDA-cleared Medtronic's GI Genius system. Together, these platforms demonstrate AI's ability to analyze imaging data in real time and highlight capabilities that could be readily transferred to capsule endoscopy.

3.2. Artificial intelligence-assisted colonoscopy, computed tomography colonography, and magnetic resonance imaging (MRI) applications

Artificial intelligence-assisted colonoscopy could augment or replace traditional colonoscopy, offering a promising method for screening and detecting polyps and flat adenomas. Data suggest that one in four neoplastic lesions is missed during screening, leading to late identification, poor prognosis, and mortality. RCTs have demonstrated increased ADRs for neoplastic changes. AI-assisted colonoscopy increased ADR to 54.8% compared to 40.4% in the control group.^{10,28} In addition, virtual interpretation of computed tomography colonography is utilized with AI assistance in polyp detection and segmentation, offering a far less invasive alternative to traditional colonoscopy with comparable accuracy. The significance of this approach lies in providing an optimized surveillance strategy and screening method in clinical practice.²⁹ The characterization of colorectal malignancies is as vital as colorectal screening and diagnosis. Highly accurate AI models, such as random forest classifiers and 3D ResNet, have been applied to MRI data to identify tumor boundaries and gauge metastatic spread. Endoscopists can now assess polyps for malignant potential in real-time, improving diagnosis and reducing the need for unnecessary resection.^{30,31} Radiomics extracts characteristics, such as the signal intensity histogram, skewness, and kurtosis, that can help assess tumor heterogeneity, invasion depth, and lymph node involvement. Applicable examples include radiomic models with AUCs between 0.85 and 0.90 in validation sets that can differentiate between T2 and T3 rectal tumors using T2-weighted MRI.³² Deep learning models, especially U-Net, nnU-Net, and Vision Transformers, automatically segment tumor regions and surrounding structures on MRI, enabling precise automated tumor delineation. Modern workflows integrate handcrafted radiomic features with automatically learned deep features to enhance staging performance. When radiomics and deep CNN features are combined, the resulting AUCs for TN staging consistently exceed those achieved by either method alone.³³

4. Challenges and limitations

Although the benefits of AI in clinical settings are widely acknowledged, several limitations are being investigated to reduce errors and enhance the technology's long-term use in workflows across various medical specialties, including radiology and diagnostic oncology. AI-based systems can occasionally misidentify non-polyp structures, such as mucosal folds, bubbles, or stool residues, resulting in false alarms. This may lead to "alarm fatigue" among endoscopists, eroding trust in AI assistance. Endoscopic videos often

contain artifacts that degrade model accuracy and increase both false negatives and false positives. For example, a study comparing two CAdE systems found that the one with a lower false positive rate (0.6%) achieved a significantly higher ADR than the system with a false positive rate of 3.2%.³² For CAdE systems to be clinically useful during live colonoscopy, they must function with minimal latency and an acceptable frame rate to avoid disrupting endoscopists' workflow or delaying decision-making, as noticeable latency (e.g., >100 ms) or a reduced effective frame rate can interfere with real-time interpretation.

Ethical concerns are increasingly focused on ensuring accuracy, precision, and the responsible use of algorithms to benefit the public rather than cause harm.³⁴ Other areas of concern include data quantity and quality, interoperability, transparency, and ease of integration into clinical practice. To protect patient privacy and ensure the ethical processing of data, AI systems used in healthcare must adhere to data protection regulations (Figure 1). The Health Insurance Portability and Accountability Act prohibits the sharing of identifiable health information without consent and requires the de-identification of patient data. Patients are granted additional "data subject rights" under the European Union's General Data Protection Regulation, including the right to be forgotten, data portability, and informed consent before their data is used. Individual

privacy must be balanced with data accessibility for model training; excessive anonymization can lower model performance, while insufficient protection increases the likelihood of re-identification. A source of bias exists as imaging datasets often come from Western, urban, or tertiary hospitals, neglecting global diversity.

With the ongoing enrichment of clinical data sets across inpatient and outpatient settings, AI models require large, diverse, and high-quality datasets to achieve optimal performance. The availability and standardization of medical data remain significant challenges. Microbial taxa that are predictive in one geographic region may be less common or even non-existent in another due to variations in the gut microbiome between populations, which are caused by differences in diet, environment, cleanliness, and genetics. As a result, models trained on one region frequently lose accuracy when applied elsewhere. Image tiles representing tissue components in a whole slide image cannot uniformly predict the status of molecular pathways and critical mutations, thereby increasing the risk of generalization errors in AI models trained on a limited number of pathology images.^{7,35} Efforts are therefore being made to establish uniform central laboratories for quality assurance, and large-scale clinical trials can be used for evaluation. Deep learning models, in particular, are frequently regarded as "black boxes," making it challenging to understand how they make decisions. Ensuring explainability and openness is essential for clinical acceptance, as pathologists and regulators must comprehend the reasoning behind an algorithm's predictions before they can trust it or act on its output. Hence, there is a need to develop explainable models to ensure proper assessment of decision-making by specialists.

Across its Center for Devices and Radiological Health, the FDA regulates medical devices that use AI and machine learning. Under the European Union Medical Device Regulation, the European Medicines Agency collaborates with the European Commission and Notified Bodies. AI-specific regulatory guidelines are still under development, with medical AI generally classified as high-risk and emphasizing explainability, human oversight, and transparency. Careful consideration of usability, interoperability, and regulatory compliance is necessary when integrating AI tools into current healthcare workflows. In addition, it is crucial to train healthcare professionals to use AI technologies correctly. A notable example includes reports encouraging the adoption of virtual colonoscopy for diagnostic purposes.³⁶

5. Conclusion

A new era is emerging as healthcare systems globally employ automation through informatics and AI. AI has

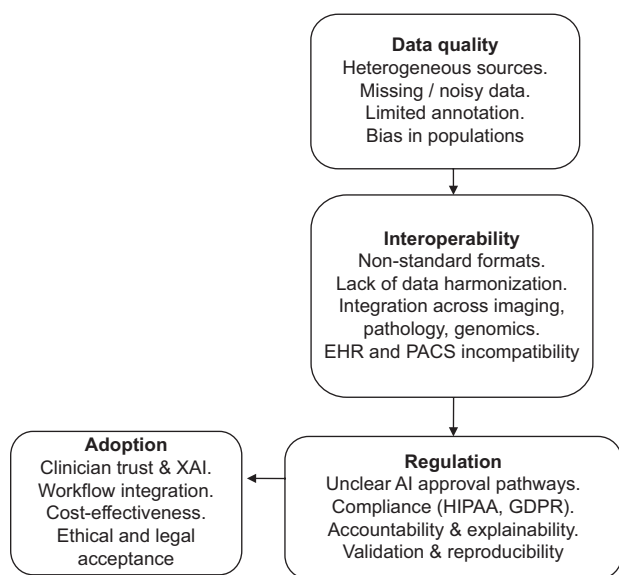


Figure 1. Schematic representation of key challenges in the clinical translation of artificial intelligence (AI) for colorectal cancer screening. The pathway illustrates the cumulative barriers from data acquisition to clinical adoption, with ensuring data quality and interoperability underpinning regulatory compliance and ultimately determining the success of real-world adoption. Abbreviations: GDPR: General data protection regulation; HIPAA: Health insurance portability and accountability act; XAI: Explainable artificial intelligence.

the potential to personalize CRC screening and therapy by tailoring interventions based on individual risk profiles and by integrating genetic, epigenetic, and clinical data. The creation of hybrid models that combine traditional diagnostic methods with emerging technologies, such as liquid biopsies and genetic screening, will enhance overall diagnostic accuracy and patient outcomes. Incorporating continuous -learning systems will ensure that AI can learn from new data, continually improve clinical results over time, and adapt to emerging patterns and biomarkers. The utilization of AI presents enormous possibilities for the prompt detection and diagnosis of CRC. Multimodal AI, which combines multiple inputs, such as radiomics, pathomics, genomes, and microbiome profiles, is replacing single-data-type analysis in CRC screening systems. Multiple hospitals or research facilities can collaboratively train AI models without exchanging raw patient data, thereby protecting data privacy and sovereignty, reducing bias, and enabling scalable validation across institutions. AI is evolving from retrospective analysis to real-time, workflow-integrated systems. AI-assisted detection tools, such as GI Genius, already highlight polyps in real time during live procedures. Future models are expected to integrate segmentation, risk scoring, and decision-support functionalities into live workflows.

Although there are still obstacles to overcome, continuous research and development activities are focused on making AI technology safe, efficient, and widely accessible. AI has the potential to significantly improve patient outcomes and reduce the burden of CRC by enhancing the accuracy and efficiency of CRC screening.

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References

1. Sak J, Suchodolska M. Artificial intelligence in nutrients science research: A review. *Nutrients*. 2021;13(2):322. doi: 10.3390/nu13020322
2. Morgan E, Arnold M, Gini A, *et al.* Global burden of colorectal cancer in 2020 and 2040: incidence and mortality estimates from GLOBOCAN. *Gut*. 2023;72(2):338-344. doi: 10.1136/gutjnl-2022-327736
3. Khan A, Hasana U, Nadeem IA, *et al.* Advances in colorectal cancer screening and detection: A narrative review on biomarkers, imaging and preventive strategies. *J Egypt Natl Cancer Inst*. 2025;37(1):20. doi: 10.1186/s43046-025-00277-z
4. Wang R, Dai W, Gong J, *et al.* Development of a novel combined nomogram model integrating deep learning-pathomics, radiomics and immunoscore to predict postoperative outcome of colorectal cancer lung metastasis patients. *J Hematol Oncol*. 2022;15(1):11. doi: 10.1186/s13045-022-01225-3
5. Skrede OJ, De Raedt S, Kleppe A, *et al.* Deep learning for prediction of colorectal cancer outcome: A discovery and validation study. *Lancet*. 2020;395(10221):350-360. doi: 10.1016/S0140-6736(19)32998-8
6. Yamashita R, Long J, Longacre T, *et al.* Deep learning model for the prediction of microsatellite instability in colorectal cancer: A diagnostic study. *Lancet Oncol*. 2021;22(1):132-141. doi: 10.1016/S1470-2045(20)30535-0
7. Bilal M, Raza SEA, Azam A, *et al.* Development and validation of a weakly supervised deep learning framework to predict the status of molecular pathways and key mutations in colorectal cancer from routine histology images: A retrospective study. *Lancet Digit Health*. 2021;3(12):e763-e772. doi: 10.1016/S2589-7500(21)00180-1
8. Davri A, Birbas E, Kanavos T, *et al.* Deep learning on histopathological images for colorectal cancer diagnosis: A systematic review. *Diagnostics (Basel)*. 2022;12(4):837. doi: 10.3390/diagnostics12040837
9. Glissen Brown JR, Mansour NM, Wang P, *et al.* Deep learning computer-aided polyp detection reduces adenoma miss rate: A United States multi-center randomized tandem colonoscopy study (CADET-CS Trial). *Clin Gastroenterol Hepatol*. 2022;20(7):1499-1507.e4. doi: 10.1016/j.cgh.2021.09.009
10. Repici A, Badalamenti M, Maselli R, *et al.* Efficacy of real-

- time computer-aided detection of colorectal neoplasia in a randomized trial. *Gastroenterology*. 2020;159(2):512-520.e7.
doi: 10.1053/j.gastro.2020.04.062
11. Wang SY, Gao JC, Wu SD. Artificial intelligence for reducing missed detection of adenomas and polyps in colonoscopy: A systematic review and meta-analysis. *World J Gastroenterol*. 2025;31(21):105753.
doi: 10.3748/wjg.v31.i21.105753
12. Antonelli G, Gkolfakis P, Tziatzios G, Papanikolaou IS, Triantafyllou K, Hassan C. Artificial intelligence-aided colonoscopy: Recent developments and future perspectives. *World J Gastroenterol*. 2020;26(47):7436-7443.
doi: 10.3748/wjg.v26.i47.7436
13. Yao L, Li X, Wu Z, *et al*. Effect of artificial intelligence on novice-performed colonoscopy: A multicenter randomized controlled tandem study. *Gastrointest Endosc*. 2024;99(1):91-99.e9.
doi: 10.1016/j.gie.2023.07.044
14. Baxi V, Edwards R, Montalto M, Saha S. Digital pathology and artificial intelligence in translational medicine and clinical practice. *Mod Pathol*. 2022;35(1):23-32.
doi: 10.1038/s41379-021-00919-2
15. McCaffrey C, Jahangir C, Murphy C, Burke C, Gallagher WM, Rahman A. Artificial intelligence in digital histopathology for predicting patient prognosis and treatment efficacy in breast cancer. *Expert Rev Mol Diagn*. 2024;24(5):363-377.
doi: 10.1080/14737159.2024.2346545
16. Patel A, Balis UGJ, Cheng J, *et al*. Contemporary whole slide imaging devices and their applications within the modern pathology department: A selected hardware review. *J Pathol Inform*. 2021;12:50.
doi: 10.4103/jpi.jpi_66_21
17. Ashtaiwi A. Optimal Histopathological magnification factors for deep learning-based breast cancer prediction. *Appl Syst Innov*. 2022;5(5):87.
doi: 10.3390/asi5050087
18. Zeng Q, Klein C, Caruso S, *et al*. Artificial intelligence predicts immune and inflammatory gene signatures directly from hepatocellular carcinoma histology. *J Hepatol*. 2022;77(1):116-127.
doi: 10.1016/j.jhep.2022.01.018
19. Griem J, Eich ML, Schallenberg S, *et al*. Artificial intelligence-based tool for tumor detection and quantitative tissue analysis in colorectal specimens. *Mod Pathol*. 2023;36(12):100327.
doi: 10.1016/j.modpat.2023.100327
20. Giammanco A, Bychkov A, Schallenberg S, *et al*. Fast-track development and multi-institutional clinical validation of an artificial intelligence algorithm for detection of lymph node metastasis in colorectal cancer. *Mod Pathol*. 2024;37(6):100496.
doi: 10.1016/j.modpat.2024.100496
21. Cai M, Zhao K, Wu L, *et al*. Artificial intelligence-based analysis of tumor-infiltrating lymphocyte spatial distribution for colorectal cancer prognosis. *Chin Med J (Engl)*. 2024;137(4):421-430.
doi: 10.1097/CM9.0000000000002964
22. Gao R, Wu C, Zhu Y, *et al*. Integrated analysis of colorectal cancer reveals cross-cohort gut microbial signatures and associated serum metabolites. *Gastroenterology*. 2022;163(4):1024-1037.e9.
doi: 10.1053/j.gastro.2022.06.069
23. Piccinno G, Thompson KN, Manghi P, *et al*. Pooled analysis of 3,741 stool metagenomes from 18 cohorts for cross-stage and strain-level reproducible microbial biomarkers of colorectal cancer. *Nat Med*. 2025;31(7):2416-2429.
doi: 10.1038/s41591-025-03693-9
24. Novielli P, Romano D, Magarelli M, *et al*. Explainable artificial intelligence for microbiome data analysis in colorectal cancer biomarker identification. *Front Microbiol*. 2024;15:1348974.
doi: 10.3389/fmicb.2024.1348974
25. Lu F, Lei T, Zhou J, *et al*. Using gut microbiota as a diagnostic tool for colorectal cancer: Machine learning techniques reveal promising results. *J Med Microbiol*. 2023;72(6).
doi: 10.1099/jmm.0.001699
26. Hüneburg R, Bucksch K, Schmeißer F, *et al*. Real-time use of artificial intelligence (CADEYE) in colorectal cancer surveillance of patients with Lynch syndrome-A randomized controlled pilot trial (CADLY). *United European Gastroenterol J*. 2023;11(1):60-68.
doi: 10.1002/ueg2.12354
27. Echle A, Ghaffari Laleh N, Quirke P, *et al*. Artificial intelligence for detection of microsatellite instability in colorectal cancer-a multicentric analysis of a pre-screening tool for clinical application. *ESMO Open*. 2022;7(2):100400.
doi: 10.1016/j.esmoop.2022.100400
28. Hassan C, Spadaccini M, Iannone A, *et al*. Performance of artificial intelligence in colonoscopy for adenoma and polyp detection: A systematic review and meta-analysis. *Gastrointest Endosc*. 2021;93(1):77-85.e6.
doi: 10.1016/j.gie.2020.06.059
29. Jain S, Maque J, Galoosian A, Osuna-Garcia A, May FP. Optimal strategies for colorectal cancer screening. *Curr Treat Options Oncol*. 2022;23(4):474-493.
doi: 10.1007/s11864-022-00962-4
30. Goyal H, Sherazi SAA, Mann R, *et al*. Scope of artificial

- intelligence in gastrointestinal oncology. *Cancers (Basel)*. 2021;13(21):5494.
doi: 10.3390/cancers13215494
31. Parsa N, Rex DK, Byrne MF. Colorectal polyp characterization with standard endoscopy: Will Artificial Intelligence succeed where human eyes failed? *Best Pract Res Clin Gastroenterol*. 2021;52-53:101736.
doi: 10.1016/j.bpg.2021.101736
32. Chung GE, Lee J, Lim SH, *et al*. A prospective comparison of two computer aided detection systems with different false positive rates in colonoscopy. *NPJ Digit Med*. 2024;7(1):366.
doi: 10.1038/s41746-024-01334-y
33. Huan L, He Q, Cao Y, Liu C, Li Y. Development and validation of a prognostic nomogram for unresectable pancreatic ductal adenocarcinoma with synchronous liver metastases: A study based on the SEER database and an external cohort. *Front Oncol*. 2025;15:1636715.
doi: 10.3389/fonc.2025.1636715
34. Sim I, Cassel C. The ethics of relational AI-expanding and implementing the Belmont principles. *N Engl J Med*. 2024;391(3):193-196.
doi: 10.1056/NEJMp2314771
35. Liyanage H, Liaw ST, Jonnagaddala J, *et al*. Artificial intelligence in primary health care: Perceptions, issues, and challenges. *Yearb Med Inform*. 2019;28(1):41-46.
doi: 10.1055/s-0039-1677901
36. Tandilava I, Urushadze O, Tsetskhladze D, Tsetskhladze G, Phutkaradze M. The role and place of virtual CT colonoscopy in complex radiological diagnosis of colon diseases. *Georgian Med News*. 2020;306:19-23.