Review Article

BIOMEDICAL
Journal of Scientific & Technical Research

ISSN: 2574 -1241

DOI: 10.26717/BJSTR.2023.49.007812

Artificial Intelligence for Colonoscopy: Beyond Polyp Detection – A Review of where we are Today and where AI can Take us

Angela Hsu*, Robin Zachariah, James Han and William Karnes

University of Irvine, California Gastroenterology Department, USA

***Corresponding author:** Angela Hsu, University of Irvine, California Gastroenterology Department, USA

ARTICLE INFO

Received: March 07, 2023

Published: March 30, 2023

Citation: Angela Hsu, Robin Zachariah, James Han and William Karnes. Artificial Intelligence for Colonoscopy: Beyond Polyp Detection – A Review of where we are Today and where AI can Take us . Biomed J Sci & Tech Res 49(3)-2023. BJSTR. MS.ID.007812.

ABSTRACT

Colorectal cancer (CRC) is the second leading cause of cancer-related death worldwide [1]. Colonoscopy with polypectomy is the most effective way to prevent CRC. The best outcome requires a detection rate that approaches the true prevalence of precancerous polyps. Unfortunately, detection rates vary widely among colonoscopists, prompting the development of new technologies and techniques to improve polyp detection. Toward this aim, Artificial Intelligence (AI) for screening and surveillance colonoscopy has emerged, including computer-assisted polyp detection (CADe) and characterization (CADx). On the heels of CADe and CADx are upcoming computer-aided algorithms designed to track colonoscopy quality metrics, which we coin "CAQ." Examples of CAQ metrics include automated detection of bowel prep score and cecal intubation/withdrawal time, all of which correlate with improved detection. In this review, we describe how the incorporation of CADe, CADx, and CAQ may optimize the colonoscopy outcomes for both patients and physicians.

Abbreviations: AI: Artificial Intelligence; CRC: Colorectal Cancer; DCNN: Deep Convolutional Neural Network; DL: Deep Learning; EC: Endo Cystoscopy; ADR: Adenoma Detection Rate; PDR: Polyp Detection Rate; AMR: Adenoma Miss Rate; ASGE: American Society for Gastrointestinal Endoscopy; PIVI: Preservation and Incorporation of Valuable Endoscopic Innovations; CADe: Computer-Assisted Polyp Detection; PCCRC: Post-Colonoscopy Colorectal Cancer

Advances in Machine Learning: from Polyp Identification (CADe) to Polyp Identification (CADx)

Deep learning (DL), a subcategory of machine learning introduced in the 1980s, utilizes multiple layers of computing nodes collectively called a Deep Convolutional Neural Network (DCNN) to analyze and identify images. Using combined extraction and classification features, DCNNs can self-learn and automatically identify distinct features of an image, thereby simulating the role of the human cortex [2,3]. The proven applicability of machine learning algorithms for still image interpretation has paved the way for real-time use in colonoscopy. For example, an early study published in 2010 described computerized algorithms that could distinguish between pit patterns on polyps with an accuracy of 98.5% relative to expert endoscopists (132 of 134 samples) [4]. Japanese researchers Takeda et al. demonstrated that a CADx trained on cellular, glandular, and vessel structure data in endocytoscopy (EC) images achieved a diagnostic precision that outperformed trainees for neoplasm detection [5]. Recent meta-analyses confirm the potential of CADx. In 2021, Parsa and Byrne examined seventeen studies subcategorized into CADx for digitally enhanced endoscopy (the largest category), chromoendoscopy, white-light imaging, and endocytoscopy [6]. All subcategories showed promising results for AI-enhanced detection and characterization of colorectal polyps. A separate meta-analysis by Nazarian et al. identified 22 studies (18 retrospective, 3 prospective) focused on AI usage for polyp characterization. Sixteen of these studies (4,001 patients) utilized colonoscopy video footage which demonstrated pooled results of 94% sensitivity, 82% specificity, and

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90% polyp detection accuracy using a CADx system. Heterogeneity, lack of standardization, and small sample size limit these early meta-analyses [7]. Large multi-center prospective clinical trials that adopt uniform quality measures are needed to combat these limitations.

Computer-Assisted Polyp Detection (CADe) Improves Adenoma Detection Rate (ADR) and reduces Adenoma Miss Rate (AMR)

Adenoma Detection Rate (ADR), defined as the percentage of screening colonoscopies with at least one adenoma identified, is a proven quality indicator for screening colonoscopy. With each 1% increase in ADR, the subsequent risk of colon cancer reduces by 3% [8]. ADR varies widely (7-53%) amongst endoscopists treating the same patient cohort presumed to have a uniform adenoma prevalence. Therefore, the wide range of ADR reflects variable endoscopist performance and provides an inviting role for AI-guided performance enhancement. Since the first real-time application of DCNN applied to colonoscopy imagery was published by Urban et al. in 2018 there have been multiple randomized control trials and meta-analyses demonstrating a significant improvement in ADR associated with the use of computer-aided detection for polyp detection (32.9% compared to 20.8%, p<0.001) [9,10]. A separate analysis predicted that CADe could improve ADR by up to 50% [11]. Recent pooled analysis (PubMed, Cochrane Library, Embase, and Web of Science) highlighted five studies (4,311 patients) that showed statistically significant increases in polyp detection rate (PDR) and ADR when AI was utilized compared to control (OR = 1.91 and 1.75; respectively). These differences were statistically significant despite discrepancies in bowel preparation [12]. Adenoma Miss Rate (AMR) refers to the rate of missed adenomas during screening colonoscopy estimated by the findings on the second colonoscopy in back-to-back tandem colonoscopy trials.

Adenoma Detection Rate (ADR) and Adenoma Miss Rate (AMR) are complementary measurements that play a role in estimating the likelihood of post-colonoscopy colorectal cancer (PCCRC) occuring between appropriately spaced colonoscopies. Missed adenomas account for 50-60% of PCCRCs [13]. In a 1997 study of 183 patients undergoing back-to-back colonoscopies, Rex et al. found that the AMR varied significantly (17% to 48%) amongst individual endoscopists, with an alarming 24% of adenomas missed on the first exam [14]. Missed adenomas are either due to failed recognition of adenomas exposed in the visual field or to failed exposure of polyps into the visual field. CADe could mitigate the former, whereas CAQ algorithms could mitigate the latter by setting alarms for failure to reach the cecum, poor preparation, or failure to expose surfaces behind colon folds. The ability of CADe to mitigate failed recognition of adenomas was demonstrated in a recent study revealing a two-fold reduction of AMR of colorectal neoplasia compared to non-AI assisted tandem colonoscopies (n=230, 0.33 vs 0.70; P<.001) [15].

Cost Savings of CADx for Optical Biopsy

CADx algorithms in colonoscopy focus on the concept of «optical biopsy» to predict histopathology in real-time to allow for “resect-and-discard” or “diagnose and leave” strategies which would significantly reduce polypectomy pathology costs. For example, adopting a resect-and-discard strategy would reduce the average cost of a colonoscopy by $125, leading to gross annual reimbursement savings of $149.2 million, $12.3 million, $1.1 million, and $85.2 million in Japan, England, Norway, and the US, respectively [16]. In 2011, the American Society for Gastrointestinal Endoscopy (ASGE) created performance requirements in order to «resect and discard» or «diagnose and leave» diminutive polyps. These performance thresholds were titled «Preservation and Incorporation of Valuable endoscopic Innovations» (PIVI). To achieve «resect and discard» thresholds, an optical biopsy method must achieve a >90% concordance in recommended surveillance intervals compared to histology for all diminutive polyps [17]. To achieve «diagnose and leave» thresholds, the optical biopsy system must obtain a >90% negative predictive value for adenomas for diminutive polyps in the rectosigmoid. Since its inception, several studies have attempted to achieve PIVI thresholds. Human-based methods utilizing the NICE criteria based on polyp features under narrow band imaging achieve “diagnose and leave” thresholds when conducted by trained academic experts but fails for most other users. Unlike NICE criteria, CADx can work independently of user expertise or a specialized light source.

In 2019, Zachariah et al. released validation data on a CADx trained to distinguish adenomas and hyperplastic polyps. Surveillance concordance was 94%, and the NPV for diminutive adenomas in the rectosigmoid was 97%, thus achieving both PIVI thresholds [18]. However, this study was retrospective and validated on static images. Interestingly, several groups have reported data sets that achieve the «diagnose and leave» thresholds but fail to report surveillance concordance and thus do not achieve true «respect and discard» thresholds [19].

Computer Assisted Quality Metrics (CAQ) to Enhance and Document Colonoscopy Quality and Optimize Procedural Workflow Efficiency

In addition to automating polyp detection (CADe) and characterization (CADx), AI also has the potential to automatically record key quality measures (CAQ) during colonoscopies such as preparation quality, cecal intubation rate, and withdrawal time. Withdrawal time, defined as the time from cecal identification to colonoscopy completion, is the primary inspection phase of colonoscopy and correlates with ADR. In a landmark study of 7,882 colonoscopies analyzed over 15 months, gastroenterologists with a greater than or equal to 6 minutes withdrawal time had significantly higher rates of neoplasia detection than those with less than 6 minutes withdrawal time (28.3% vs 11.8%, p= 0.005). [20] This finding led

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to the implementation of 6 minutes withdrawal time as a «Quality Indicator» for GI endoscopic procedures. [21] Recent studies have demonstrated that AI-based algorithms can detect the appearance of the appendiceal orifice with >95% accuracy despite variable prep scores. [22] Accurate detection of cecal intubation and automated calculation of withdrawal time can help improve endoscopist awareness of these metrics and reduce the burden of post-colonoscopy documentation. Deep learning algorithms already implemented in clinical practice such as «ENDOANGEL» can utilize video monitoring to identify endoscopy slippage and cecum/withdrawal time; factors which immediately feedback to the performing endoscopists so that technique can be adjusted in real-time [23].

The ENDOANGEL algorithm was trained using a library of over 3,000 blurred and clear images captured during colonoscopy lavage with the goal of recognizing colonoscope slipping. The algorithm was able to detect segments of missed colonic mucosa by recognizing sudden changes in consecutive frames, thus alerting the endoscopist when a blind spot was detected. In a trial of 704 patients randomized to either ENDOANGEL or unassisted colonoscopy (control group), ADR was significantly higher in the ENDOANGEL group (16% compared to 8%; OR 2.30, p=0.0010) with a statistically significant difference in withdrawal time (6.3 minutes compared to 4.7 minutes; p<0.00016). Authors of this study also take note of the added convenience that AI-assisted programs provide, such as the automated documentation of cecal intubation time and calculation of withdrawal time. Additional automated tasks, such as identification of polypectomy tools and labeling of colonoscopy images on procedural reports are in beta testing with the goal of creating a more efficient post-colonoscopy workflow.

Conclusion

Artificial Intelligence has revolutionized the field of colonoscopy for colon cancer screening. Numerous studies have shown that using CADe can increase ADR and reduce AMR, with an expected reduction in PCCRC rates. CADx for polyp characterization may soon open the door to «resect and discard» vs «diagnose and leave» polypectomy strategies, saving the US healthcare economy millions of dollars while allowing point-of-care polypectomy results and surveillance intervals. Meanwhile, burgeoning CAQ algorithms promise to improve colonoscopy quality further while relieving tedious and error-prone procedure documentation tasks.

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ISSN: 2574-1241

DOI: 10.26717/BJSTR.2023.49.007812

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