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Wireless Capsule Endoscopy with AI-Assisted Lesion Detection: Diagnostic Accuracy Assessment

Doyle C[1*], Kralj I[2] and Marino G[3]

[1]*Department of Biomedical Engineering, University of Galway, Galway, Ireland*
[2]*Department of Gastroenterology, University of Zagreb, Zagreb, Croatia*
[3]*Department of Computer Science, Sapienza University of Rome, Rome, Italy*

ABSTRACT

Background: Wireless capsule endoscopy has become a first-line investigation for suspected small-bowel bleeding, Crohn's disease, and polyposis surveillance, but interpretation of the tens of thousands of frames each study generates is time-consuming and subject to interobserver variability. Objective: This narrative review synthesizes published literature on capsule endoscopy imaging technology and on deep-learning algorithms developed to automate detection of small-bowel and colonic lesions, focusing on reported diagnostic accuracy. Methods: We reviewed engineering studies of capsule device architecture and mucosal-quality assessment, convolutional neural network algorithms trained to detect erosions, ulcerations, blood content, protruding lesions, angiectasia, and Crohn's disease ulcers, and prospective multicentre studies comparing AI-assisted with standard human reading. Findings: Retrospective validation studies report area-under-the-curve values generally between 0.91 and 0.96 and lesion-specific sensitivities frequently exceeding 90%, while the two largest prospective multicentre studies to date show that AI-assisted reading reduces total reading time by approximately 85-92% while matching or exceeding the lesion-detection performance of unassisted expert readers. Conclusions: AI-assisted lesion detection in capsule endoscopy has reached a level of retrospective and prospective diagnostic accuracy that supports its expanding clinical use, though further open benchmark datasets and outcome-linked trials are needed to guide broader adoption.

Keywords: *wireless capsule endoscopy; artificial intelligence lesion detection; convolutional neural network; small bowel bleeding; diagnostic accuracy*

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Corresponding Author: *Conor Doyle*

E-mail Address: *conor.doyle@universityofgalway.edu*

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Introduction

Wireless capsule endoscopy was introduced at the turn of the century as a swallowable, battery-powered pill camera capable of transmitting images from the small bowel without sedation, intubation, or radiation exposure, and its original description in Nature established the core engineering concept of a self-contained optical dome, light-emitting diodes, a complementary metal-oxide-semiconductor imager, and a radiofrequency transmitter that together enabled painless visualization of a gut segment previously accessible only by intraoperative or balloon-assisted enteroscopy [1]. Over the subsequent two decades, capsule endoscopy became the first-line investigation for suspected small-bowel bleeding, Crohn's disease, and polyposis surveillance, but its principal practical limitation shifted from image acquisition to image interpretation: a single small-bowel examination generates on the order of 50,000 to 100,000 frames, and human review of this volume of video is time-consuming, fatiguing, and subject to considerable interobserver variability, particularly for infrequent lesions that occupy only a handful of frames in an otherwise unremarkable study [2]. This interpretive burden created an early and durable rationale for computer-aided detection, and the last decade has seen that rationale realized through convolutional neural networks and other deep-learning architectures trained to flag frames or video segments containing erosions, ulcers, angiectasia, protruding lesions, and active bleeding. This narrative review synthesizes the published literature across three interlocking domains: the imaging and device architecture that generates the video stream to be interpreted, the deep-learning algorithms developed to automate detection of small-bowel and colonic lesions within that stream, and the diagnostic accuracy and clinical validation data that describe how well these algorithms perform against expert human readers and reference standards, together with the datasets and translational obstacles that continue to shape the field.

Device Architecture and Imaging Technology

The architecture described in the original capsule endoscopy report has proven remarkably durable: an ingestible capsule roughly the size of a large vitamin pill houses an optical dome, an illumination source, a complementary metal-oxide-semiconductor image sensor, a short-range radiofrequency transmitter, and a battery sufficient for several hours of intermittent image capture as the device is propelled passively by peristalsis through the gastrointestinal tract [1]. Because the capsule cannot be steered, oriented, or paused by the operator, image quality is intrinsically variable, frames are frequently blurred by peristaltic motion or obscured by luminal debris and bubbles, and the device's transit time through the small bowel is itself uncontrolled, so the resulting video is markedly heterogeneous in both content and quality compared with a driven endoscope. Subsequent device generations extended the same basic architecture to the colon, with colon-capsule systems adding a second camera head to capture bidirectional images and thereby improve mucosal coverage during the highly variable propulsion dynamics of the colon [3]. This continued reliance on passive, uncontrolled transit is precisely what generates the interpretive workload that computer-aided detection is intended to address: an examination that can last eight or more hours, encompass tens of thousands of frames, and vary substantially in the proportion of technically adequate images is poorly suited to real-time human oversight and instead requires exhaustive post-hoc review, ordinarily performed by a trained reader stepping through the entire video at a fixed frame rate [2].

The mucosal cleanliness and visualization quality achieved during transit have direct downstream implications for computer-aided detection performance, prompting a parallel body of engineering work on automated quality control rather than lesion detection per se. Nam and colleagues developed a deep-learning-based scoring system that automatically calculates a small-bowel cleansing score analogous to the subjective scales historically applied by human readers, providing an objective, reproducible index of preparation adequacy that can be generated at the same computational stage as lesion-detection algorithms [4]. A related neural-network-based algorithm developed by Histace and colleagues similarly automated the assessment of small-bowel cleanliness directly from capsule video, addressing the practical reality that lesion-detection sensitivity depends heavily on the fraction of mucosa that is actually visualized rather than obscured by debris [5]. Together, these quality-control tools illustrate that the imaging architecture and the interpretive algorithms built on top of it are not independent: uncontrolled illumination, variable transit speed, and inconsistent bowel preparation together define the operating envelope within which any downstream detection algorithm, however well trained, must perform.

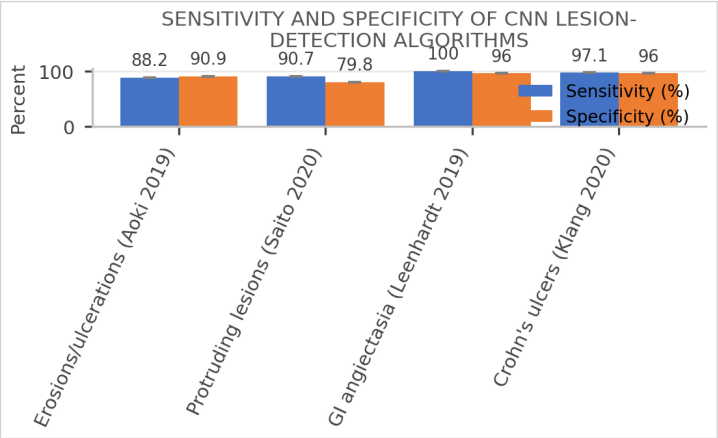
Deep Learning Algorithms for Automated Lesion Detection

The application of convolutional neural networks to capsule endoscopy accelerated markedly once large, expert-annotated image datasets became available, and a substantial body of single-center and multicenter work by Japanese, French, and Israeli groups established the basic feasibility of frame-level lesion classification across the major small-bowel pathologies. Ding and colleagues trained a deep-learning model on capsule endoscopy studies from thousands of patients to identify a broad panel of small-bowel abnormalities and normal anatomic variants, reporting per-lesion sensitivity exceeding 99% and an overall diagnostic accuracy of 99%, compared with 75% for a panel of experienced gastroenterologists reviewing the same studies without algorithmic assistance [6]. Working from a different, more granular angle, Aoki and colleagues trained a deep convolutional neural network specifically to identify erosions and ulcerations in capsule endoscopy images, reporting an area under the receiver operating characteristic curve of 0.958 with a sensitivity of 88.2% and specificity of 90.9% on an independent test set [7]. The same Tokyo-based group subsequently extended this architecture to blood-content detection, a feature closely tied to active or recent luminal bleeding, achieving a sensitivity of 96.6% for identifying frames containing blood [8], and to protruding lesion detection and classification, for which Saito and colleagues reported an area under the curve of 0.911, sensitivity of 90.7%, and specificity of 79.8% at the image level, evaluated across 17,507 test images drawn from 73 patients, with a substantially higher patient-level detection rate of 98.6% once per-video rather than per-frame performance was considered [9]. Otani and colleagues further generalized this line of work with a convolutional neural network trained to distinguish multiple discrete categories of small-bowel lesion within a single unified classification framework rather than one detector per lesion type [10].

Representative deep-learning lesion-detection algorithms in wireless capsule endoscopy: target lesion, reported diagnostic performance, and validation dataset.

Study	Target lesion	Reported performance	Validation set
Ding et al. 2019	Broad panel of small-bowel abnormalities and normal variants	Sensitivity >99%; accuracy 99% vs 75% for gastroenterologists	Multicenter, thousands of patients
Aoki et al. 2019	Erosions and ulcerations	AUC 0.958; sensitivity 88.2%; specificity 90.9%	Independent test set
Aoki et al. 2020	Blood content	Sensitivity 96.6%	Independent test set
Saito et al. 2020	Protruding lesions	AUC 0.911; sensitivity 90.7%; specificity 79.8%; patient-level detection 98.6%	17,507 images, 73 patients
Leenhardt et al. 2019	GI angiectasia	Sensitivity 100%; specificity 96%	CAD-CAP angiectasia image bank
Klang et al. 2020	Crohn's disease ulcers	Sensitivity 97.1%; specificity 96%	Independent test set

Reported sensitivity and specificity of representative deep convolutional neural network lesion-detection algorithms in wireless capsule endoscopy, drawn from the original validation study of each algorithm (Aoki et al. 2019, erosions/ulcerations; Aoki et al. 2020, blood content, specificity not reported in source; Saito et al. 2020, protruding lesions; Leenhardt et al. 2019, angiectasia; Klang et al. 2020, Crohn's disease ulcers).



A parallel and independently developed algorithm from the French CAD-CAP consortium targeted vascular lesions specifically: Leenhardt and colleagues trained a neural network on a large annotated angiectasia image bank and reported a sensitivity of 100% and specificity of 96% for detecting gastrointestinal angiectasia, a lesion class that is small, subtle, and disproportionately responsible for missed diagnoses during conventional human review [11]. Beyond the small bowel, He and colleagues addressed a geographically important but comparatively under-served detection task, training a deep-learning system to identify hookworms in wireless capsule endoscopy images, a parasitic infection that remains a leading cause of small-bowel bleeding and iron-deficiency anemia in endemic regions but has received far less algorithmic attention than inflammatory or vascular lesions [12]. Disease-specific detection has also been pursued outside routine bleeding surveillance: Klang and colleagues trained a convolutional neural network to distinguish ulcerated from normal mucosa in patients with known Crohn's disease, reporting a sensitivity of 97.1% and specificity of 96% for ulcer detection, a task directly relevant to endoscopic scoring of inflammatory activity [13]. Colon capsule endoscopy has attracted an analogous but smaller body of algorithmic work: Gilabert and colleagues developed a polyp-detection and screening-time-reduction system for colon capsule video [3], and Mascarenhas and colleagues reported a deep-learning system for automatic diagnosis of protruding lesions specifically within colon capsule endoscopy studies, extending the small-bowel protruding-lesion literature to the lower gastrointestinal tract [14]. Colonic neoplasia detection has likewise been addressed directly: Yamada and colleagues trained a deep convolutional neural network to detect colorectal neoplasia in wireless colon capsule endoscopic images, applying the same underlying architecture family used for small-bowel erosion and blood detection to a distinct anatomic compartment and lesion type [15].

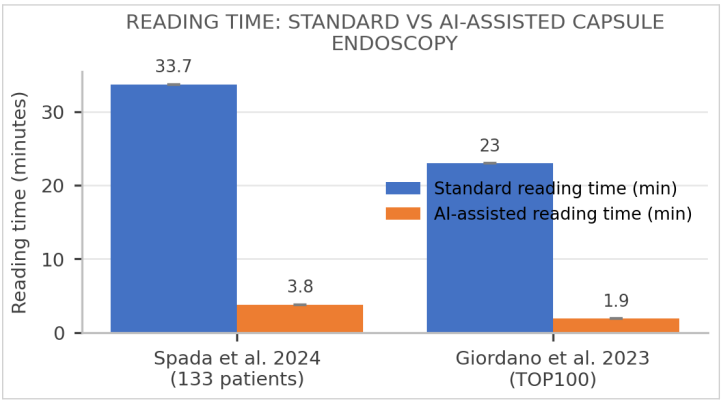
Diagnostic Accuracy and Clinical Validation of AI-Assisted Reading

Reported diagnostic accuracy figures on curated, retrospectively assembled test sets, of the kind summarized above, establish algorithmic feasibility but do not by themselves demonstrate that AI assistance improves outcomes when embedded in real clinical reading workflows. A distinct and more clinically decisive body of prospective validation work has addressed this gap directly. Soffer and colleagues conducted a systematic review and meta-analysis pooling deep-learning performance across the accumulated capsule endoscopy literature, providing a summary estimate of diagnostic accuracy across lesion types and confirming that reported area-under-the-curve values for the major detection tasks generally exceeded 0.90, while also cautioning that heterogeneity in study design, reference standards, and patient selection limited direct cross-study comparison [16]. Building on this retrospective evidence base, Spada and colleagues conducted a prospective multicenter study directly comparing AI-assisted with standard human reading of small-bowel capsule endoscopy in patients under investigation for suspected small-bowel bleeding, finding that mean reading time fell from 33.7 minutes with standard reading to 3.8 minutes with AI assistance, while the AI-assisted approach identified clinically relevant P1 and P2 bleeding lesions in 98 of 133 patients (73.7%) compared with 82 of 133 patients (62.4%) under standard reading, meeting pre-specified criteria for both non-inferiority and superiority [17]. Giordano and colleagues independently evaluated a different AI reading tool, TOP100, in a diagnostic accuracy study of patients with overt small-bowel bleeding, reporting a per-patient sensitivity of 90.5%, specificity of 100%, a positive predictive value of 100%, and a negative predictive value of 77.1%, alongside a reduction in median reading time from 23 minutes with standard review to 1.9 minutes with AI assistance, a relative time reduction of roughly 92% [18].

Prospective diagnostic-accuracy studies of AI-assisted versus standard capsule endoscopy reading in suspected small bowel bleeding.

Study	Design	Reading time (standard vs AI-assisted)	Detection/accuracy outcome
Spada et al. 2024	Multicentre prospective, 133 patients	33.7 min vs 3.8 min (~89% reduction)	P1/P2 lesion detection 73.7% (AI) vs 62.4% (standard)
Giordano et al. 2023	Diagnostic accuracy study, overt small bowel bleeding	23 min vs 1.9 min (~92% reduction)	Sensitivity 90.5%; specificity 100%; PPV 100%; NPV 77.1%

Mean or median small-bowel capsule endoscopy reading time with standard human review versus AI-assisted reading in the two largest prospective multicentre diagnostic-accuracy studies to date, illustrating the consistent 85-92% relative reduction in reading time reported with AI assistance.



Taken together, these prospective validation studies indicate that AI-assisted reading achieves two related but distinct benefits: a substantial and consistently reproduced reduction in the time required for human review, on the order of 85 to 92% across the two largest multicenter series, and either equivalent or improved

lesion detection relative to unassisted expert reading, rather than the trade-off between speed and sensitivity that might otherwise be anticipated when automating a diagnostic task [17,18]. The underlying retrospective literature synthesized by Soffer and colleagues suggests this pattern is not confined to bleeding-lesion detection alone but recurs across erosion, ulcer, angiectasia, and protruding-lesion classification tasks, each validated independently against expert-annotated reference standards with area-under-the-curve values generally in the 0.91 to 0.96 range [16,7,9]. At the same time, the substantial variation in reported specificity, from 79.8% for protruding-lesion detection to 96 to 100% for angiectasia and ulcer classification, underscores that diagnostic performance is highly lesion-specific, and that a single aggregate accuracy figure for "AI-assisted capsule endoscopy" as a category likely obscures clinically important differences in false-positive burden across pathology types [9,11,13].

Datasets, Benchmarks, and Translational Challenges

Progress in this field has depended heavily on the availability of large, expert-annotated image and video datasets, since supervised deep-learning architectures require substantial labeled training data to achieve the accuracy figures described above. Smedsrud and colleagues released the Kvasir-Capsule dataset, comprising more than 47,000 labeled images and 117 video files spanning fourteen lesion and anatomical landmark classes drawn from small-bowel and colon capsule examinations, explicitly intended as an open benchmark to support reproducible comparison of detection algorithms across research groups rather than the proprietary, single-center datasets that underpinned much of the earlier device-specific literature [19]. Complementary proprietary databases, such as the CAD-CAP angiectasia image bank underlying the Leenhardt algorithm, have similarly served as training and validation resources but are not uniformly available to outside investigators, a constraint that limits independent replication and cross-dataset generalizability testing [11]. A recent systematic literature review and meta-analysis by Sahafi and colleagues surveyed this expanding evidence base across artificial-intelligence applications in gastrointestinal wireless capsule endoscopy, reinforcing the broader observation that reported performance is strongly shaped by dataset composition, annotation protocol, and the specific lesion taxonomy adopted by each research group, and that comparability across studies remains an unresolved methodological challenge for the field as a whole [20]. Trasolini and Byrne likewise reviewed the trajectory of artificial intelligence and deep learning specifically for small-bowel capsule endoscopy, concluding that while detection accuracy for individual lesion categories has reached a level plausibly sufficient for clinical deployment, translational barriers, including regulatory clearance pathways, integration with existing capsule-reading software platforms, and prospective outcome-linked validation beyond diagnostic accuracy alone, remain incompletely addressed [21].

These translational barriers are compounded by the underlying device-level constraints already noted: variable bowel preparation, uncontrolled transit time, and motion artifact continue to limit the fraction of mucosa that is both visualized and technically interpretable, regardless of how accurate the downstream classifier is on well-curated frames, which is precisely the rationale for automated cleanliness scoring tools developed alongside lesion-detection algorithms [4,5]. Furthermore, most reported diagnostic accuracy figures, including the area-under-the-curve values in the 0.91 to 0.96 range described above, derive from retrospective test sets curated by the same institutions that generated the training data, and the number of prospective, multicenter studies directly comparing AI-assisted with unassisted human reading in unselected clinical populations remains small relative to the size of the retrospective algorithmic literature, even though the two largest such studies to date, by Spada and colleagues and by Giordano and colleagues, both reported consistent and clinically meaningful reductions in reading time without loss of diagnostic sensitivity [17,18]. Closing this gap between retrospective algorithmic validation and prospective clinical evidence is likely to be the principal determinant of how quickly and how broadly AI-assisted capsule endoscopy reading is adopted into routine gastroenterology practice.

Conclusion

The published literature on wireless capsule endoscopy with AI-assisted lesion detection demonstrates a coherent and rapidly maturing evidence base, built upward from a stable, two-decade-old device architecture whose principal bottleneck has always been image interpretation rather than image acquisition [1,2]. Deep convolutional neural networks trained on large, expert-annotated datasets now achieve area-under-the-curve values generally between 0.91 and 0.96 and lesion-specific sensitivities frequently exceeding 90%, across erosions and ulcerations, blood content, protruding lesions, angiectasia, and Crohn's disease ulcers [7,8,9,11,13,6]. Critically, this retrospective algorithmic performance has now been corroborated by prospective, multicenter clinical validation studies showing that AI-assisted reading reduces total reading time by roughly 85 to 92% while matching or exceeding the lesion-detection performance of unassisted expert human readers [17,18]. Continued expansion of open, standardized benchmark datasets, together with further prospective outcome-linked trials, will be necessary to translate these encouraging diagnostic accuracy figures into consistent, guideline-supported clinical adoption across the full range of small-bowel and colonic indications for capsule endoscopy [19,20,21,16].

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Doyle C conceived the review, conducted the literature search, and drafted the manuscript. Kralj I contributed to the literature screening and clinical framing and critically revised the manuscript for important intellectual content. Marino G contributed additional technical context and approved the final version for submission.

Ethics Statement

Not applicable. This is a narrative review of previously published literature and did not involve new experimental data, human participants, or animal subjects.

Data Availability

No new data were generated or analyzed for this review. All sources synthesized are cited in the reference list and are available through their original publishers.

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