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Artificial Intelligence (AI) in Gastrointestinal Capsule Endoscopy: Hardware, Algorithmic Applications, and Clinical Integration in healthcare.

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Abstract

Gastrointestinal (GI) capsule endoscopy has evolved from a passive ingestible imaging device into an increasingly automated diagnostic platform supported by artificial intelligence (AI). By generating tens to hundreds of thousands of images per examination, capsule procedures create a substantial interpretation burden and opportunity for AI-assisted image triage, lesion detection, and workflow optimization. This narrative review evaluates the enabling hardware architecture of contemporary GI capsule endoscopy systems; summarize AI applications in small-bowel and colon capsule endoscopy; and identify the clinical engineering, regulatory, validation, and implementation issues relevant to safe adoption. This narrative technology review synthesizes peer-reviewed literature, selected technical sources, manufacturer documentation, and regulatory materials concerning capsule endoscopy hardware, AI-assisted image analysis, clinical performance, and deployment considerations.

This review also explored the mathematical and machine-learning algorithms utilized in capsule technology. Contemporary capsule endoscopes integrate miniature optical systems, complementary metal-oxide-semiconductor image sensors, light-emitting diode illumination, battery power, radio-frequency telemetry, onboard control electronics, and biocompatible packaging within a constrained ingestible form factor. Power, size, thermal, transmission, and computing limitations generally require AI analysis to occur after image acquisition on a workstation or cloud-connected platform rather than within the capsule. Deep-learning methods—predominantly convolutional neural networks—have been applied to frame triage, bleeding and vascular-lesion detection, ulcer and erosion identification, protruding-lesion classification, inflammatory bowel disease assessment, polyp detection, bowel-preparation scoring, and automated reporting support. Small-bowel applications are comparatively mature, whereas colon capsule AI remains less developed for lesion localization, cross-frame matching, size estimation, and patient-level clinical validation. AI-enabled capsule endoscopy should be assessed as an integrated clinical system rather than as an image-classification algorithm alone. Successful deployment requires verification of intended use and regulatory status, device–software compatibility testing, cybersecurity and data-governance controls, reader training, workflow design that mitigates automation bias, software version control, and post-market performance monitoring.

KEYWORDS: Artificial intelligence (AI), Capsule endoscopy (CE), Wireless capsule endoscopy (WCE), Small-bowel capsule endoscopy (SBCE), Colon capsule endoscopy (CCE), Pan-enteric capsule endoscopy, Convolutional neural network (CNN), Computer-aided detection (CADe), Deep learning (DL).

INTRODUCTION

Gastrointestinal (GI) Capsule endoscopy is a minimally

invasive diagnostic procedure in which a patient swallows a small, camera-equipped capsule that acquires images as it travels through the gastrointestinal tract by normal peristalsis.



Introduced into clinical practice around the beginning of the twenty-first century, capsule endoscopy is now widely used for evaluation of suspected small-bowel bleeding and has expanded to selected applications in colon imaging, inflammatory bowel disease assessment, and pan-enteric examination.^[1,5] Technology's clinical value is accompanied by a substantial data-management challenge. A single small-bowel examination may produce tens of thousands of images, while dual-camera colon capsule examinations can generate several hundred thousand frames. Reviewing these image volumes is time-intensive and may be affected by reader fatigue, interobserver variation, and the risk that subtle or transient lesions will be missed. Artificial intelligence (AI), particularly deep-learning methods such as convolutional neural networks, is increasingly used to address this bottleneck through automated frame triage, lesion flagging, disease classification, and workflow support. For clinical engineering departments, capsule endoscopy is not simply an ingestible imaging device. It is an integrated clinical system involving capsule hardware, wearable receiving equipment, image-review software, local or cloud-based data infrastructure, clinical reporting workflows, cybersecurity controls, and software validation processes. This review provides a technically grounded overview of capsule hardware architecture, AI-enabled image-analysis methods used in commercial and investigational systems, and the procurement, regulatory, integration, and lifecycle-management considerations in modern healthcare.

Materials and Methods

This is a narrative review followed by a methodology informed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses framework, adapted for a narrative technology review rather than a formal systematic review or meta-analysis. The objective was to identify literature and manufacturer/regulatory sources describing: (a) the engineering architecture of GI capsule endoscopy devices and (b) applications of AI in capsule endoscopy image interpretation and workflow.

Information Sources and Search Strategy

A structured search was conducted across PubMed/MEDLINE, Embase, Scopus, and Google Scholar, supplemented by targeted searches of manufacturer technical documentation and regulatory announcements, covering material available through August 2026. Search terms combined free-text and controlled vocabulary using Boolean operators, including combinations of “artificial intelligence,” “machine learning,” “deep learning,” “computer-aided detection,” “capsule endoscopy,” “wireless capsule endoscopy,” “colon capsule endoscopy,” and “pill camera.”

Eligibility Criteria

Sources were included if they: (a) addressed gastrointestinal capsule endoscopy hardware, engineering architecture, or AI-based image analysis; (b) were published or updated through 2026 or represented a foundational technical reference where more recent equivalents were unavailable; and (c) were available in English with sufficient technical or clinical detail

to support synthesis. Sources were excluded if they were opinion pieces without underlying data, addressed endoscopic modalities unrelated to capsule endoscopy without capsule-specific findings, or were inaccessible in full text.

Data Synthesis

Given the heterogeneity of source types—including peer-reviewed reviews, primary clinical studies, technical engineering analyses, and regulatory filings—and the variation in reported outcomes, findings were synthesized narratively rather than pooled quantitatively. Where quantitative performance data were reported in an included source, figures are presented descriptively in the relevant section and in Table 1.

Table 1. PRISMA-informed source selection flow.

PRISMA Stage	Records (n)
Records identified through database searching (PubMed/MEDLINE, Embase, Scopus, Google Scholar) and targeted web/manufacture sources	68
Duplicate records removed	9
Records screened by title and abstract	59
Records excluded at screening (not GI capsule endoscopy; not AI-related; non-English; editorial/opinion without data)	22
Full-text sources assessed for eligibility	37
Full-text sources excluded (insufficient technical detail; superseded by more recent source; regulatory listing only)	15
Sources included in qualitative synthesis (this review)	22

Data Synthesis

Given the heterogeneity of source types (peer-reviewed reviews, primary clinical studies, technical engineering analyses, and regulatory filings) and outcome measures, findings were synthesized narratively rather than pooled quantitatively. Where quantitative performance data were reported in an included source, figures are presented descriptively in the relevant section and in Table 1.

Results and discussion

Device Architecture and Engineering Constraints

Modern capsules are compact, single-use, ingestible devices. Small-bowel capsules are typically approximately 11 × 26 mm, while colon capsules may be larger, reaching approximately 11.6 × 32.8 mm, to accommodate dual imaging heads and the extended power supply needed for longer colonic transit time (Robertson & Singh, 2026; “Structural Dynamics and Evolution of Capsule Endoscopy,” 2018; TechInsights, 2026).

The core subsystems within the capsule housing include a complementary metal-oxide-semiconductor (CMOS) image sensor, light-emitting diode illumination, one or more miniature batteries, a radio-frequency transmitter and antenna, and, in some designs, an application-specific integrated circuit that manages image acquisition and transmission timing (“Structural Dynamics and Evolution of Capsule Endoscopy,” 2018; TechInsights, 2026) as shown in Figure 1.

Power management is a dominant engineering constraint. Because battery volume is fixed by the capsule’s ingestible form factor, image-sensor and transmitter designs favor low-power CMOS technology. Several platforms use adaptive frame-rate control to conserve energy, such as activating imaging after an expected transit delay or adjusting capture rate to estimated motility state (Robertson & Singh, 2026; “Structural Dynamics and Evolution of Capsule Endoscopy,” 2018). The exterior housing must also be biocompatible, resistant to the gastrointestinal chemical environment, and biologically inert throughout transit (TechInsights, 2026).

Image data are transmitted wirelessly, typically through ultra-high-frequency radio telemetry or electric-field propagation, to a wearable receiver such as a sensor belt or portable recorder worn by the patient during the procedure (Robertson & Singh, 2026). Some dual-camera small-bowel platforms provide panoramic fields of view exceeding 340° and operating times of 12 hours or more to support imaging throughout the gastrointestinal tract (“Usefulness of Panoramic 344° Viewing,” n.d.). Experimental stereo-camera designs have also been developed to enable three-dimensional reconstruction of mucosal lesions; however, constraints related to capsule size and battery capacity continue to limit onboard processing (“3D Reconstruction of Small-Bowel Lesions,” n.d.). These limitations are a principal reason that AI analysis is typically conducted after image acquisition and data offload rather than in real time within the capsule.

Artificial Intelligence Applications

Capsule procedures generate very large image volumes relative to available clinician reading time. Accordingly, AI has been applied primarily to reduce interpretation burden, support lesion detection, and improve reading consistency. The dominant technical approach is supervised deep learning, most often CNN-based systems trained to perform frame-level classification, lesion detection, or image segmentation (“Advances in Artificial Intelligence for Gastrointestinal Endoscopy,” 2026; Casanova Rimer et al., 2026).

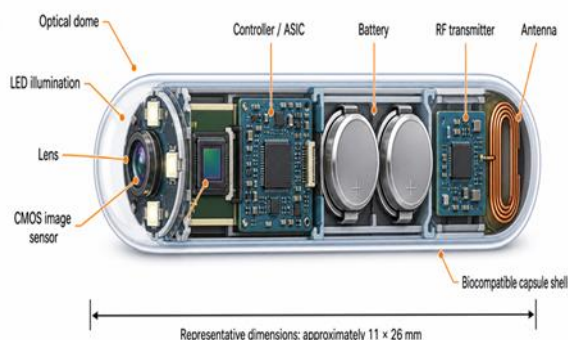


Figure 1. Schematic cross-section of a capsule endoscope, illustrating major internal subsystems: optical dome and LED illumination, CMOS image sensor, battery, on-board controller/ASIC, and RF telemetry. Dimensions and component placement are representative and vary by manufacturer and capsule type.

Small-Bowel Capsule Endoscopy

AI systems for small-bowel capsule endoscopy are designed to flag frames likely to contain clinically relevant findings, reducing the number of images requiring detailed review by a human reader (“Integration of Artificial Intelligence-Enhanced Capsule Endoscopy,” 2026; Casanova Rimer et al., 2026).

In one multicenter retrospective evaluation across six hospitals using a widely deployed capsule platform, an open-source AI model applied to small-bowel video review was reported to increase per-lesion sensitivity from approximately 86% with conventional reading to nearly 99% with AI-assisted review, while also reducing interpretation time (“AI Model Boosted Accuracy in Capsule Endoscopy Detection,” 2026). This result should be interpreted in light of the study’s retrospective design, lesion-level outcome definition, reference standard, case mix, and validation population.

Beyond bleeding detection, AI models have also been investigated as diagnostic support tools for Crohn’s disease and celiac disease, expanding the potential role of capsule AI beyond obscure gastrointestinal bleeding (Casanova Rimer et al., 2026; “Integration of Artificial Intelligence-Enhanced Capsule Endoscopy,” 2026).

Individual model-development studies have reported high accuracy for selected lesion types. Deep transfer-learning frameworks for intestinal bleeding detection have achieved F1 scores exceeding 98% on public benchmark datasets, with segmentation functionality to delineate the apparent bleeding region (Ghosh & Chakareski, 2021). Multicenter CNN models for pan-endoscopic detection of vascular lesions have reported overall accuracy near 98% across more than 1,000 capsule examinations (“Deep Learning and Capsule Endoscopy,” n.d.). CNN-based classifiers for enteric protruding lesions, including small-bowel tumors, have also reported accuracy around 97% and sensitivity near 96%, with rapid frame-processing performance (“Deep Learning for Automatic Identification,” 2022).

More recent deep-learning localization models evaluated through external validation have reported substantial reductions in small-bowel reading time while maintaining abnormality-detection rates comparable to experienced endoscopists (“Deep Learning-Based Localization and Lesion Detection,” 2025). Multiple-CNN ensemble approaches have similarly reported very high diagnostic accuracy for selected findings, including bleeding and foreign bodies, in benchmark image datasets (“Enhanced Accuracy for Classification,” n.d.).

Cross-platform generalizability remains an important concern. Models trained and evaluated on a single capsule type may

demonstrate high internal performance but can show meaningful degradation when applied to images obtained using other capsule brands or device generations (“Deep Learning Multi-Domain Model,” n.d.). This limitation supports the need for training datasets that include multiple device platforms, image qualities, clinical sites, and patient populations.

Table 2. Summary of AI applications by capsule endoscopy domain.

Domain	Representative AI Function	Reported Clinical Impact
Small bowel capsule endoscopy	CNN-based frame triage and lesion flagging (e.g., SEE-AI)	Per-lesion sensitivity reported to rise from roughly 86% to 99% versus conventional reading, with reduced interpretation time
Colon capsule endoscopy	Polyp detection, ulcer/erosion detection, bowel-preparation scoring	Improved polyp and mucosal-lesion detection; polyp size estimation and anatomical localization remain underdeveloped
Inflammatory and other conditions	Disease-severity scoring and classification support	Diagnostic support demonstrated for Crohn's disease and celiac disease
Regulatory / commercial	AI reading modules embedded in commercial platforms	Vendor submissions to regulatory bodies (e.g., a December 2025 510(k) filing for an AI-assisted reading module) signal an active clearance pipeline

Colon Capsule Endoscopy

Colon capsule endoscopy presents a larger imaging burden, with dual cameras operating at approximately 8 to 15 frames per second during colonic transit and potentially generating several hundred thousand frames per examination (“Future of Colon Capsule Endoscopy,” 2026). AI research in this domain focused on polyp detection, ulcer and erosion detection, and automated bowel-preparation quality assessment. Polyp matching across frames, lesion-size estimation, and accurate anatomic localization remain comparatively underdeveloped and represent active areas of clinical and engineering research (“Future of Colon Capsule Endoscopy,” 2026).

CNN-based polyp-detection tools embedded in colon capsule video-review software have been evaluated as adjuncts to

standard reading workflows rather than replacements for expert readers. Their goals include reducing screening time while maintaining lesion-detection performance comparable to expert review (“Artificial Intelligence to Improve Polyp Detection,” 2022).

Regulatory documents for colon capsule platforms have historically defined clinical performance in relation to polyp detection compared with optical colonoscopy in selected patients, including those with an incomplete prior colonoscopy (FDA, 2012). AI-assisted colon capsule workflows should therefore be evaluated against clinically meaningful patient-level endpoints rather than frame-level performance alone.

Related real-time AI polyp-detection systems developed for conventional optical colonoscopy have received regulatory clearance and have been associated with improved adenoma detection in some randomized evaluations (MassDevice, 2024; MobiHealthNews, n.d.). Although these systems are not capsule endoscopy technologies, they offer relevant design, validation, workflow, and human-factors lessons for colon capsule AI.

Workflow and Data Infrastructure

In addition to lesion detection, AI and associated software may contribute to quality assessment of completed studies, automated report drafting, worklist prioritization, and cloud-enabled infrastructure for remote or telemedicine-supported review (“Advances in Artificial Intelligence for Gastrointestinal Endoscopy,” 2026; “Integration of Artificial Intelligence-Enhanced Capsule Endoscopy,” 2026).

AI-Assisted Capsule Endoscopy Workflow

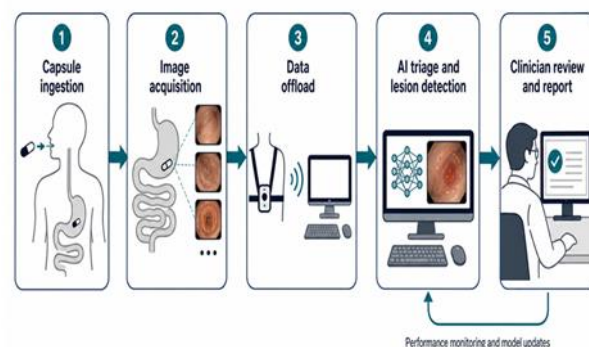


Figure 2. AI-assisted capsule endoscopy workflow, from ingestion through data offload, AI-based frame triage and lesion detection, clinician review, and post-market performance monitoring that informs subsequent model updates.

Proposed models linking colon capsule endoscopy with cloud infrastructure and telemedicine seek to streamline the pathway from image acquisition to clinical decision-making and may reduce the need for follow-up conventional colonoscopy in selected patients (“Future of Colon Capsule Endoscopy,” 2026). These approaches require careful assessment of connectivity, data transfer, interoperability, data retention, cybersecurity, patient privacy, and clinical escalation pathways as shown in Figure 2.

Mathematical Foundations of Machine Learning Methods

The AI systems described in this review are predominantly based on CNNs trained through supervised learning. CNNs extract increasingly complex image features through sequential convolutional operations, nonlinear activation functions, pooling or down sampling operations, and classification or detection heads (Casanova Rimer et al., 2026; Ghosh & Chakareski, 2021).

A CNN processes each capsule endoscopy frame through convolutional layers. Each layer applies learnable filters, often called kernels, across the image to generate feature maps that emphasize local patterns such as edges, color changes, texture variation, ulcer margins, active bleeding, or polyp morphology. Stacking multiple layers allows a model to develop hierarchical representations, progressing from low-level visual features to higher-level lesion patterns.

After convolutional operations, a nonlinear activation function is applied so that the network can model complex, nonlinear relationships between image characteristics and diagnostic categories. The rectified linear unit is commonly used because of its computational efficiency and its role in reducing vanishing-gradient effects during training.

At the final classification layer, SoftMax may convert raw output scores into a probability distribution across mutually exclusive classes, such as normal mucosa, bleeding, ulceration, vascular lesion, or polyp. The highest predicted probability is commonly used as the model's class prediction; however, the probability should not automatically be interpreted as a calibrated clinical risk estimate without specific calibration analysis.

During training, model parameters are adjusted to minimize a loss function comparing model predictions with expert-derived ground-truth labels. Categorical cross-entropy is commonly used for multiclass classification tasks. Model weights are updated iteratively using gradient-based optimization and backpropagation until performance stabilizes on a separate validation dataset.

Model performance is commonly reported using sensitivity, specificity, precision, F1 score, and area under the receiver operating characteristic curve. These metrics are derived from the numbers of true-positive, true-negative, false-positive, and false-negative classifications. In capsule endoscopy, the unit of analysis must be specified because frame-level metrics may not reflect lesion-level, examination-level, or patient-level performance. For example, multiple adjacent frames showing the same lesion may inflate image-level performance estimates without demonstrating a proportional clinical benefit.

Although AUC values in the range of approximately 0.93 to 0.99 have been reported in selected CNN-based lesion-detection studies, these values can be influenced by class imbalance, case selection, image correlation, and internal validation design (Ghosh & Chakareski, 2021; "Deep Learning Multi-Domain Model," n.d.). High AUC values alone do not establish clinical utility, patient-level diagnostic

benefit, or generalizability across capsule hardware and patient populations.

Regulatory Status and Clinical Adoption

AI-enabled capsule endoscopy is progressing from research validation toward commercial deployment, although adoption remains uneven. Established capsule manufacturers have incorporated or are developing AI-assisted reading capabilities within their software platforms, while newer entrants continue to pursue regulatory pathways for AI reading modules ("Integration of Artificial Intelligence-Enhanced Capsule Endoscopy," 2026).

For example, CapsoVision announced that it submitted a 510(k) application to the U.S. Food and Drug Administration in December 2025 for an AI-assisted reading module intended to improve pathology detection and reduce clinician review time (CapsoVision, 2025). A 510(k) submission should not be interpreted as FDA clearance; the regulatory status of the specific software version and intended use must be confirmed through official FDA records before clinical procurement or deployment.

A 2026 narrative review of AI across gastrointestinal endoscopy modalities concluded that evidence remains concentrated on surrogate outcomes, including per-frame or per-lesion detection measures, rather than patient-centered outcomes such as changes in diagnosis, treatment, outcomes, or healthcare utilization ("Advances in Artificial Intelligence for Gastrointestinal Endoscopy," 2026). The review identified generalizability across patient populations and capsule hardware, explainability of outputs, regulatory oversight, automation bias, and workflow integration as major barriers to broader adoption.

Validation Challenges and Limitations

Several challenges warrant continued attention from gastroenterology, clinical engineering, information technology, informatics, quality, and cybersecurity teams.

- **Generalizability:** Models trained on images from a single capsule platform, patient population, or clinical site may not perform reliably with different hardware generations, image-processing pipelines, bowel-preparation quality, disease prevalence, or demographic groups ("Deep Learning Multi-Domain Model," n.d.).
- **Explainability:** Clinicians need sufficient visibility into why an image or region was flagged. Visual overlays, lesion bounding boxes, heat maps, confidence scores, and accessible model documentation may support appropriate clinical review, but none should replace independent clinician judgment.
- **Automation bias:** Readers may over-rely on algorithmic flags or under-scrutinize unflagged regions. AI-assisted workflows should therefore retain clinician accountability, establish requirements for review of AI-negative content, and include audit mechanisms for missed lesions.

- **Data infrastructure:** Cloud-connected or telemedicine-supported review models introduce requirements for secure transmission, storage, access controls, audit logging, retention policies, interoperability, and vendor oversight (“Future of Colon Capsule Endoscopy,” 2026).
- **Lifecycle management:** AI software should be subject to version control, acceptance testing, local compatibility verification, change management, cybersecurity assessment, and ongoing monitoring after implementation. A software update, model retraining event, new capsule model, or modified image-processing pipeline may require revalidation before routine clinical use.

Conclusion

AI integration is transforming capsule endoscopy from a passive imaging tool into a workflow-embedded diagnostic aid. The strongest current evidence is in small-bowel capsule endoscopy, where AI-assisted systems may improve lesion flagging and reduce review burden. Colon capsule AI is advancing but remains less mature, particularly for cross-frame lesion matching, size estimation, anatomical localization, and patient-level clinical validation (Casanova Rimer et al., 2026; “Future of Colon Capsule Endoscopy,” 2026).

The underlying hardware remains constrained by the ingestible form factor’s requirements for miniaturization, power efficiency, biocompatibility, image transmission, and battery capacity. These limitations continue to shape where AI computation occurs, with most analysis performed after image acquisition rather than within the capsule itself.

For clinical engineering practice, successful adoption will depend on more than algorithmic performance. Healthcare organizations should evaluate intended use, regulatory status, local compatibility, clinical validation, reader training, workflow design, data governance, cybersecurity, version control, and post-market performance monitoring. Continued collaboration among manufacturers, gastroenterologists, clinical engineers, informatics teams, and healthcare technology management professionals will be needed to move the field from promising image-level metrics toward demonstrated patient-centered benefit.

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COMPETING INTERESTS

The author has no competing interests to declare.

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AUTHOR CONTRIBUTIONS

Supreet Kaur performed the analysis and wrote the manuscript and guided the methodological approach.

Andrew Blanford critically revised the manuscript.

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