North Carolina Society of Gastroenterology 2024 Annual Meeting



BACK TO THE FUTURE OF GI ENDOSCOPY: ARTIFICIAL INTELLIGENCE, THE NEXT FRONTIER?

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Joint Providership



American Society for Gastrointestinal Endoscopy

Disclosures

- Consultant for Medtronic
- Consultant for Olympus

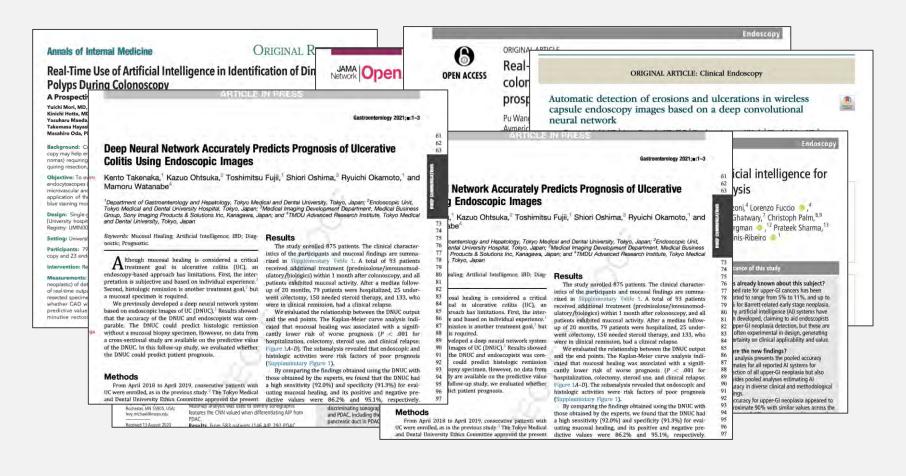


Learning Objectives

 Summarize advances in artificial intelligence in the field of endoscopy and how they can be applied to current clinical practice



Why is This Important?





OF GASTROENTEROLOGY

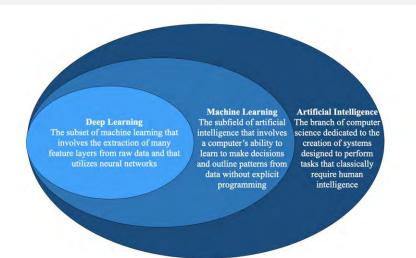
Common Terminology in AI Research

Artificial Intelligence: computer systems that can perform tasks that normally require 'human intelligence'. Examples: visual perception, speech recognition, natural language processing, self-driving cars

Machine learning: A set of computational methods that involves using mathematical models to learn to make decisions and outline patterns from data. Examples: Linear regression, boosted trees, random forests, support vector machines

Deep learning: A subset of machine learning that relies on multi-layered neural networks to extract information from multiple feature inputs to learn from complex inputs

Computer vision: technology that allows computers to "see" and interpret visual content (photos, video)

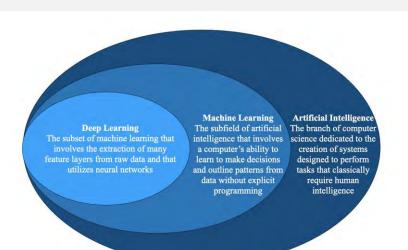




Common Terminology in AI Research

Large Language Model: Models that process vast amounts of text data (usually scraped from the internet)

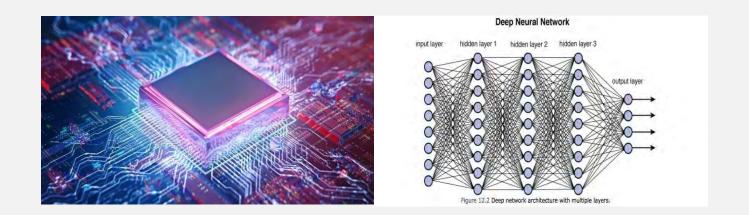
- Usually transformer architecture
- "Generative." Take an input text → predict the next word/token
- Adaptable





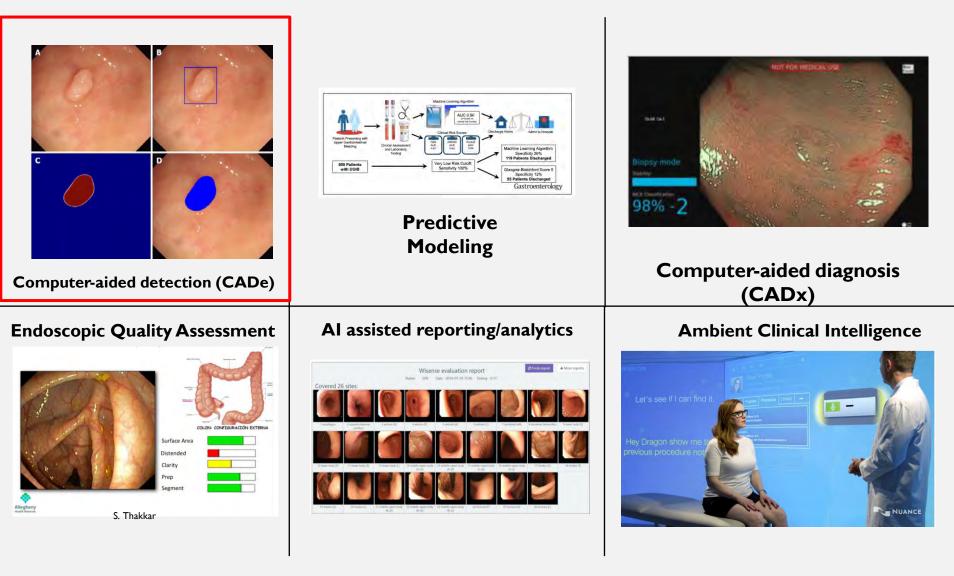
Why Now? (2012-Present)

- Tremendous growth in computational power
- Availability of big data
- Advanced machine learning algorithms





Applications



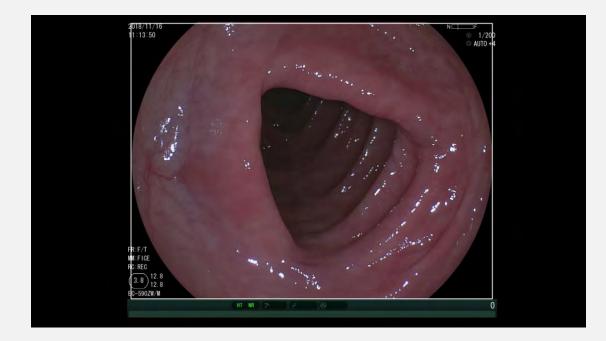
Computer Aided Detection

- The most 'advanced' application of AI
- Several FDA approved CADe systems in the U.S.
- Near-real time delineation of polyps during colonoscopy



Repici et al. Gastroenterology 5/3/20; 512-520.E7



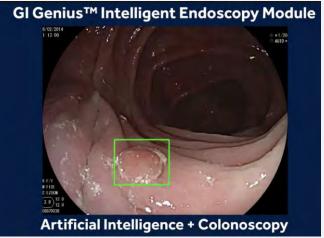


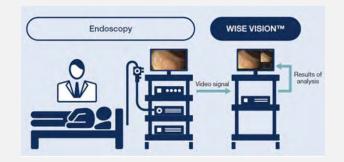
Glissen Brown et al. VideoGIE. 4/2020; P135-137



Computer Aided Detection

- GI-Genius, Medtronic, Minneapolis, MN
- Endoscreener Wision, AI, Shanghai, China and Micro-Tech Endoscopy, Ann Arbor, MI
- Magentiq-Colo, Magentiq EYE LTD, Haifa, Israel
- SKOUT, Iterative Health, Cambridge MA USA and Provation, Minneapolis, MN
- More pending





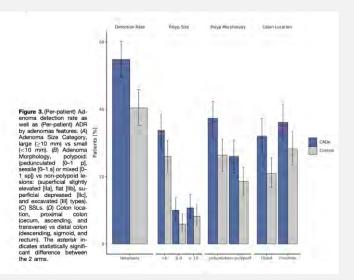


The Evidence

Efficacy of Real-Time Computer-Aided Detection of Colorectal Neoplasia in a Randomized Trial

Alessandro Repici,¹ Matteo Badalamenti,¹ Roberta Maselli,¹ Loredana Correale,¹ Franco Radaelli,² Emanuele Rondonotti,² Elisa Ferrara,¹ Marco Spadaccini,¹ Asma Alkandari,³ Alessandro Fugazza,¹ Andrea Anderloni,¹ Piera Alessia Galtieri,¹ Gaia Pellegatta,¹ Silvia Carrara,¹ Milena Di Leo,¹ Vincenzo Craviotto,¹ Laura Lamonaca,¹ Roberto Lorenzetti,⁴ Alida Andrealli,² Giulio Antonelli,⁴ Michael Wallace,⁵ Prateek Sharma,⁶ Thomas Rosch,⁷ and Cesare Hassan⁴

- 685 patients undergoing screening, surveillance, or diagnostic colonoscopy across 3 endoscopy centers in Italy
- Patients randomized 1:1 to receive HDWL colonoscopy or Al-assisted colonoscopy (single screen)
- Significant increase in ADR (54.8% vs 40.4%) with a relative risk of 1.30 (95% CI, 1.14–1.45
- Higher APC
- No significant difference in withdrawal time or resection for FPs



Repici et al. Gastroenterology. 5/2020; 512-520.E7



The Evidence

META-ANALYSIS

Effect of computer-aided colonoscopy on adenoma miss rates and polyp detection: A systematic review and meta-analysis

Sagar Shah,* Nathan Park,[†] Nabil El Hage Chehade,[‡] Anastasia Chahine,[†] Marc Monachese,[†] Amelie Tiritilli,[†] Zain Moosvi,[§] Ronald Ortizo[†] and Jason Samarasena[†] 😳

*Department of Internal Medicine, University of California Los Angeles Ronald Reagan Medical Center, Los Angeles, ³H. H. Chao Comprehensive Digestive Disease Center, University of California Irvine Medical Center, Orange, California, ¹Division of Internal Medicine, Case Western Reserve University MetroHealth Medical Center, Cleveland, Ohio, and ⁵Division of Gastroenterology, Hepatology and Nutrition, University of Pittsburgh, Pittsburgh, Pennsylvania, USA

- Meta-analysis of 14 RCTs containing 10,928 patients
- 52% increase in ADR in CADe vs. control (OR, 1.52; 95% CI, 1.39–1.67, P = 0.04, I2 = 47%).
- 65% reduction in AMR (OR, 0.35; 95% CI, 0.25– 0.49, P < 0.001, I2 = 50%)
- 93% increase adenomas > 10 mm de- tected (OR 1.93; 95% CI, 1.18–3.16, P < 0.01, I2 = 0%).
- Decrease in SSLMR

	Comp. Assisted		Traditional		Odds Ratio				ds Ratio
tudy or Subgroup	Events	Total	Events	Total	Weight	M-H, Fixed, 95% CI	Year	M-H, Fo	ed, 95% CI
.4.1 Non-Tandem S	tudies			-			-		and the second second
rang 2019	152	\$22	109	536	10.8%	1.61 [1.21, 2.14]	2019		· ·
ang 2020	165	484	132	478	12.4%	1.36 (1.03, 1.76)	2020		*
in 2020	199	508		518	10.6%	2.05 (1.56, 2.58)	2020		*
ong 2020	58	355	27	349	3.2%	2,33 (1.44, 3.78]	2020		
epici 2020	187	341	139	344	8.9%	1.79 (1.32, 2.42)	2020		+
u 2020	89	305	52	315	5,2%	2.06 [1.40, 3.02]	2020		
haukat 2022	326	682	297	677	22.0%	1.17 (0.95, 1.45)			* ·
epici 2022	176	330	147	330	9.7%	1.42 [1.05, 1.93]	2022		ar:
ubtotal (95% CI)		3530		3547	82.8%	1.56 [1.41, 1.73]			
atal events	1352		1027						10
leterogeneity. Chi? =				60%					
est for overall effect	Z = 8.53 (P	< 0.000	01)						
4.2 Tandem Studie	s								
rown 2021	57.	313	48	110	3.4%	1.31 (0.78, 2.23)	2021		
amba 2021	111	-172	93	174	4.6%	1.58 (1.03, 2.44)	2021		
ang 2020 (tandem)	78	384	66	185	5.4%	1.33 (0.87, 2.02)	2021		-
allace 2022	72	116	70	114	3.5%	1.03 [0.60, 1.75]	2022		+
ubtotal (95% CI)		585		583	17.2%	1.33 [1.05, 1.68]			•
otal evenis.	318		277						
eterogeneity. Chil =				0%					
est for overall effect.	Z = 2.38 (P	= 0.02)							
otal (95% CI)		4115		4130	100.0%	1.52 [1.39, 1.67]			1
otal events	1670		1304						
eterogeneity: Chi" =	20.66, df =	11 (P =	0.04); /	= 47%				0.005 0.1	10 200
est for overall effect.	Z = 8.77 (P	< 0.000	011					6.005 0.1 Favors Traditiona	

Shah et al. Journal of Gastroenterology & Hepatology 11/9/2022 Nov 9.



Tips and Tricks



Figure 2. An example of a single monitor setup, where computer-aided detection output is displayed on the primary endoscopy screen. (Image @2020 Meditonic. All rights reserved. Used with the permission of Meditonic.)

Bilal et al. Am J Gastroenterol 7/2020; 115(7):963-966.



Tips and Tricks

Using Computer-Aided Polyp Detection During Colonoscopy

Mohammad Bilal, MD¹, Jeremy R. Glissen Brown, MD¹ and Tyler M. Berzin, MD, FASGE, FACG¹

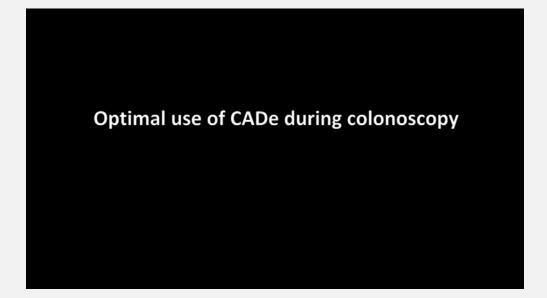
Am J Gastroenterol 2020;115:963–966. https://doi.org/10.14309/ajg.000000000000646; published online May 13, 2020

- Mucosal inspection techniques paramount
- Toggle on during withdrawal after cleaning
- Limit bubbles, suction polyps
- Toggle on during tool deployment but off during intervention

Bilal et al. Am J Gastroenterol 7/2020; 115(7):963-966.



Tips and Tricks



Glissen Brown et al. VideoGIE. 4/2020; PI35-I37

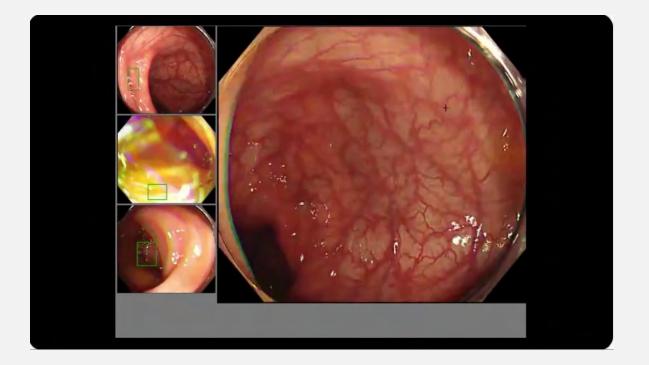


Questions and Controversies in CADe

- Hold outs and delayed uptake
- Question of de-skilling and CADe in the training curriculum
- Lack of benefit in some trials (see above)
- Task specific "Al" sows doubt
- Cost



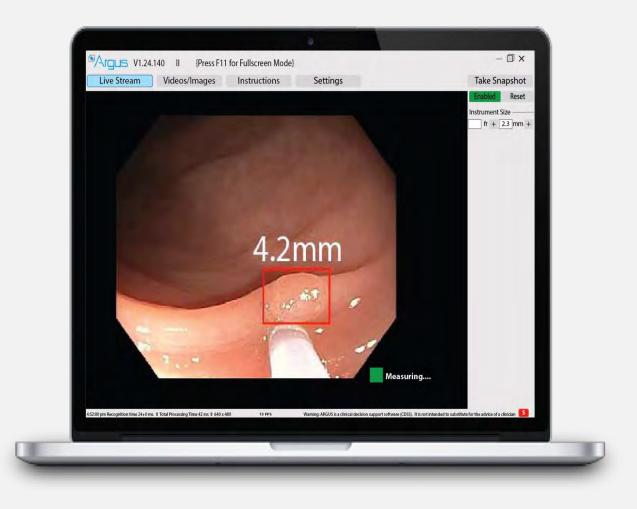
Future Directions: Combined Systems



Video Credit: https://lpixel.net/



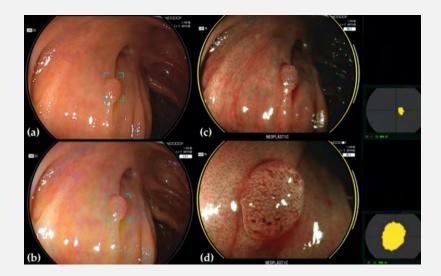
Future Directions in Colonoscopy

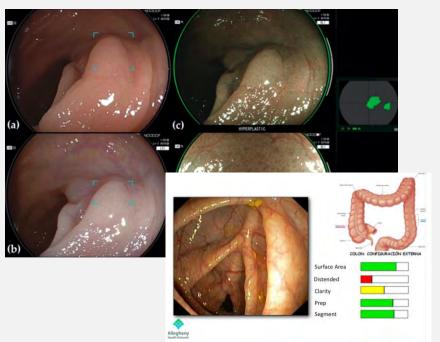


Images courtesy of EndoSoft



Future Directions in Colonoscopy





Kamitani et al. J Clin Med. 2022 May 22;11(10):2923 Image courtesy of Dr. Shyam Thakkar and Allegheny Health Network



- CADe/CADx for detection of UGI malignancies and BERN (Arribas et al Gut 2020)
- CADx for pathology slides (lizuka et al. Sci Rep 2020)
- VCE: Automatic detection of protruding lesions, flat lesions, CeD, parasites (Saito GIE 2020, Ding Gastroenterology 2019, Zhou Comput Biol Med 2017)

Endoscopy

ORIGINAL RESEARCH

Standalone performance of artificial intelligence for upper GI neoplasia: a meta-analysis

Julia Arribas,¹ Giulio Antonelli [•],^{2,3} Leonardo Frazzoni,⁴ Lorenzo Fuccio [•],⁴ Alanna Ebigbo [•], ⁵ Fons van der Sommen,⁶ Noha Ghatwary,⁷ Christoph Palm,^{8,9} Miguel Coimbra,¹⁰ Francesco Renna,¹¹ J J G H M Bergman [•], ¹² Prateek Sharma,¹³ Helmut Messmann,⁵ Cesare Hassan [•],² Mario J Dinis-Ribeiro [•],¹

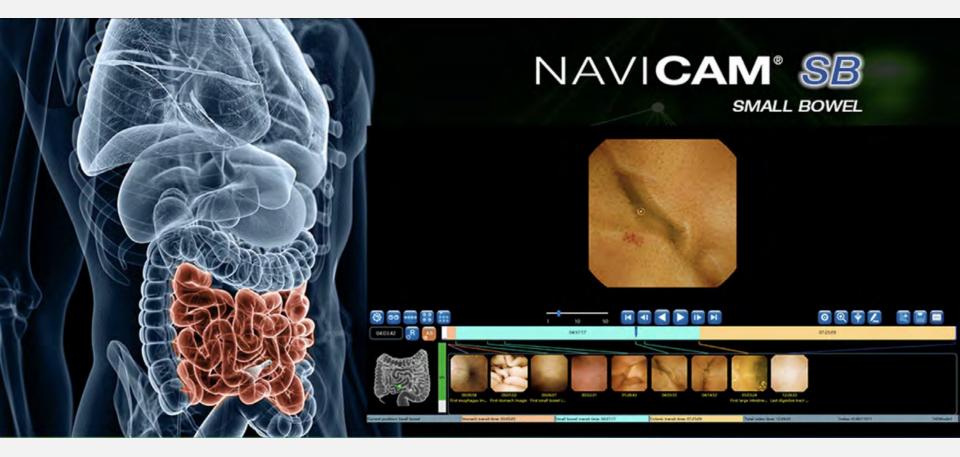


Figure 2. Representative images of protruding lesions correctly detected by the convolutional neural network (CNN) in the validation set (*blue box*, true lesion, *green box*, region identified as a protructing lesion by the CNN, number, the probability score determined by the CNN). The *blue* rectangular bounding boxes show the annotation of protruding regions as determined by experts. The green rectangular bounding boxes were applied by the CNN, with the name of lesion subcategory and its probability score.

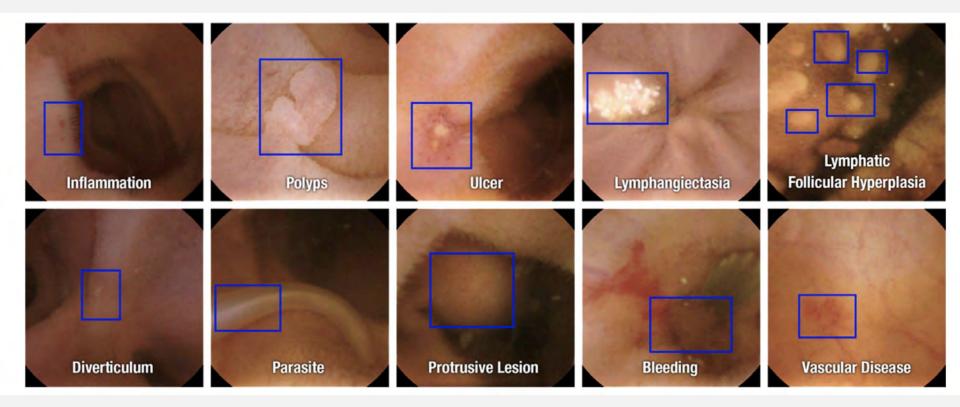
Saito et al. GIE. 7/2020; 92(1):144-151



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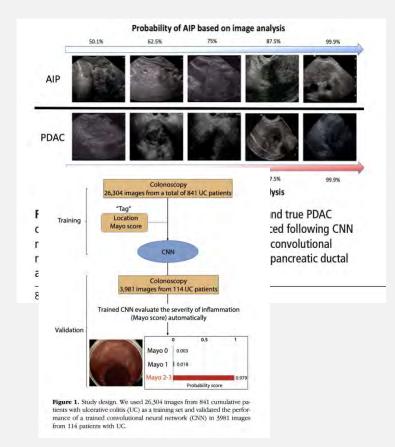




Saito et al. GIE. 7/2020; 92(1):144-151



- EUS: CADx for benign vs. malignant hepatic masses (*Marya GIE 2020*); AP vs. PDAC (*Marya Gut 2020*)
- IBD: Automatic segmentation of CTe images (*Stidham IBD* 2020) endoscopic RD and Mayo score (*Bossuyt et al Gut 2020; Ozawa 2019*)



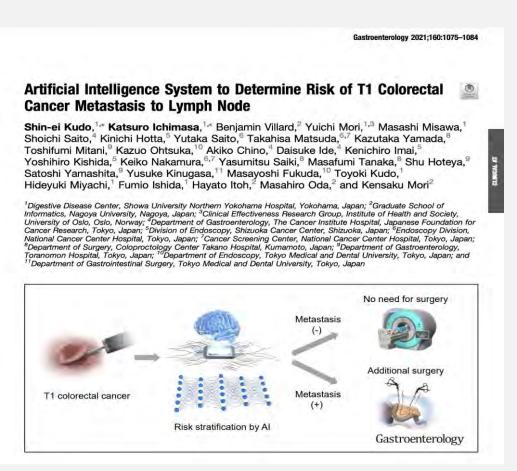
Marya et al. GIE. 5/2021; 93(5):1121-1130.e1. Bossuyt et al. Gut. 10/2020; 69(10):1778-1786.



- Predictive Modeling
- Natural Language Processing (automated report generation; ChatGPT)
- And more!



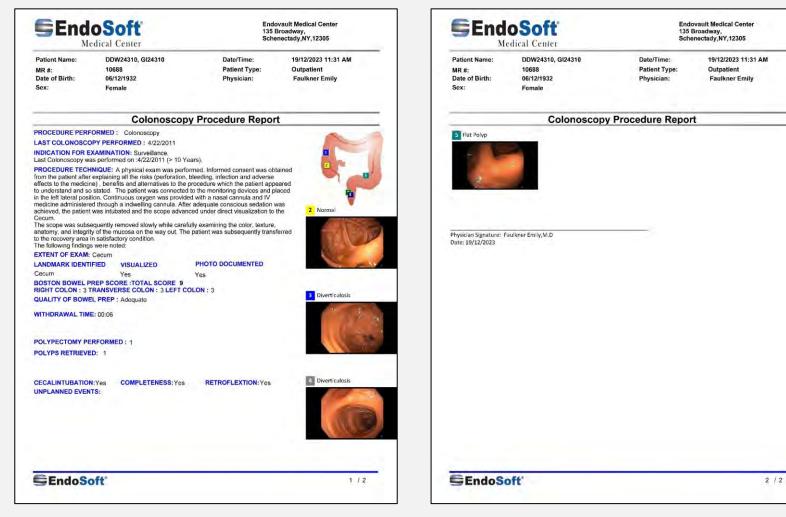
Predictive Modeling



Kudo et al. Gastroenterology. 3/2021; 160(4):1075-1084.e2.



Natural Language Processing



Images courtesy of Endosoft



Generative Al And Foundation Models

Figure. Artificial Intelligence (AI) 1.0, 2.0, and 3.0

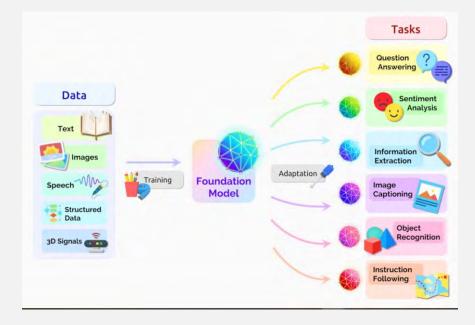
	1950s								
Approximate beginning year		2011	2018-2022						
	AI 1.0 Symbolic AI and probabilistic models	AI 2.0 Deep learning	AI 3.0 Foundation models						
Core functionality and key features	Follows directly encoded rules (if-then rules or decision trees)	Predicts and/or classifies information Task-specific (1 task at a time); requires new data and retraining to perform new tasks	Generates new content (text, sound, images) Performs different types of tasks without new data or retraining; prompt creates new model behaviors						
Training method	Rules based on expert knowledge are hand-encoded in traditional programming	Learning patterns based on examples labeled as ground truth	Self-supervised learning from large datasets to predict the next word or sentence in a sequence						
Performance capabilities	Follows decision path encoded in its rules. Eg, ask a series of questions to determine whether a picture is a cat or a dog.	Classifies information based on training: "Is this a cat or a dog?" "How many dogs will be in the park at noon?"	Interprets and responds to complex questions: "Explain the difference between a cat and a dog."						
Examples of performance	IBM's Deep Blue beat the world champion in chess Health care: Rule-based clinical decision support tools	Photo searching without manual tagging, voice recognition, language translation Health care: diabetic retinopathy detection, breast cancer and lung cancer screening, skin condition classification, predictions based on electronic health records	Writing assistants in word processors, software coding assistants, chatbots Health care: Med-PaLM and Med-PaLM-2, medicall tuned large language models, PubMedGPT, BioGPT						
Examples of challenges and risks	Human logic errors and bias in encoded rules lead to limited capability with real-world situations	Out-of-distribution problems (real-time data differs from training data) Catastrophic forgetting (not remembering early parts of a long sequence of text) Bias related to underlying training data	Hallucinations (plausible but incorrect responses based solely on predictions) Grounding and attribution Bias related to underlying training data and semantics of language in datasets						

Howell et al JAMA 2024 Jan 16;331(3):242-244.



Generative Al And Foundation Models

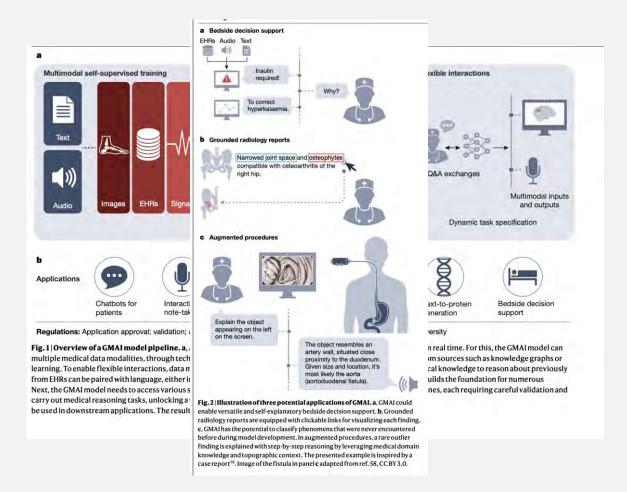
- Foundation models:
 - Eg ChatGPT, DALL-E2
 - Neural networks (eg transformer architecture)
 - Unsupervised learning
 - Broad, flexible outputs, generative



Bommasani et al arXiv:2108.07258



Generalist Medical Al



Moor and Rajpurkar et al. Nature 2023



CME/MOC Question:

Best Practices for CADe include all of the following except:

- a. Toggling the device off during insertion and cleaning and on during a "clean" withdrawal
- b. Toggling device on during intervention
- c. Toggling the device off during intervention
- d. Limiting bubbles and suction polyps during withdrawal

Joint Providership





CME/MOC Answer:

Best Practices for CADe include all of the following except:

a. Toggling the device off during insertion and cleaning and on during a "clean" withdrawal

b. Toggling device on during intervention

- c. Toggling the device off during intervention
- d. Limiting bubbles and suction polyps during withdrawal

Joint Providership





Take Home Points

- CADe is a solved problem in colonoscopy and multiple algorithms are FDA approved for clinical use
- Best practices are evolving but include careful insufflation and cleaning prior to use, toggling on during withdrawal and off during intervention
- Explosion in growth of other deep learning applications. CADe is only the beginning



Thank you!

