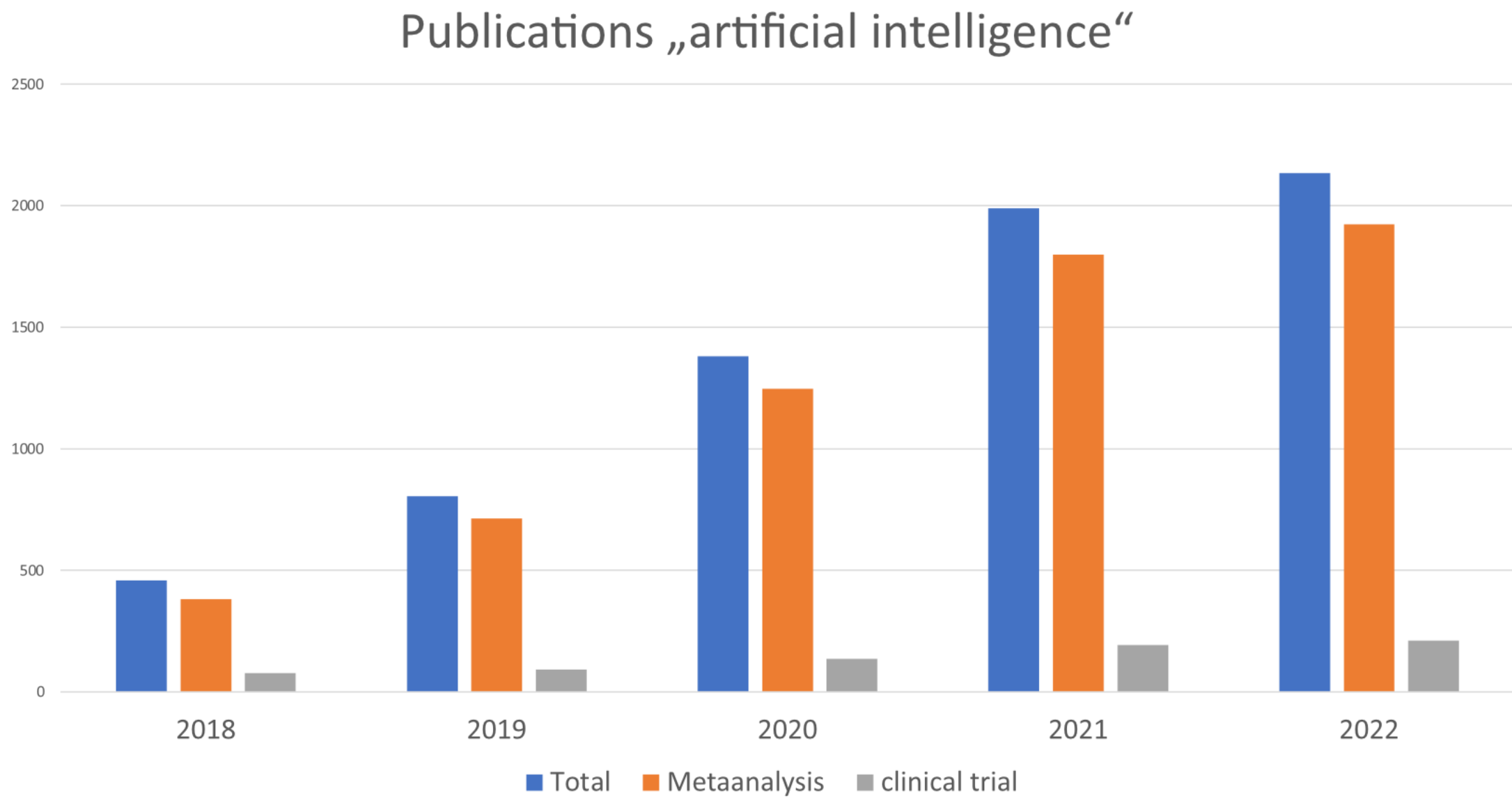
Schweizerische Arbeitsgruppe für Koloproktologie
Groupe suisse d'etudes coloproctologiques
Gruppo svizzero die Studio per coloproctologia
Swiss study group for coloproctology

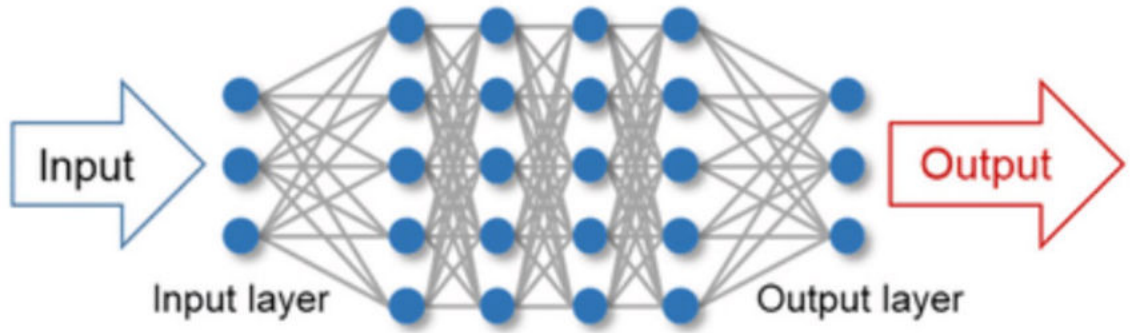
KEY-NOTE-Lecture

Artificial intelligence: How will it change the future of coloproctologists?

Peter Bauerfeind
Zürich/Luzern


Publications „artificial intelligence“
2500
2000
1500
1000
500
0
2018
2019
2020
2021
2022
Total
Metaanalysis
clinical trial

artificial intelligence: how does it work?

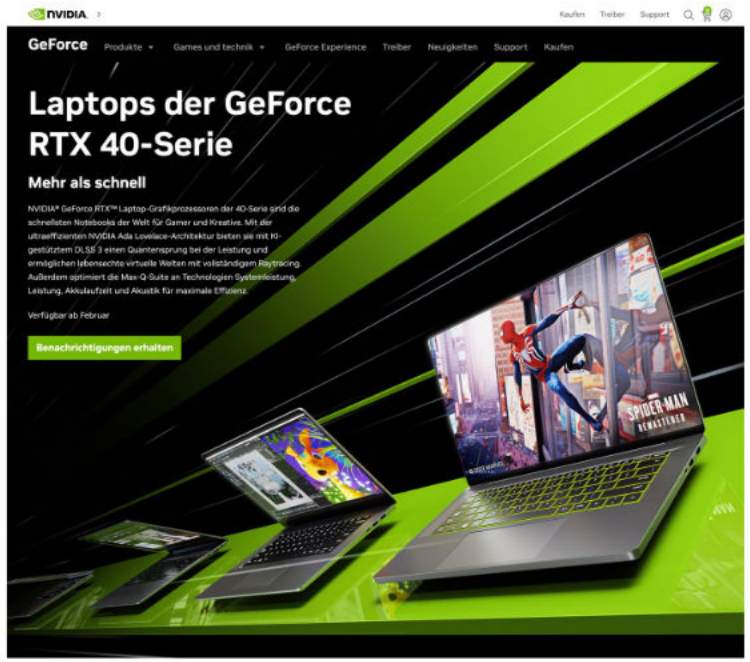


Car

deep learning
shallow learning
neuronal network
convolutional neuronal network (CNN)
deep convolutional neuronal network (DCNN)
recurrent neural network (RNN)

artificial intelligence: what does it need?

very fast computer



deep learning software

big data

Images
Video
Pathology
Genetic
Lab
....

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News

Aug 30, 2016

High School Student Using Artificial Intelligence to Fight Breast Cancer

By Brad Nemire

Discuss (0) 0 Like

Tags: CUDA, cuDNN, GeForce, Healthcare / Life Sciences, Higher Education / Academia, Image Recognition, Machine Learning & Artificial Intelligence, News

How I Searched My Way To A Cure | Abu Qader | TEDxTeen

https://www.youtube.com/watch?v=FrDAmYjjq7U

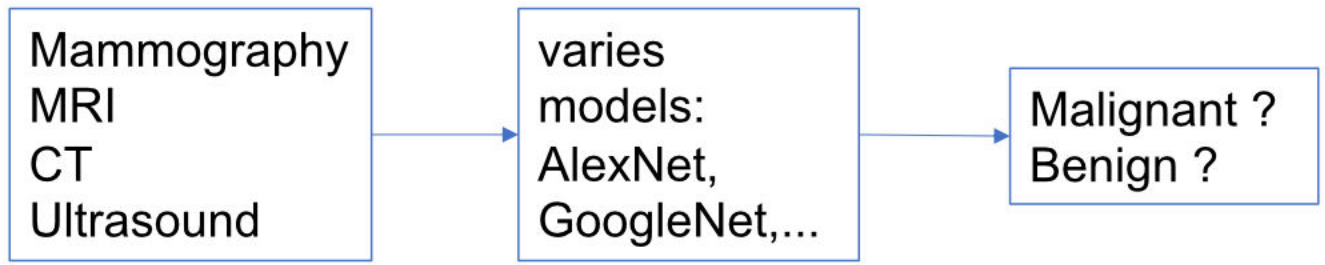
https://developer.nvidia.com/blog/high-school-student-using-artificial-intelligence-to-fight-breast-cancer/

Artificial intelligence: breast cancer diagnosis

Jones et al (2022) Front. Oncol. 12:980793. doi: 10.3389/fonc.2022.980793

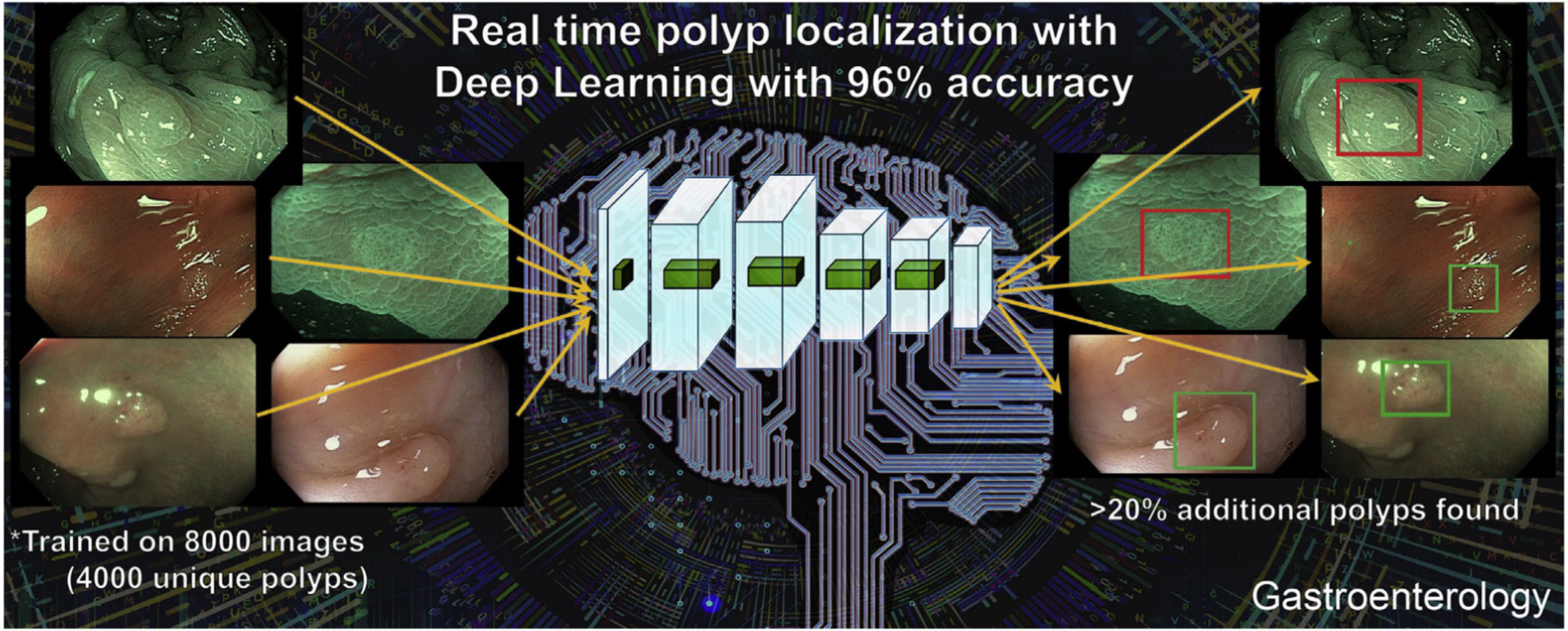
12 Studies (2016-2021)

78 -2393 images



Conclusions:

- gute AUC: 0.78 – 0.97
- too small data sets
- ...few models in clinical practice use



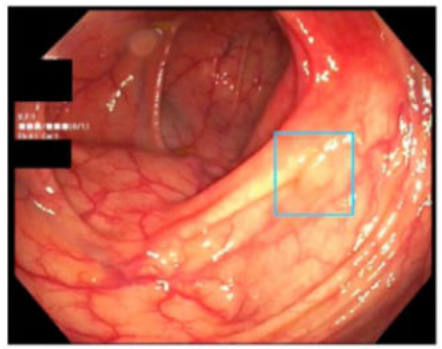
Urban et al. Gastroenterology 2018;155:1069–1078 (USA)

AI improves Adenoma Detection Rate ADR

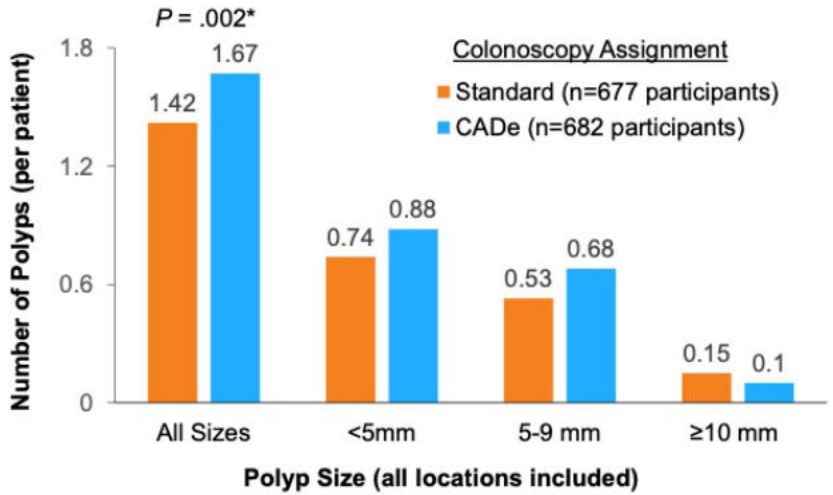
Shaukat...Brugge: Gastroenterology 2022;163:732–741 (USA)

Improvement in Adenomas per Colonoscopy Using a Computer-Aided Detection Device

Randomized trial, standard vs. CADe colonoscopy	1359 screening and surveillance participants	5 U.S.-based academic and community centers	22 experienced endoscopists	↑ 27% in adenomas per colonoscopy



Detection of a 4-mm adenoma in the hepatic flexure by the computer-aided detection (CADe) device



Gastroenterology

AI improves Adenoma Miss Rate AMR

Wallace...Hassan: Gastroenterology 2022;163:295-304 (USA/EU)

230 patients: Back to back colonoscopy trial (GI-Genius, Medtronic)

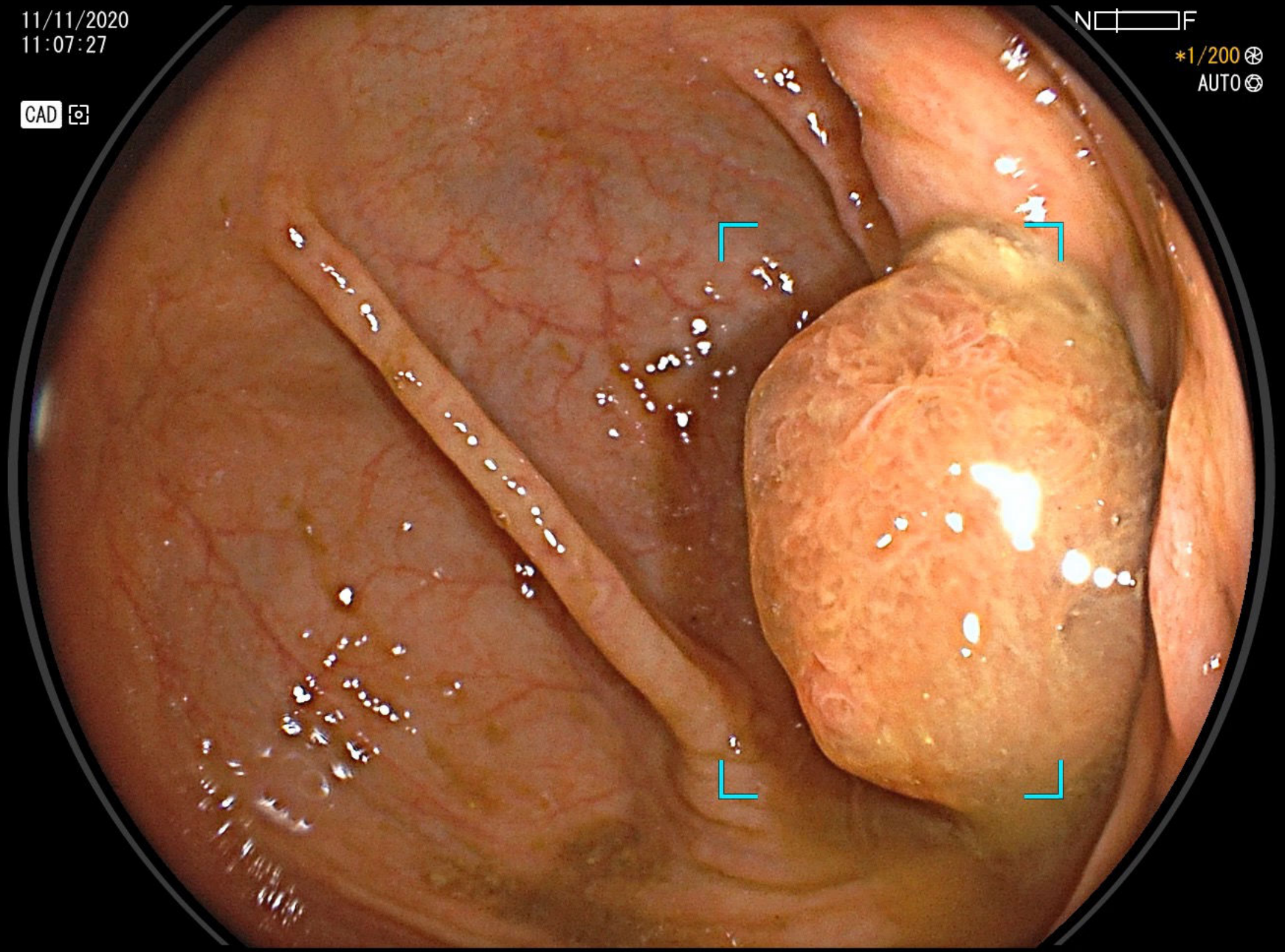
116 AI first, 114 standard colonoscopy first

AMR:	**with AI:**	**15.5%**
	without AI:	**32.4%**

Computer-aided diagnosis (CADx) for colorectal polyps

Aim: adenoma or nonadenoma ?

- Leaving-In-Situ
- Resect and discard



HT NR
SE

3.2
11.7
11.8

S1: F/T
S2: LM
S3: MOV
S4: OM_DW
S5: OM_UP

EC-760ZP-V/L
1C731K167
BL-7000

20178
1

How good is CADx for colorectal polyps ?

Parsa et al. Best Practice & Research Clinical Gastroenterology 52-53 (2021)

- Sensitivities: 90-98 %
- Mostly retrospective studie

Commercially available: GI Genius (Medtronic)
Cad Eye (Fujinon)

→ Prospective studies necessary

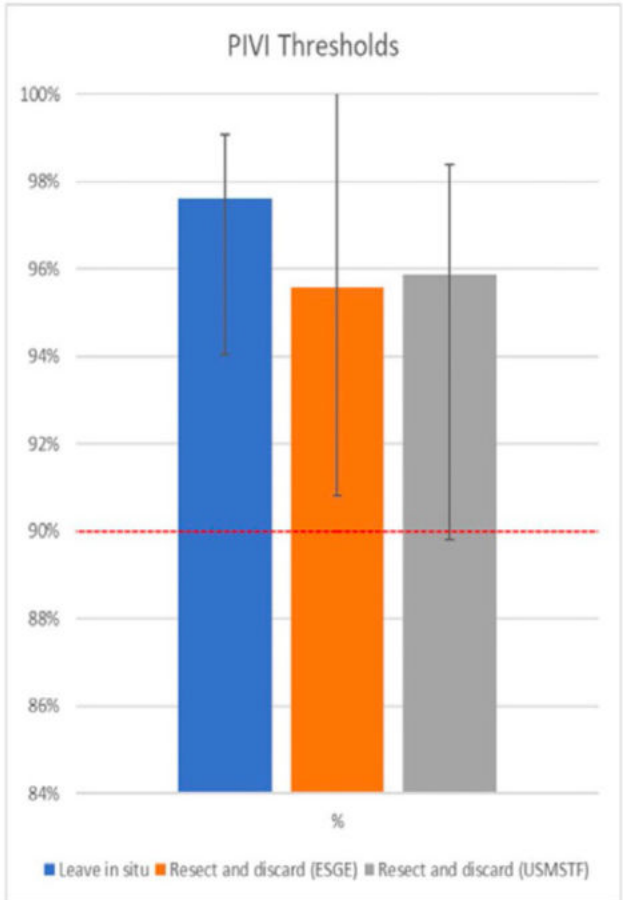
CADx: good differention between adenoma and nonadenoma

Hassan et al. Clinical Gastroenterology and Hepatology 2022;20:2505–2513

4 experienced endoscopists vs GI Genius

Table 2. Diagnostic Performance for Diminutive Polyps of the Rectosigmoid Tract by CADx in White-Light and the Endoscopist (Advanced Imaging)

	Optical diagnosis	
	CADx–white light	Endoscopist–blue light (high confidence)
Polyps, n/N[a]	291/295 (98.6%)	279/295 (94.6%)
Negative predictive value	**97.6% (94.1%–99.1%)**	**97.6% (94.8%–99.1%)**
Sensitivity	82% (66.5%–92.5%)	81.2% (63.5%–82.8%)
Specificity	93.2% (89.4%–96%)	98% (95.3%–99.3%)
Positive predictive value	65.3% (50.4%–78.3%)	83.9% (66.3%–94.5%)
Accuracy	91.8% (88%–94.6%)	96.1% (93.1%-98%)



CADx: good differention between adenoma and nonadenoma

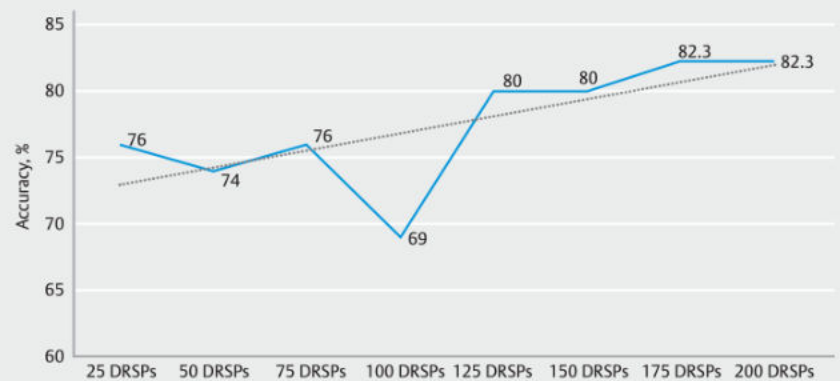
Rondonotti et al. Endoscopy 2023

9 experts and 9 nonexperts vs. CAD EYE (Fujinon)

596 diminutive (≤ 5mm) rectosigmoid polyps (DRSPs) → «resect and discard»
389 patients

NPV for DRSPs (PIVI-1):	91.0% (95 %CI 87.1 %– 93.9 %)
PIVI-2 threshold ESGE:	97.4 % (95 %CI95.7%–98.9 %)
PIVI-2 threshold USMSTF:	92.6 % (95 %CI 90.0 %–95.2

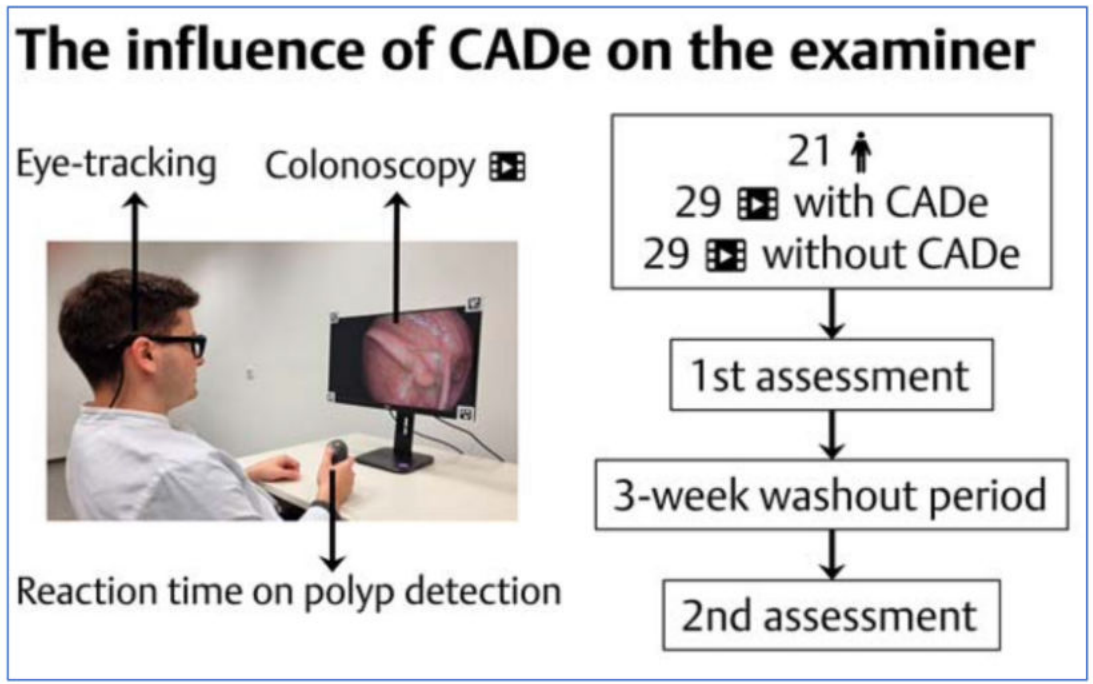
5.5% high risk adenome

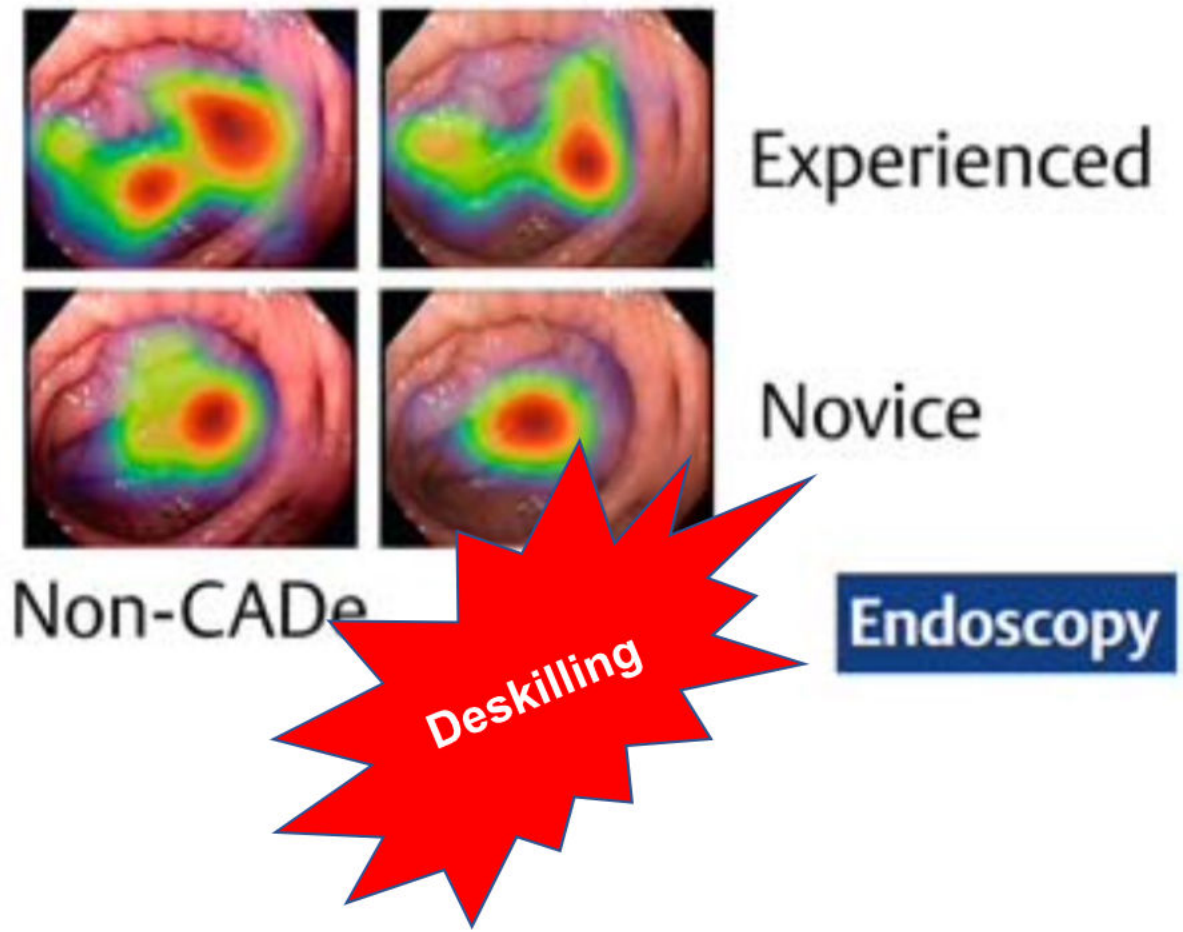


► **Fig. 2** The trend (dotted line) in accuracy through the series of consecutive diminutive rectosigmoid polyps evaluated by nonexperts. DRSP, diminutive rectosigmoid polyp.

Conclusion: CADe and CADx are good !

but….

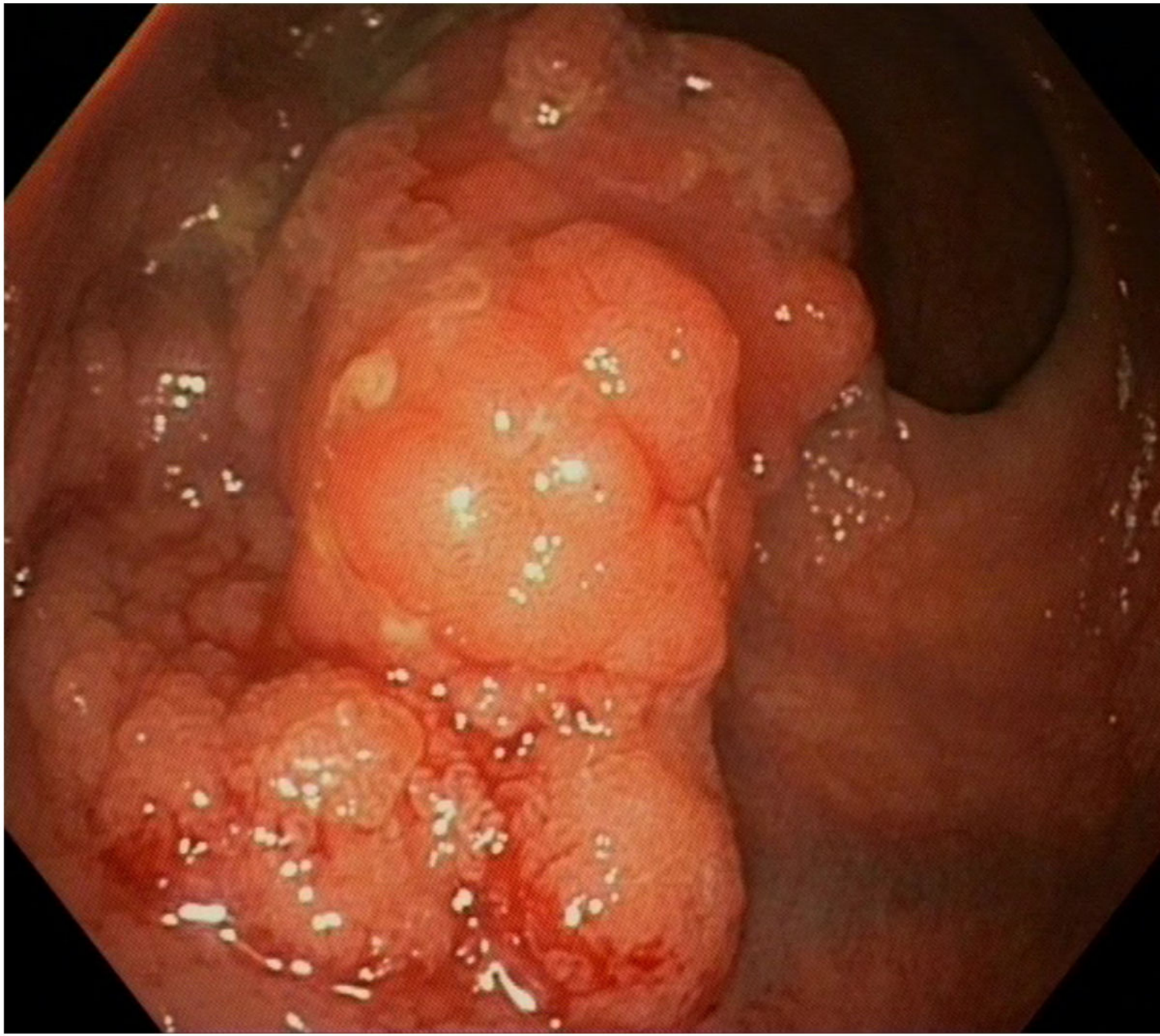




Troya Endoscopy 2022; 54: 1009–1014

Rectal Cancer Adenoma

- Staging ?
- Risk of LN ?
- Malignant ?
- Biopsy, where ?
- Deep invasion ?
- Endoscopically resectable ?



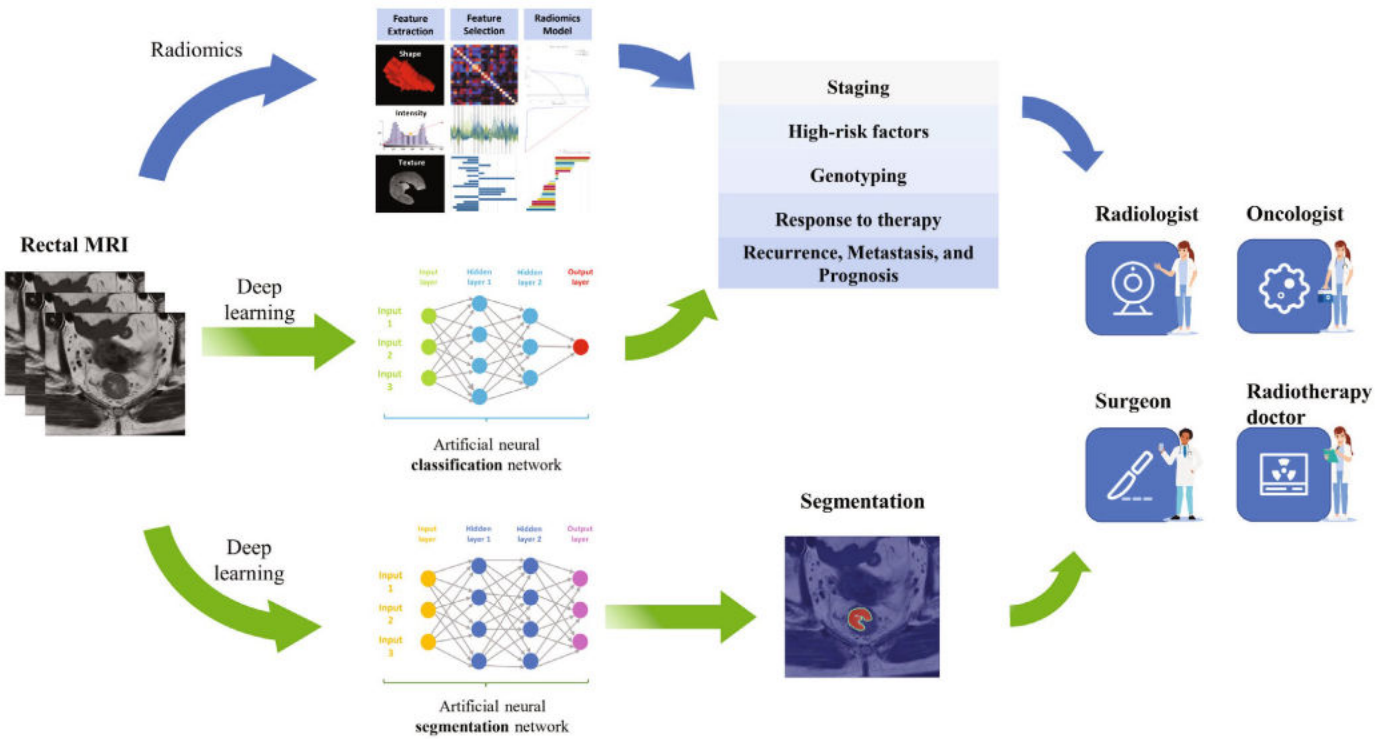
Rectal cancer: Therapy-relevant overstaging

Scheele et al. Visc Med. 2018 Aug; 34(4): 301–306

	EUS	CT	MRI
N	63	143	38
Therapy-relevant overstaging			
T3/4 category	10 (16%)	18 (13%)	10 (26%)
N+ category	13 (21%)	29 (20%)	11 (29%)
UICC II/III	13 (21%)	18 (13%)	10 (26%)

MRI in rectal cancer/adenoma: role of AI ?

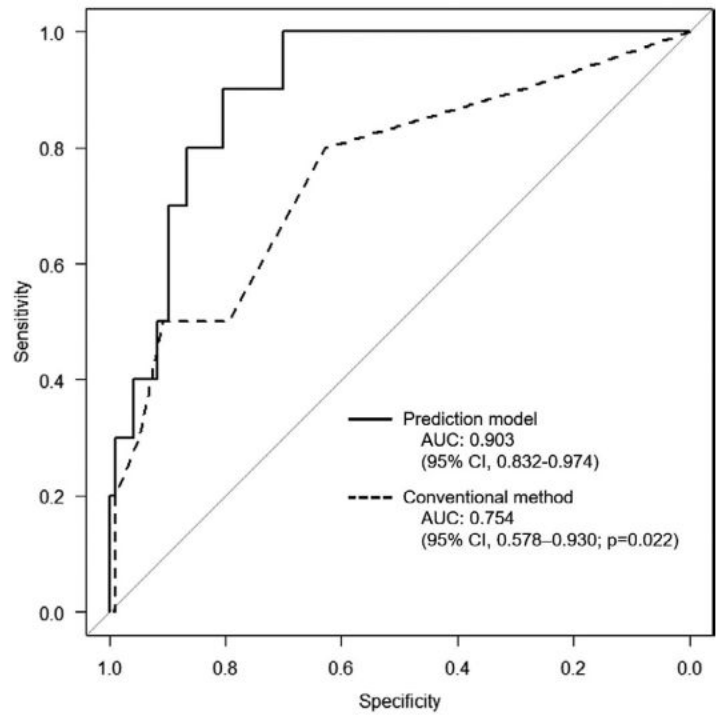
Wong et al. J. MAGN. RESON. IMAGING 2023;57:45–56.



Predicting Lateral Lymph Node Metastasis

Kasai Ann Gastroenterol Surg. 2022;6:92

Prediction One" (Sony)



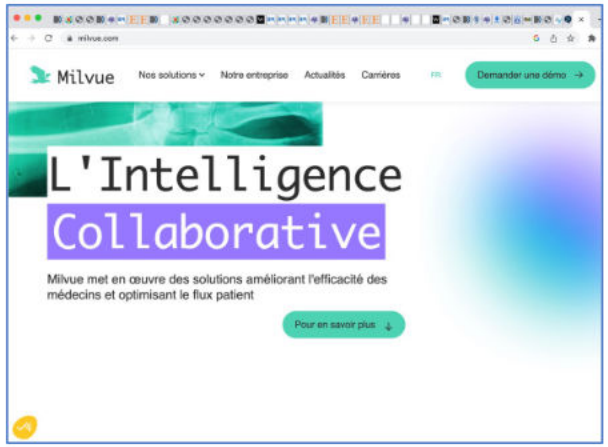
RESEARCH

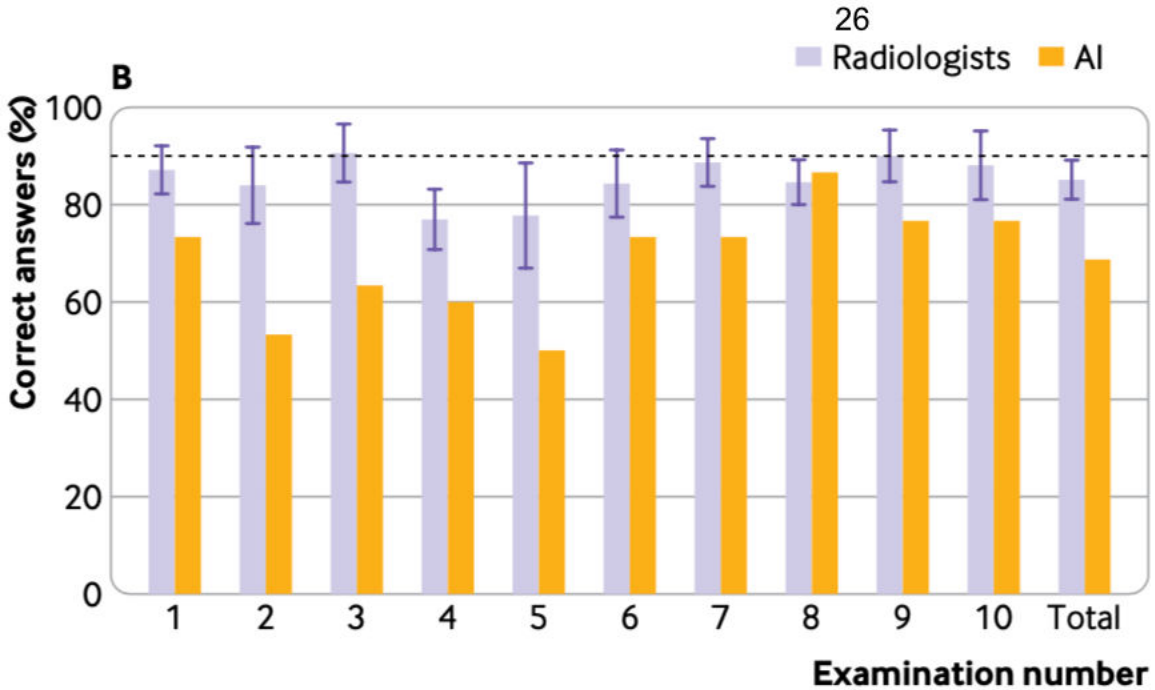
OPEN ACCESS

Check for updates

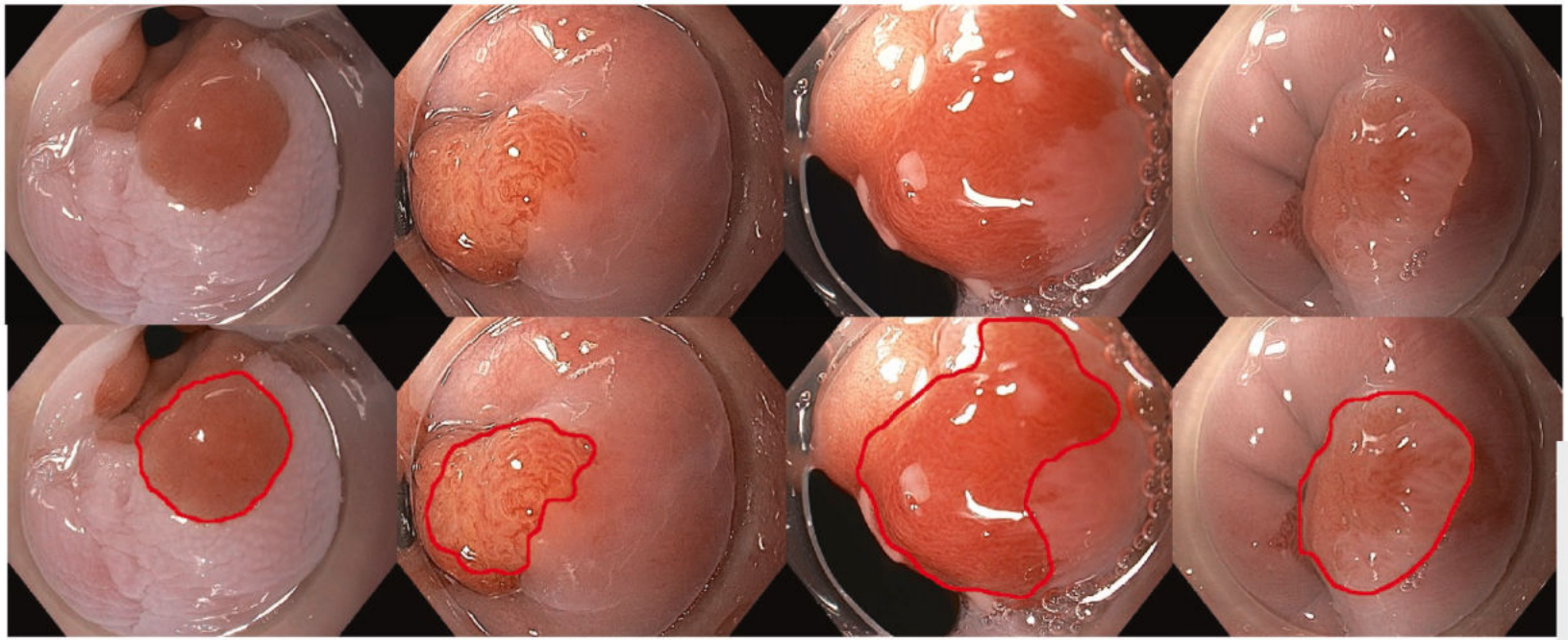
Can artificial intelligence pass the Fellowship of the Royal College of Radiologists examination? Multi-reader diagnostic accuracy study

Susan Cheng Shelmerdine,[1,2,3,4] Helena Martin,[4] Kapil Shirodkar,[5] Sameer Shamshuddin,[5] Jonathan Richard Weir-McCall,[6,7] on behalf of the FRCR-AI Study Collaborators

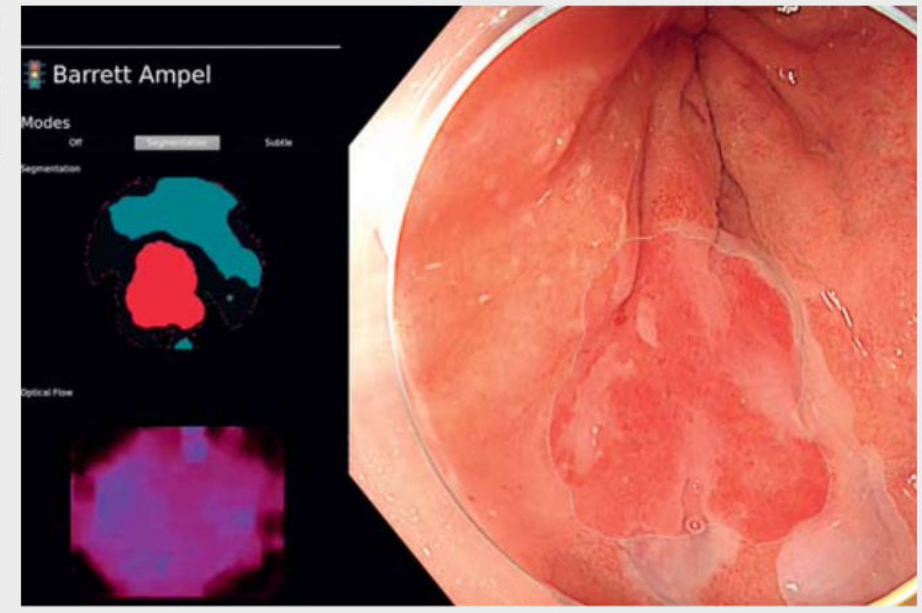




AI for Barrett is more advanced...



Ebigbo Endoscopy 2022; 54: E587



Real-time use of artificial intelligence in the evaluation of cancer in Barrett's oesophagus

Alanna Ebigbo [1], Robert Mendel,[2,3] Andreas Probst,[1] Johannes Manzeneder,[1] Friederike Prinz,[1] Luis A de Souza Jr.,[4] Joao Papa,[5] Christoph Palm,[2,3] Helmut Messmann[1]

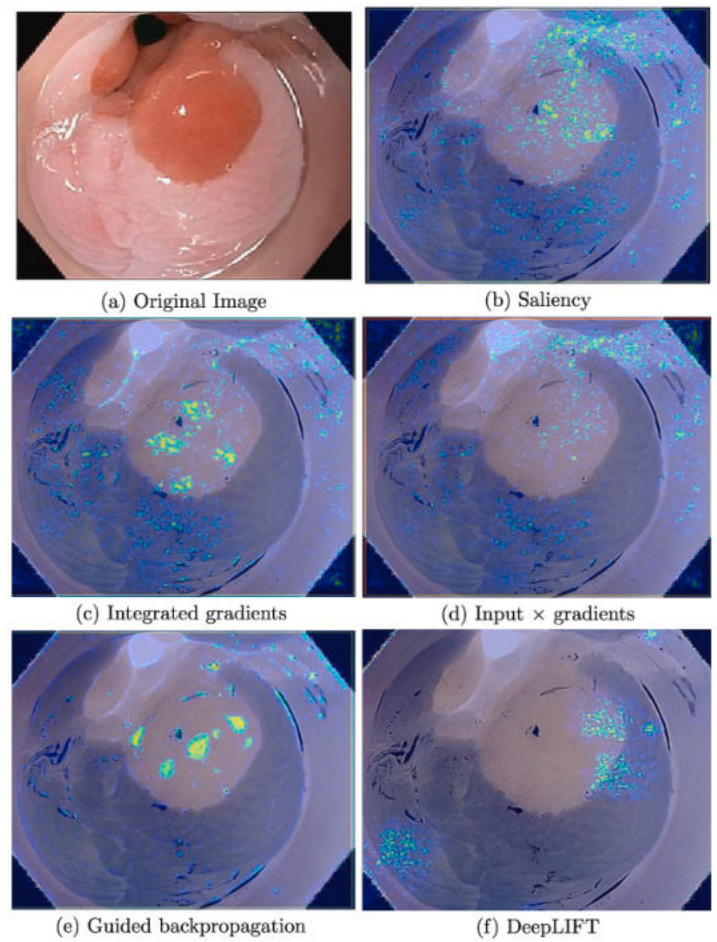
. Gut 2020;69:615–616

AI Barrett: comparison of deep learning methods

de Souza et al. Computers in Biology and Medicine 135 (2021)

Protocol	Architecture	Accuracy	Sensitivity	Specificity	Time (min)
20-fold	AlexNet	0.81 ± 0.17	0.82 ± 0.17	0.81 ± 0.19	119.45 ± 21.11
	SqueezeNet	0.77 ± 0.20	0.75 ± 0.15	0.78 ± 0.32	182.13 ± 22.27
	ResNet50	0.81 ± 0.14	**⋆0.89 ± 0.12**	0.72 ± 0.20	237.58 ± 19.18
	VGG16	**0.84 ± 0.24**	0.78 ± 0.26	**0.85 ± 0.39**	144.53 ± 18.02
LOPO-CV	AlexNet	0.85 ± 0.05	0.82 ± 0.10	0.89 ± 0.09	146.33 ± 20.46
	SqueezeNet	0.88 ± 0.07	0.86 ± 0.09	0.89 ± 0.08	206.39 ± 20.44
	ResNet50	**⋆0.87 ± 0.12**	**0.89 ± 0.08**	0.844 ± 0.113	251.05 ± 17.57
	VGG16	0.86 ± 0.05	0.85 ± 0.11	**⋆0.89 ± 0.10**	156.17 ± 14.28

pixel impact visualizations (PIV)



(a) Original Image (b) Saliency (c) Integrated gradients (d) Input × gradients (e) Guided backpropagation (f) DeepLIFT

T1 CRC: when is additional surgery necessary ?

High risk-Lesions (LN risk > 3%)

- > T1b (sm1)
- G3
- L1
- V1
- R1

NEW:

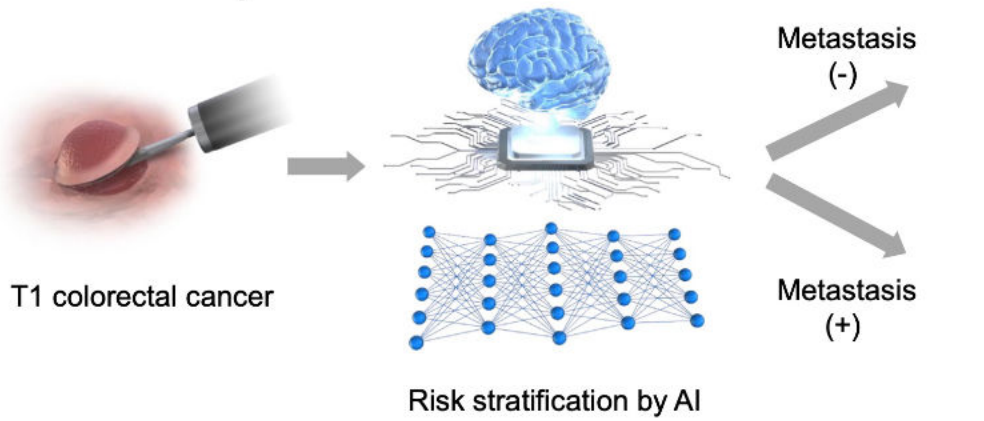
Only L1 is relevant for LN risk
Rönnow et al Ann Surg 2022

Submucosal invasion >sm1 is NO independent risk factor for LN
Zwager et al Gastroenterology 2022

AI: when is additional surgery necessary ?

Kudo Gastroenterology 2021;160:1075–1084

3134 patients
939 validation patients



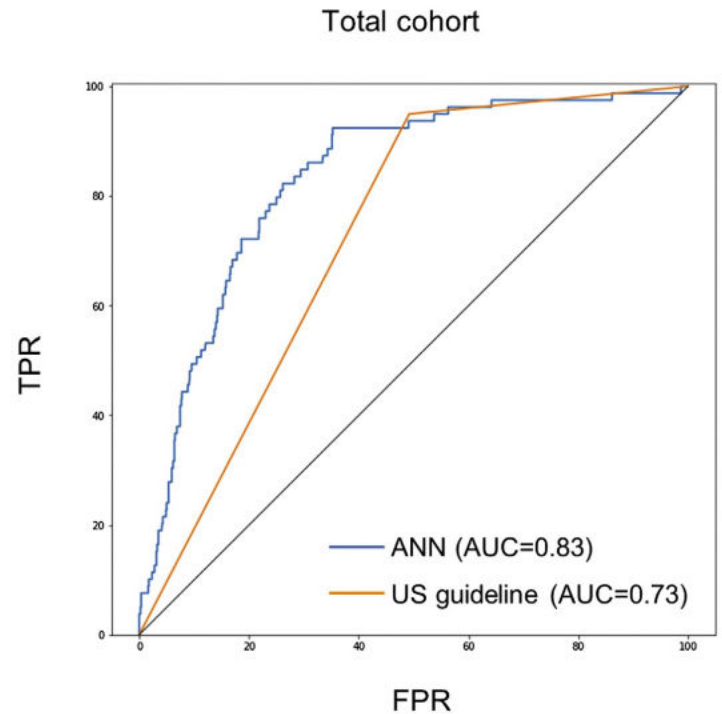
No need for surgery

Additional surgery

Gastroenterology

machine-learning artificial neural network (ANN):

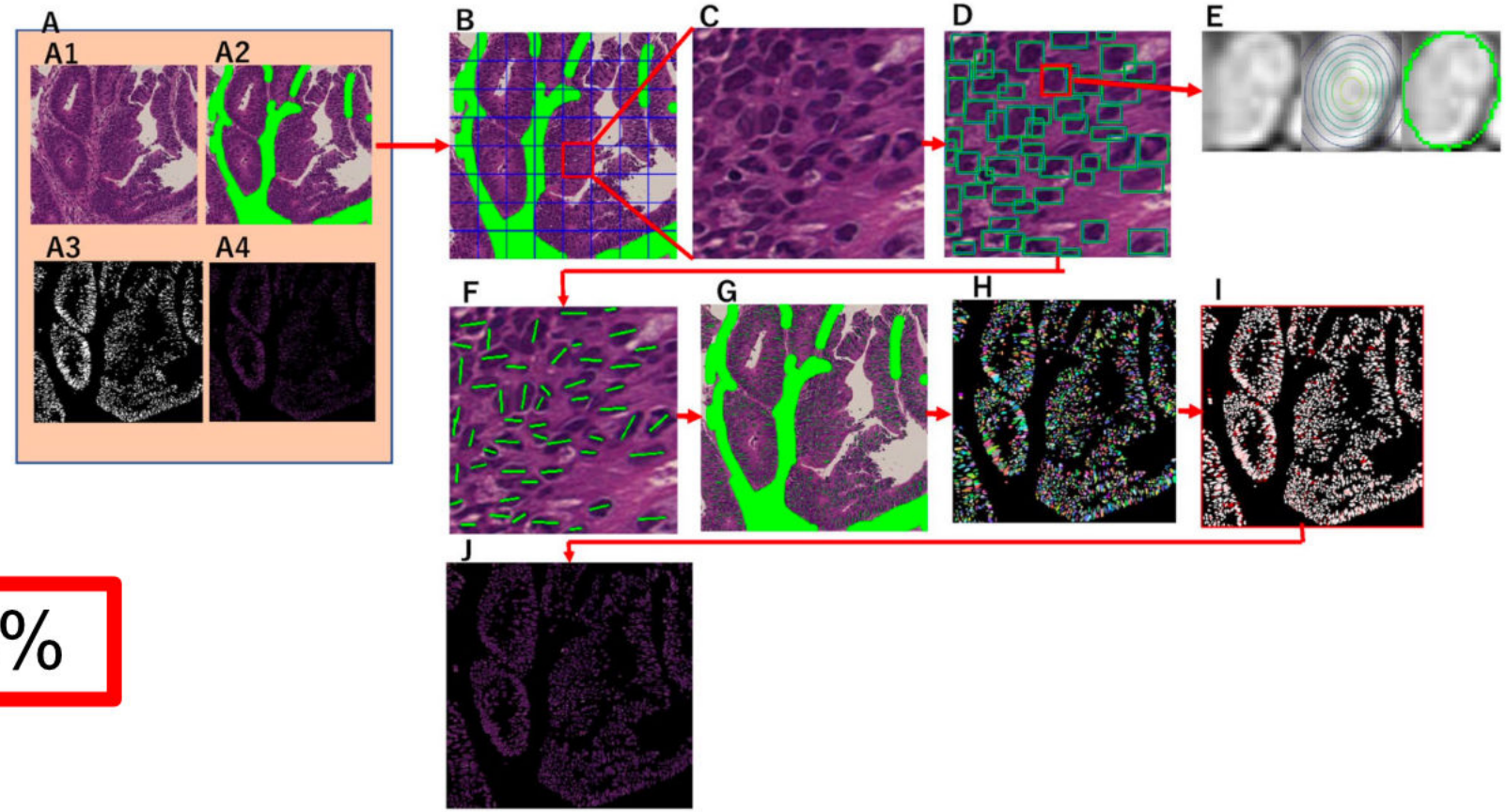
Traditional histology criteria
Age
sex



LN risk in T1b: AI analysis of cell nuclei

Kasahara International Journal of Clinical Oncology (2022)

141 T1b Cases (surgery)



Accuracy= 86.3%

Fig. 2 Process of nucleus segmentation by deep learning: **A** the original HE images and mask images (Fig. 1B, C, E, F), **B**, **C**, **D** detection of cell nucleus position using original image, **E** the images of cell nuclei expanded from the center to the contour line, **F** image of the long axis of the nucleus extracted on Fig. 2D based on Fig. 2E, **G**, **H**, **I** mask image created by DL based on the major axis of the nucleus, and **J** the final image of the nucleus, created after the extraction of the nucleus. *DL* deep learning

AI in histopathology: MSI detection

Deep learning model for the prediction of microsatellite instability in colorectal cancer: a diagnostic study

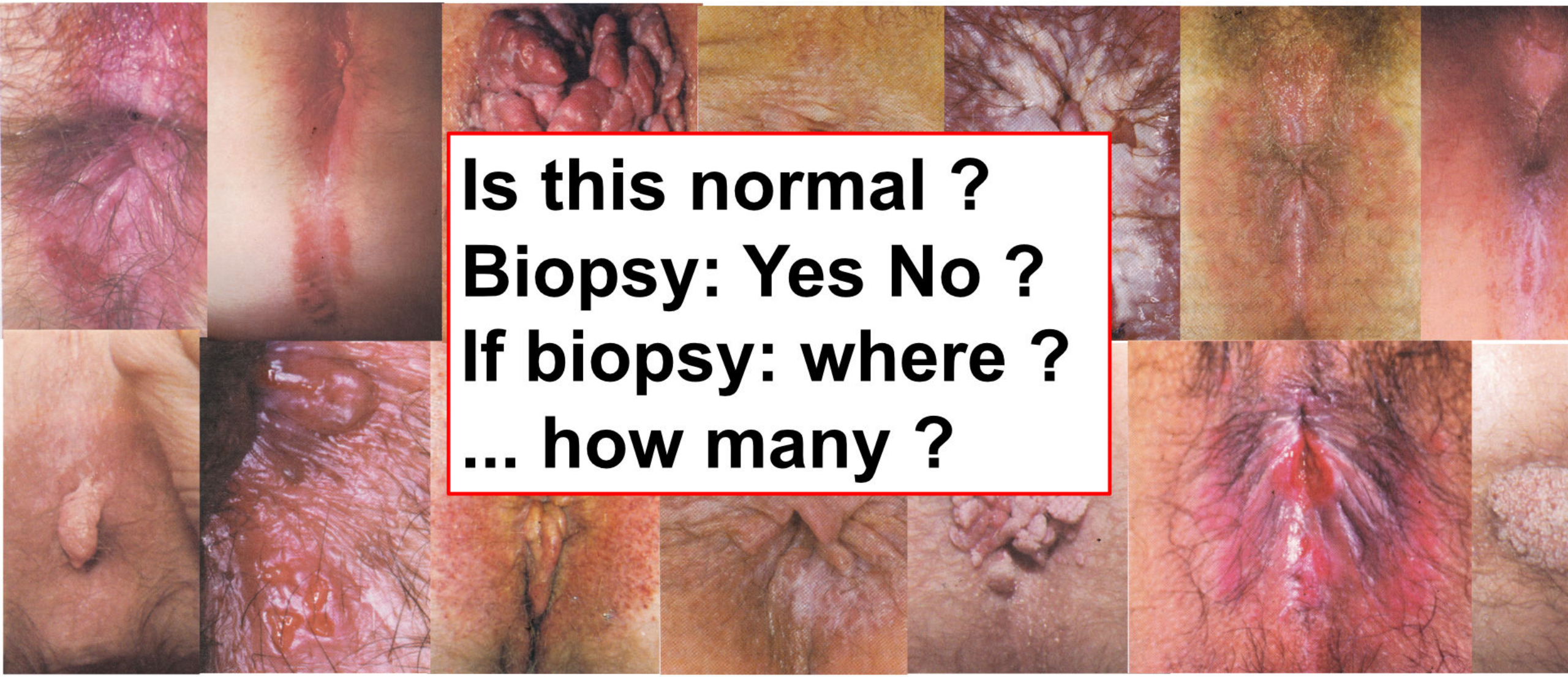
Yamashita et al. Lancet Oncol 2020; 22: 132–41

Gastroenterology 2020;159:1406–1416

Clinical-Grade Detection of Microsatellite Instability in Colorectal Tumors by Deep Learning

Amelie Echle,[1] Heike Irmgard Grabsch,[2,3] Philip Quirke,[3] Piet A. van den Brandt,[4] Nicholas P. West,[3] Gordon G. A. Hutchins,[3] Lara R. Heij,[5,6,7] Xiuxiang Tan,[5,6,7] Susan D. Richman,[3] Jeremias Krause,[1] Elizabeth Alwers,[8] Josien Jenniskens,[4] Kelly Offermans,[4] Richard Gray,[9] Hermann Brenner,[8,10,11] Jenny Chang-Claude,[12,13] Christian Trautwein,[1] Alexander T. Pearson,[14] Peter Boor,[7] Tom Luedde,[1,15] Nadine Therese Gaisa,[7] Michael Hoffmeister,[8] and Jakob Nikolas Kather[1,3,11,16]

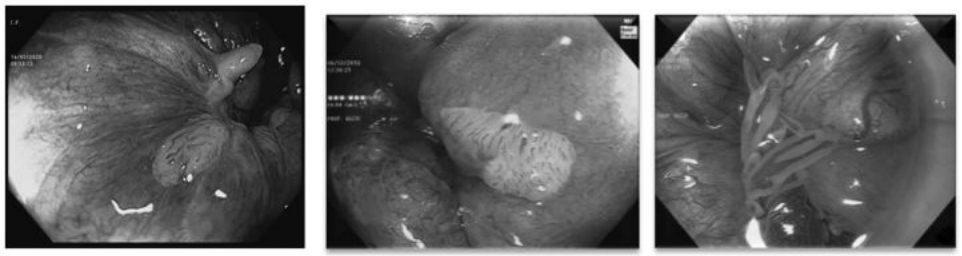
Anal lesions: AI ?



Anal intraepithelial lesions and NBI

Pecere et al. Eur J Gastroenterol Hepatol 35: 31–35, 2023

(a) three different LSIL with NBI pattern type I with the typical elongation of IPCL.



(b) HSIL lesions with NBI pattern II showing thickened and tortuous IPCL.

(c) mosaic-like pattern arising from the anal transitional zone and classified as NBI type III. Histology showed IC and SISCCA.

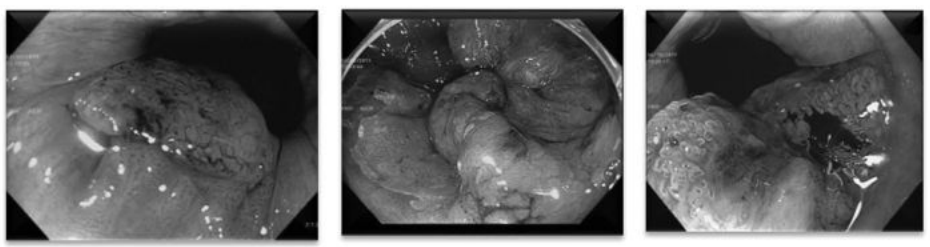


Table 4. Diagnostic accuracy of narrow-band imaging in predicting histology

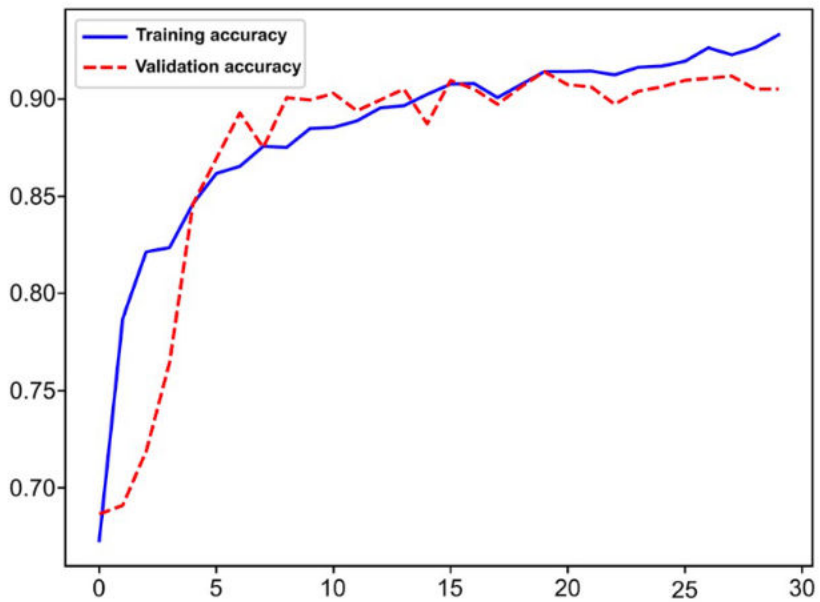
		95% CI
Sensitivity	100%	92.3–100%
Specificity	94.1%	83.8–98.3%
Positive predictive value	97.6%	88.6–99.8%
Negative predictive value	100%	92.3–100%

CI, confidence interval.

AI and high-resolution anoscopy for detection of anal squamous cell carcinoma precursors

Saraiva et al. Techniques in Coloproctology (2022) 26:893–900 (F)

1517 imagesHSIL
3509 imagesLSIL



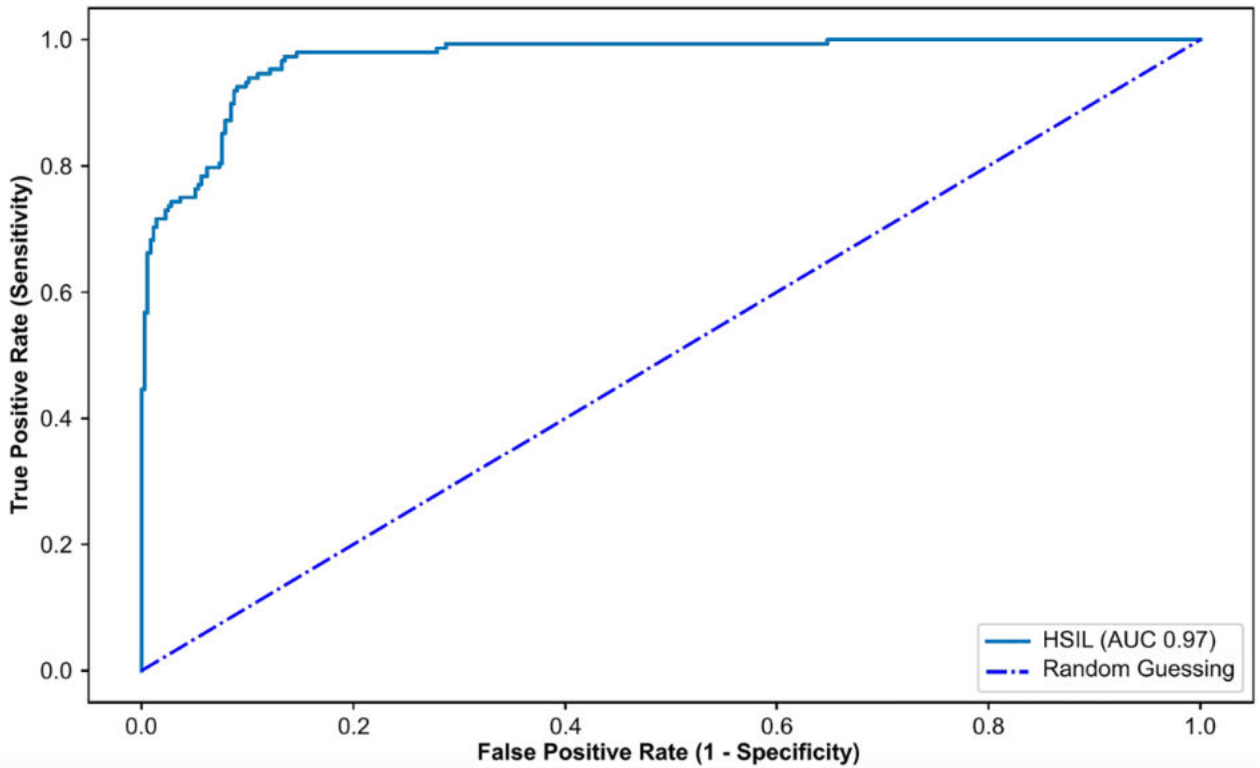


Fig. 3 Evolution of the accuracy of the convolutional neural network during training and validation phases, as the training and validation datasets were repeatedly inputted in the neural network

AI in robotic surgery:
Autonomous Robotic Laparoscopic Surgery for Intestinal Anastomosis

Saeidi et al. Sci Robot. 2022 January 26; 7(62): eabj2908. doi:10.1126/scirobotics.abj2908

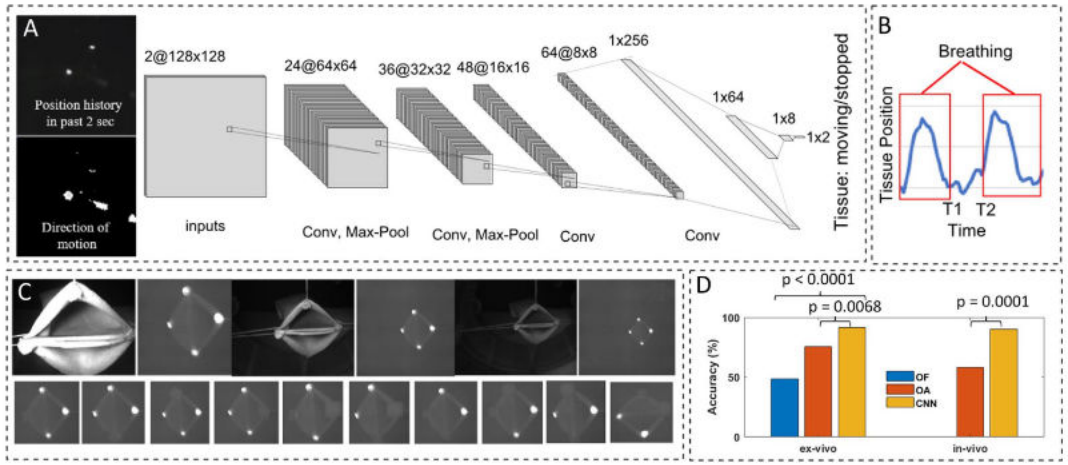
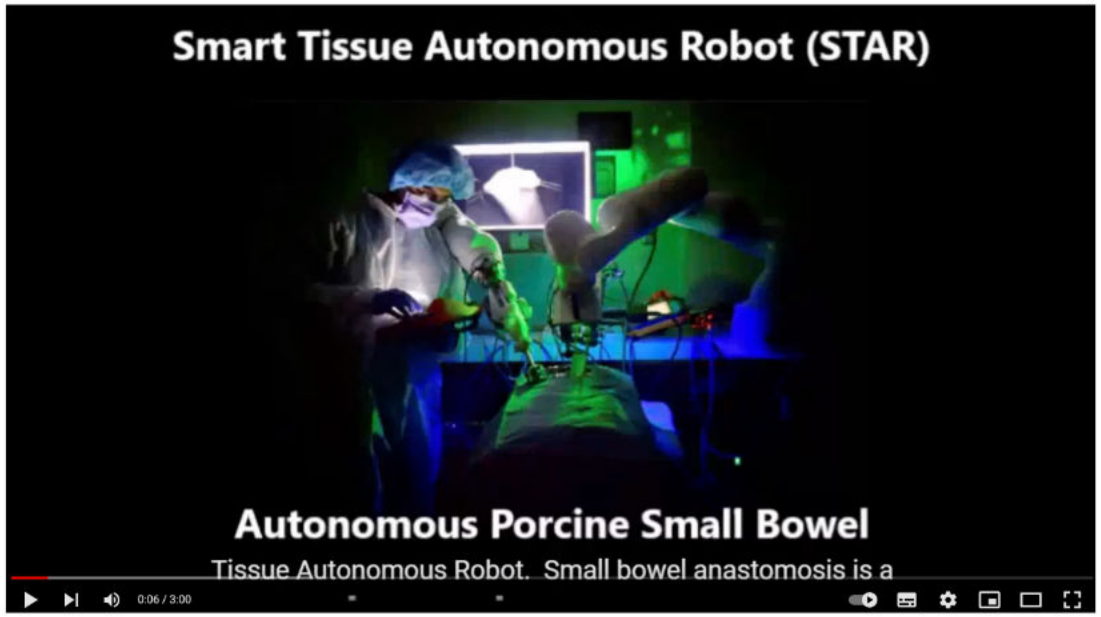


Fig. 2. Tissue motion tracking.
(A) The CNN-based breathing motion tracker. (B) Examples of the vertical motion of NIR marker during *in vivo* tests. (C) Robustness test configurations for the phantom conditions. (D) The accuracy test results for the breathing motion tracker via optical flow with fixed threshold (OF), optical flow with adjustable threshold (OA), and the CNN-based method (CNN).



https://www.youtube.com/watch?v=cybRmhsvOss

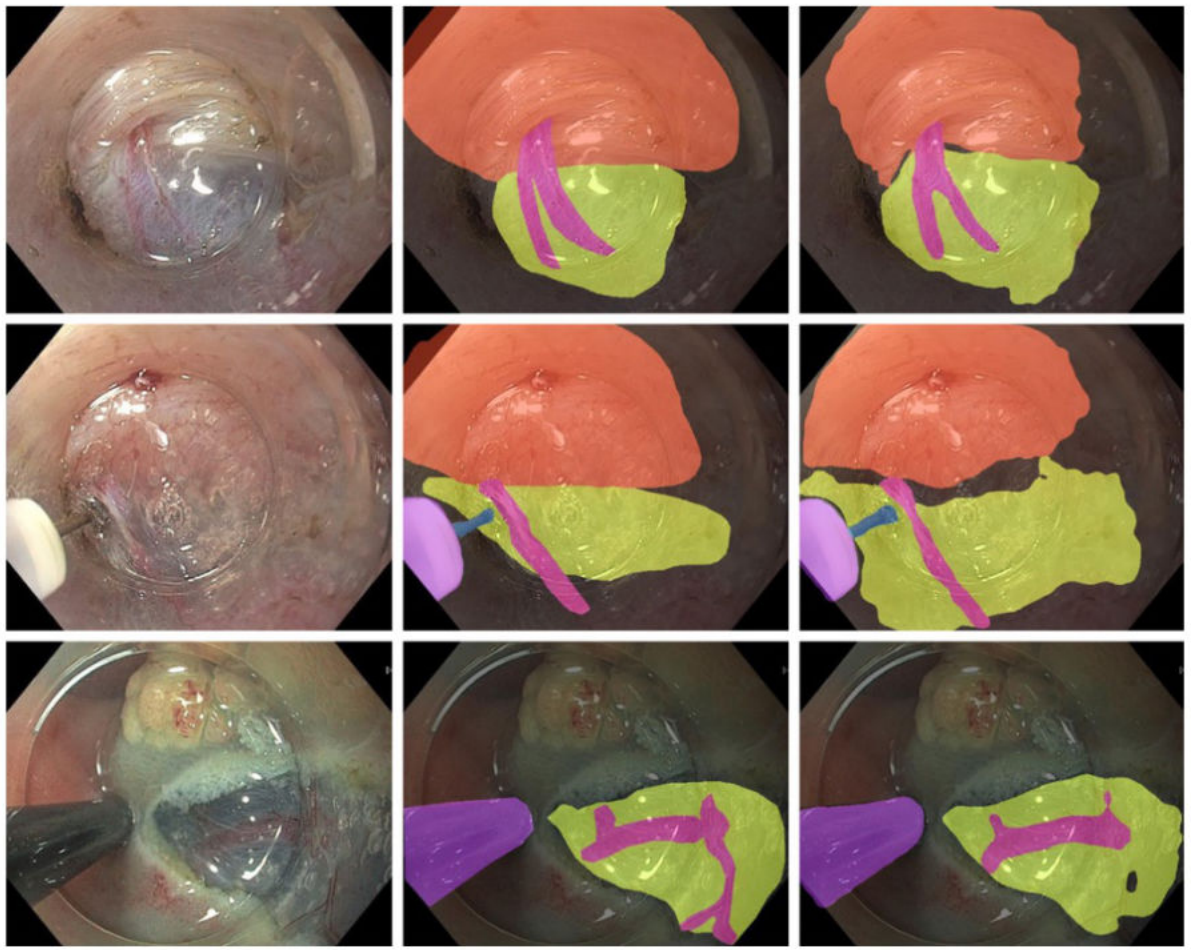
AI in ENDOSCOPIC surgery:
Autonomous Robotic Laparoscopic Surgery for Intestinal Anastomosis

Endoscopy news

OPEN ACCESS

Vessel and tissue recognition during third-space endoscopy using a deep learning algorithm

Alanna Ebigbo ,[1] Robert Mendel,[2] Markus W Scheppach ,[1] Andreas Probst,[1] Neal Shahidi ,[3] Friederike Prinz,[1] Carola Fleischmann,[1] Christoph Römmele ,[1] Stefan Karl Goelder,[4] Georg Braun,[1] David Rauber,[2] Tobias Rueckert,[2] Luis A de Souza Jr,[5] Joao Papa,[6] Michael Byrne,[7] Christoph Palm,[2] Helmut Messmann[1]



Gut 2022

Summary and Conclusion:

Artificial intelligence WILL NOT change the NEAR future of coloproctologists