Supplementary Materials: Artificial Intelligence Applied to Colonoscopy: Is it Time to Take a Step Forward?

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Table S1. Computer-assisted diagnosis (CADx) studies (adapted and modified from references [1-3]).

Author, year (reference)	Design	Adquisition of information	Training / testing sets	Type of AI	Endoscopic image technology	S/E/PPV/NPV/AC	Postpolypectomy surveillance interval agreement
Takemura, 2010[4]	R	Still images	Training set: 72 polyps. Testing set: 134 images.	Automatic quantification and classification of pit patterns	Magnification chromoendoscopy	S: 97.8% E: 97.8% PPV and NPV no reported AC: 98.5%	Not studied
Tischendorf, 2010[5]	P	Still images	Training set: 209 polyps. Testing set: not specified.	Vascularization features. Automated classification with SVM.	NBI + magnification colonoscopy	S: 90 % E: 70 % PPV and NPV no reported AC: 85.3 %	Not studied
Gross, 2011[6]	P	Still images	Training set: 434 polyps. Testing set: not specified.	Differentiation between neoplastic and non-neoplastic colorectal polyps. Automated classification with SVM.	NBI + magnification colonoscopy	S: 95.0 % E: 90.3 % PPV: 93.5 % NPV: 92.4 % AC: 93.1 %	Not studied
Takemura, 2012[7]	R	Still images	Training set: 1519 polyps. Testing set: 371 polyps	Predicting the histology of colorectal tumors on narrow-band imaging magnifying colonoscopy images. Automated classification with SVM.	NBI + magnification colonoscopy	S: 97.8 % E: 97.9 % PPV: not reported. NPV: not reported AC: 97.8 %	Not studied
Aihara, 2013[8]	P	Diagnosis in real-time	32 patients with 102 colorectal lesions (no training / testing sets)	Software that facilitates real-time numerical color analysis of still images	Autofluorescence endoscopy	S: 94.2 % E: 88.9 % PPV: 95.6 % NPV: 85.2 % AC: not reported	Not studied

Mori, 2015[9]	R (pilot study)	Still images	Testing set: 176 polyps. No training set	Fully automated diagnostic system (EC-CAD) for nuclear segmentation and classification	Endocytoscopy in polyps < 10 mm	S: 92 % E: 79 % PPV: not reported NPV: not reported AC: 89.2 %	Not studied
Mori, 2016[10]	R	Still images	Training set: 6051 images. Testing set: 205 polyps.	Fully automated diagnostic system (EC-CAD) for nuclear segmentation and classification. Automated classification with SVM.	Endocytoscopy in polyps < 10 mm	S: 88 % E: 92 % PPV: 99 % NPV: 85 % (97 % for rectosigmoid polyps) AC: 89 %	96 – 98 %
Kominami, 2016[11]	P	Diagnosis in real-time	Training set: 2247 images. Testing set: 118 polyps.	Prediction of histologic diagnoses of colorectal lesions. Automated classification with SVM.	NBI + magnification colonoscopy	S: 93 % E: 93.3 % PPV: 93 % NPV: 93.3 % AC: 93.2 %	92.7 %
Misawa, 2016[12]	P	Still images	Training set: 979 images. Testing set: 100 images.	Prediction of histologic diagnoses. Automated classification with SVM.	Narrow-Band Imaging Endocytoscopy	S: 84.5 % E: 97.6 % PPV: 98 % NPV: 82 % AC: 90 %	Not studied
Komeda, 2017[13]	R	Still images from videos	Training set: 1800 images. Testing set: 10 images.	Distinction between adenomatous or nonadenomato us lesion with CNN.	white-light colonoscopy, narrow-band imaging and chromoendosc opy.	AC: 70%.	Not studied.
Chen, 2018[14]	P	Diagnosis in real-time	Training set: 2157 images. Testing set: 284 images.	Deep neural network in polyps < 5 mm.	NBI	S: 96.3 % E: 78.1 % PPV: 89.6 % NPV: 91.5 % AC: 90.1 %	Not studied
Mori, 2018[15]	P	Diagnosis in real-time	Training set: 2157 images. Testing set: 466 polyps.	Microvascular evaluation with NBI mode and cellular visualization	Endocytoscopy , NBI and methylene	S: 91.3 – 93.8 % E: 88.7 – 91 % PPV: 92.9 – 94.4 %	Not studied.

				after staining with methylene blue. Automated classification with SVM.	blue staining in polyps < 5 mm	NPV: 86.3 – 89.9 % (for rectosigmoid polyps: 93.7 – 96.5 %) AC: not reported.	
Byrne, 2019[16]	P	Diagnosis in real-time in videos.	Training set: 223 videos (validation set: 40 videos). Testing set: 125 videos.	Differentiation of adenomatous and hyperplastic diminutive colorectal polyps with CNN.	NBI	S: 98 % E: 83 % PPV: 90 % NPV: 97 % AC: 94 %	Not studied
Sanchez-Montes, 2019[17]	P	Still images.	Training set: not reported. Testing set: 225 polyps.	Histology prediction system based on colorectal polyp textural surface patterns (dysplastic vs nondysplastic polyps). Support vector machine	Colonoscopoy with high definition white light + magnification or chromoendoscopy + NBI.	S: 92.3 % E: 89.2 % PPV: 93.6 % NPV: 87.1 % (for rectosigmoid polyps < 5 mm: 96.7 %) AC: 91.1 %	Not studied
Jin, 2020[18]	P	Still images	Training set: 2150 polyps. Testing set: 300 polyps.	CNN for evaluation of diminutive colorectal polyps.	NBI	S: 81.6 % E: 90.8 % PPV: 90.8 % NPV: 76.7 % AC: 86.7 %	Not studied
Song, 2020[19]	R	Still images	Training set: 12480 images (624 polyps). Testing set: 545 polyps.	Classification of serrated lesiones, benign adenomas or superficial cancers and deep submucosal cancers with a deep learning model.	NBI + magnification	S: 58.8 – 84.1 % E: 75 – 93.7 % PPV: 47.6 - 78 % NPV: 67.7 - 95 % AC: 81.3 % (overall)	Not studied
Kudo, 2020[20]	R	Still images	Training set: 69142 images. Testing set: 100 images.	Analysis of cell nuclei, crypt structure, and microvessels in endoscopic images for distinguishing neoplasms from	Endocytoscopy + methylene blue staining or NBI	S: 96.9 % E: 94.3 - 100 % PPV: 96.9 - 100 % NPV: 94.3 – 94.6 % AC: 96 - 98 %	Not studied.

				non-neoplasms (polyps ≤ 10 mm).			
Zachariah, 2020[21]	P	Still images	Training set: 6223 Testing set: 634 images.	CNN for distinguishing adenomatous lesions vs hyperplastic / serrated lesions (any size).	White-light colonoscopy or NBI	S: 91 % E: 88 % PPV: 74 % NPV: 97 % AC: 89 %	94 %
Ozawa, 2020[22]	R	Still images	Training set: 16418 images (4752 polyps) and 4013 normal images) Testing set: 7077 images.	CNN for distinguishing adenomatous vs non-adenomatous lesions.	White-light colonoscopy or NBI	S: 92 % E: not reported PPV: 86 % NPV: 85 - 90 % AC: 83 %	Not studied
Zorron Cheng Tao Pu, 2020[23]	R	Still images	Training set: two sets of 1235 and 123500. Validation/testing set: 69 images.	CNN for lesiones detected by NBI (including serrated lesions).	White-light colonoscopy or NBI or BLI.	AC: 93 – 96% S, E, PPV and NPV not reported.	Not studied
Zhou, 2020[24]	R	Still images	Training set: 5545 images. Testing set: 1451 images and 82 videos.	Deep learning Architecture for detection of serrated lesions and lateral spreading tumors.		S > 98% E, PPV, NPV and AC not reported.	Not studied
van der Zanden, 2021[25]	P	Still images	Training set: 2449 images. Testing set: 60 images.	Artificial neural networks for classification of hyperplastic, adenomatous and serrated lesions.	High-definition white-light colonoscopy + BLI	S: 95.6 % E: 93.3 % PPV: 97.7 % NPV: 87.5 % AC: 86.7 – 95 %	Not studied
Weigt, 2022[26]	P	Still images and videos	Training set: 1202 polyps and 3571 frames without lesions. Testing set: 267 images.	CNN for classification of neoplastic vs non-neoplastic lesions.	White-light colonoscopy + BLI	S: 85 % E: 78.9 % PPV and NPV not reported. AC: 83.6 %	Not studied
Hassan, 2022[27]	P	Diagnosis in real-time	Training set: 63,445 images (validation set: 8645 images;	CNN for differentiating between adenoma and	White-light colonoscopy without magnification	S: 82 % E: 93.2 % PPV: 65.3 % NPV: 97.6 %	> 95 %

			pre-testing set: 26,412 images). Testing set: 295 lesions.	nonadenoma ≤ 5-mm rectosigmoid lesions.		AC: 91.8 %	
Hossain, 2023[28]	P	Still images	Training set: 55890 images (internal validation set: 8557 images). Testing set: 115 polyps.	Deep learning model for classification into adenomatous and non-adenomatous polyps.	White-light colonoscopy + NBI + BLI	S: > 92 % E: 60 - 65 % PPV: not reported NPV: 75 - 86 % AC: 82 - 85 %	> 90 %
Rondonotti, 2023[29]	P	Diagnosis in real-time	Same characteristics as described in Weigt *et al.* [26]	CNN (CAD_EYE) for characterization in BLI mode of rectosigmoid polyps (< 5 mm).	White-light colonoscopy BLI	S: 88.6 % E: 88.1 % PPV: 85.1 % NPV: 91 % AC: 88.4 %	> 92.6 %

AC: accuracy; AI: artificial intelligence; BLI: blue-laser imaging; CNN: convolutional neural network; E: specificity; NBI: narrow band imaging; NPV: negative predictive value; PPV: positive predictive value; P: prospective; R: retrospective; S: sensitivity; SVM: support vector machine.

Table S2. Artificial intelligence prediction of submucosal invasion in retrospective studies.

Author (year)	**Study type**	**Aim**	**Number of patients**	**Sensitivity**	**Specificity**	**Accuracy**	**AUC**
Minami et al. (2022)[30]	Retrospective Design and prospective validation of a CNN. Single center study	Differentiate shallow and deep submucosal invasion	196 patients : - 91 Learning set (706 images) - 49 validation set (394 images) - 56 test set (560 images)	Validation set: 87.2% Test set: 75.7%	Validation set: 35.7%	74.4%	0.758
Lui TKL et al (2019)[31]	Retrospective Design and prospective validation of a CNN. Single center study	Prediction of curative endoscopic resection	-Training set: 1692 lesions (8000 images) - Test set: 76 lesions (567 images)	Test set: 88.2%	Test set: 77.9%	85.5%	0.837
Luo Y et al (2021)[32]	Retrospective Design and prospective validation of a CNN. Single center study	Differentiate shallow and deep submucosal invasion	813 lesions: - 657 training set (7734) - 156 test set (1634)	Test set (including advanced CRC): 91.2% Test set (only early cancer): 65.3%	Test set(including advanced CRC): 91%´ Test set (only early cancer): 68.5%	91.1%(including advanced CRC): Test set (only early cancer):68.3%	0.97(including advanced CRC): Test set (only early cancer): 0.729
Tokunaga M et al (2021)[33]	Retrospective Design and prospective validation of a CNN. Single center study	Prediction of adequacy for curative endoscopic resection	1035 lesions: - 824 training set (2751) - 211 test set (691)	Test set (including advanced CRC): 96.7%	Test set(including advanced CRC): 75%´	Test set(including advanced CRC): 90,3%	Test set(including advanced CRC): 0.91%´

						Test set (only deep early cancer):51.2%	
Yao L et al (2022)[34]	Retrospective Design and validation of a CNN. Multicenter study	Differentiate shallow and deep submucosal invasion	533 lesions: - 339 training set - 194 test set	Test set (including advanced CRC): 78.8% Test set (only early cancer): 50%	Test set (including advanced CRC): 96.2% Test set (only early cancer): 96.2%	Test set (including advanced CRC): 90.4% Test set (only early cancer): 91.2%	

AUC: area under the curve; CNN: convolutional neural network; CRC: colorectal cancer.

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