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Supplementary information

Synthetic data generation: challenges and perspectives for gastrointestinal medicine

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Supplementary Material

Synthetic data generation: challenges and perspectives for gastrointestinal medicine

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Supplementary Table 1 | Benchmark datasets for gastrointestinal image data generation

Dataset	Modality	Samples (N)		Patients	Data	Categories		Annotations
		Image	Video	(N)	Classes	Findings	Other[a]	
CVC-ColonDB[1]	Colonoscopy	300	13	13	1	PL	NA	MA
CVC-ClinicDB[2]	Colonoscopy	612	31	23	1	PL	NA	MA
SUN[3]	Colonoscopy	158,690	1013	*NA*	2	NORM; PL	NA	BB
Colonoscopic-VideoDB[4]	Colonoscopy	*NA*	76	78	3	PL	NA	LBL
HyperKvasir[5]	Colonoscopy; Gastroscopy	110,079	374	NA	23	BE; OE; HA; NORM; PL; UC	Y	MA; BB; LBL
KUMC[6]	Colonoscopy	37,899	155	80	2	PL	NA	BB; LBL
ETIS[7]	Colonoscopy	196	34	34	1	PL	NA	MA
EndoScene[8]	Colonoscopy	912	44	*NA*	1	NORM; PL	NA	NBM
Kvasir-SEG[9]	Colonoscopy	1,000	NA	*NA*	1	PL	NA	M; BB
Kvasir[10]	Colonoscopy	8,000	NA	*NA*	8	NORM; PL; OE; UC;	Y	LBL
CVC-ClinicVideoDB[11]	Colonoscopy	11,954	18	18	1	NORM; PL	NA	MA
LDPolyp[12]	Colonoscopy	40,266	160	160	2	NORM; PL	NA	BB
BKAI-IGH[13]	Colonoscopy	120	160	NA	1	PL	NA	MA
PolypGEN[14]	Colonoscopy	6,282	26	NA	2	NORM; PL	NA	MA
Ps-DeVCEM[15]	VCE	28,304	455	40	14	AG; DIV; ERO; ERY; ED; GRA; HE; NORM; NF; PL; PPL; TUM; UL	Y	LBL
Kvasir-Capsule[16]	VCE	4,741,504	117	*NA*	14	AG; ERO; ERY; LPH; NORM; PL; UL; LUM	Y	BB; LBL
KID[17]	VCE	2,371	47		5	AG;AP;BL;ERY;COB;LPH;LUM; NORM;PL;UL	NA	M; LBL
TCGA[18]	Histopathology	398	NA	398	2	MSI; MSS	NA	LBL
NLCS[19]	Histopathology	1,457	NA	1457	2	MSI; MSS	NA	LBL
GlaS[20]	Histopathology	165	NA	16	2	BEN; MAL	NA	M; CNT; LBL
DigestPath[21]	Histopathology	872	NA	476	2	BEN; MAL	NA	M; CNT; LBL
PathMNIST[22]	Histopathology	107,180	NA	NA	9	DEB; NORM; STR; TUM	Y	LBL

HepaticVessel[23]	CT Liver	443	NA	443	2	NORM; TUM	NA	VA (TUM-VES)
LiTS[24]	CT Liver	201	NA	131	2	NORM; TUM	NA	VA (OR-TUM)
FLUS[25]	US Liver	550	NA	55	2	NSTL; STL	NA	LBL

[a]Other categories include categories for therapeutic or procedural interventions, artefacts or evaluation of the image quality.

Y: Yes.

AG, Angiectasia; AP, Aphthae; BB, Bounding Box location; BE, Barrett Oesophagus; BEN, Benign Lesion; BL, Bleeding; CNT, Lesion Contours; COB, Cobblestone mucosa; CT, Computed Tomography; DEB, Cellular Debris,

DIV, diverticulosis; ED, Oedema; ERO, Erosion; ERY, Erythema; GRA, granularity; HA, Haemorrhoids; HE, Haemorrhage; INF, Inflammation; LBL, Class Label; LPH, Lymphangiectasia; LUM, Luminal Findings; MA, Binary Masks; MAL, Malignant Lesion; MSS, Microsatellite Stable Image; MSI, Microsatellite Instability Condition; NA, Not Available; NBM, Non-Binary Mask; NSLD: Non steatotic liver disease; OE, Oesophagitis; OR, Organs; PL, Polyps; PPL, Pseudo Polyps; STR, Cancer-Associated Stroma; STL, Steatotic Liver; TUM, Tumour; UC, Ulcerative Colitis; UL, Ulcerations; US, Ultrasonography; VA, Volume Annotations; VCE, Video Capsule Endoscopy; VES, Vessels

Supplementary Table 2 | State-of-the-art gastrointestinal endoscopic image generation methods

Study	Modality (Synthetic Data)	Method	Input Condition, Output(s)	Dataset(s)	Evaluation		Best Results (%)				
								Training Datasets			
					Users	Task	Metric	Real	SD	SD (A)[d]	% Aug[e]
Sharma *et al*. (2024)[26]	Colonoscopy (PL)	LDM[c27]	TXT, IMG	D1;D2;D3	N	CLS	Accuracy	67.95	NA	63.87	*NA*
Dorjsembe *et al*. (2024)[28]	Colonoscopy (PL)	DM	MA, IMG	D7;D5;D9	N	SEG	IoU	70.67	71.56	NA	
Du *et al*. (2023)[29]	Colonoscopy (PL)	DM	MA, IMG	D2;D7;D8;D9	N	DTC SEG	Precision IoU	75.60; 84.90	NA; NA	81.60; 88.50	66.67
Machácek *et al*. (2023)[30]	Colonoscopy (PL)	LDM[c]	MA, IMG&MA	D5;D9	N	SEG	IoU	75.28	70.18	77.51	58.82
Pishva *et al*. (2023)[31]	Colonoscopy (PL)	DM[c]	MA, IMG&MA	D2;D5;D7;D9	N	SEG	IoU	76.20	NA	78.50	50.00
Golhar *et al*. (2022)[32]	Colonoscopy	GAN	LBL, IMG	D4;D5;D6;PD	N	CLS	Accuracy	78.70	NA	84.70	66.67
Sams *et al*. (2022)[33]	Colonoscopy (PL)	GAN	MA, IMG	D2;D10	N	DTC	IoU	60.66	NA	64.83	26.32
Turan & Durmus (2022)[34]	Colonoscopy (UC)	GAN	UN, IMG	D5	Y	CLS	Accuracy	80.92	NA	84.91	85.60
Yoon *et al*. (2022)[35]	Colonoscopy (PL-SSL)	GAN	UN, IMG	PD	Y	DTC	AUC	90.00	NA	96.00	29.05
Qadir *et al*. (2022)[36]	Colonoscopy (PL;NORM)	GAN	MA, IMG	D2;D7;D11	N	DTC SEG	Accuracy IoU	58.40; 56.53	NA; NA	66.78; 63.00	36.38
Thambawita *et al*. (2022)[37]	Colonoscopy (PL)	GAN[c]	MA, IMG&MA	D5	N	SEG	IoU	82.66	79.83	NA	NA
Kanayama *et al*. (2019)[38]	Gastroscopy (PL)	GAN	BB, IMG	PD	N	DTC	Precision	59.60	NA	63.20	15.29
Shin *et al*. (2018)[39]	Colonoscopy (PL)	GAN	MA& CNT-BG,	D2;D11	N	DTC	Accuracy	51.28	NA	65.45	37.80

			IMG								
Gatoula *et al*. (2025)[40]	VCE (INF; NORM)	VAE	UN, IMG	D16;D17	Y	NA	NA	NA	NA	NA	NA
Chou *et al*. (2025)[41]	VCE (PL)	GAN	UN, IMG	D9;PD	Y	SEG	Dice	88.31	NA	89.05	95.24
Li *et al*. (2024)[42]	VCE; Colonoscopy (GI Lesions[a])	LDM[c]	DL-FEAT, VID	D4;D16	N	CLS	F1-score	74.50	NA	87.00	83.33
Chlopowiec *et al*. (2024)[43]	VCE (AG;ERO;ERY;LPH;UL)	GAN[c]	BB, IMG	D16	N	CLS	AUC	86.78	NA	87.90	60.69
Diamantis *et al*. (2024)[44]	VCE (INF;NORM)	VAE	UN, IMG	D16;D17	Y	CLS	AUC	80.0	80.20	NA	NA
Vats *et al*. (2023)[45]	VCE (GI Lesions[b])	GAN	UN, IMG	D15;D16	Y	NA	NA	NA	NA	NA	NA
Xiao *et al*. (2023)[46]	VCE (ERO;PL; LUM;UL;)	GAN	UN, IMG	D16	N	DTC	Accuracy	93.78	NA	96.65	66.67

[a] Not explicitly mentioned, [b] Various from respective datasets.
[c] denotes model is pre-trained on non-medical data
[d] SD (A) indicates that the SD were used for augmentation.
[e] %Aug: Percentage of synthetic images used for the augmentation of real datasets
AG, Angiectasia; AUC, Area Under the ROC Curve; BB, Bounding Box locations; CLS, Classification; CNT-BG, Contour of Endoscopic Background; DL-FEAT, Image Features Learned from Non-Medical Image Vision Foundation Model; DM, Diffusion Model; DTC, Detection; ERO, Erosion; ERY, Erythema; GAN, Generative Adversarial Network; IMG, Image; INF, Inflammation; IoU, Intersection over Union; LBL, Class Labels; LDM, Latent Diffusion Model; LPH, Lymphangiectasia; LUM, Luminal findings (that is, fresh blood); MA, Binary Mask; NA, Not Available; NORM, Normal Tissue; N, No; PD, Private Dataset; PL, Polyps; PL-SSL, Polyps Sessile Serrated Lesion; PL-WL;NB, Polyps White Light and Narrow Band; SEG, Segmentation; TXT: Text; UL, Ulcerations; UN, Unconditional training; VAE, Variational Autoencoder; VCE, Video Capsule Endoscopy; VID, Video; Y, Yes

Supplementary Table 3 | State-of-the-art non-endoscopic gastrointestinal image generation methods

Study	Modality	Method	Input Condition	Dataset(s)	Evaluation		Best Results (%)				
								Training Datasets			
					Users	Task	Metric	Real	SD	SD (A)[a]	% Aug[b]
Ding *et al*. (2024)[47]	Histopathology (PATH;NORM)	GAN	UN, IMG	D22	N	CLS	Accuracy	86.00	NA	89.20	48.89
Li & Kainz (2024)[48]	Histopathology (PATH;NORM)	LDM	UN, IMG	D22	N	CLS	Accuracy	83.90	77.79	*NA*	NA
Li *et al*. (2022)[49]	Histopathology (PATH)	GAN	MA IMG&MA	D20	N	SEG	IoU	70.10	NA	84.50	50.00
Krause *et al*. (2021)[50]	Histopathology (MSI; MSS)	GAN	LBL, IMG	D18;D19	Y	CLS	AUC	74.14	74.32	77.67	60.00
Zheng *et al* (2024)[51]	CT (HEP-TUM)	GAN	UN, IMG	D23;D24;PD	N	CLS	AUC	68.00	NA	87.00	22.38
Chen *et al* (2024)[52]	CT (HEP-TUM)	LDM	MA, IMG	D24	Y	SEG	Dice	62.30	NA	70.90	NA
Liu *et al* (2023)[53]	CT (HEP-TUM)	GAN	IMG&MA, IMG	D24	N	SEG	Dice	67.30	NA	71.40	NA
Hardy *et al* (2023)[54]	US (MASLD;NSLD)	LDM[c]	LBL&SM, IMG	D25	N	CLS	AUC	87.10	NA	90.40	81.97
Zhao *et al* (2020)[55]	MRI; CE (LIV-TUM)	GAN	IMG-NCE, IMG	PD	N	DET	Accuracy	79.20	NA	89.40	NA
Liu *et al* (2019)[56]	CT CRC	GAN	DL-M, MA	PD	N	SEG	Dice	91.54	NA	91.81	NA
Frid-Adar *et al* (2018)[57]	CT (LIV-TUM)	GAN	UN, IMG	PD	Y	CLS	Sensitivity	78.60	NA	85.70	37.50

[a] SD (A) indicates that the SD were used for augmentation.
[b] %Aug: Percentage of synthetic images used for the augmentation of real datasets.
[c] denotes model is pre-trained on non-medical data
AUC, Area Under the ROC Curve; CE, Contrast Enhanced; CLS, Classification; CRC, Colorectal Cancer; CT, Computed Tomography; DL-M, Probabilistic Maps Computed by a DNN Segmenting Tumour Locations; DTC, Detection; GAN, Generative Adversarial Network; IMG, Image; IMG-NCE, Image Non-Contrast

Enhanced; IoU, Intersection over Union; LAY, Gland Layout; LDM, Latent Diffusion Model; LBL, Class Labels; LIV-TUM, Liver Tumour; MA, Binary Masks; MASLD, Metabolic dysfunction–associated steatotic liver disease; MRI, Magnetic Resonance Imaging; MSI, Microsatellite Instable Images; MSS, Microsatellite Stable Images; NA, Not Available; NORM, Normal tissue; NSLD, Non steatotic liver disease; N, No; PATH, Pathological tissue; PD, Private Dataset; SD, Synthetic Data; SEG, Segmentation; SM, Semantic Maps; TXT, Text; UN, Unconditional training; US, Ultrasonography; Y, Yes

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