Deep Interactive Segmentation of Medical Images: A Systematic Review and Taxonomy

Zdravko Marinov*, Paul F. Jäger*, Jan Egger, Jens Kleesiek, Rainer Stiefelhagen

Appendix A
Click Guidance Signals

Clicks are defined as 3D or 2D points, i.e., $c_i \in \mathbb{R}^3$ or $c_i \in \mathbb{R}^2$, depending on the dimensions of the input image. We define the set of clicks provided by the annotator as $\mathcal{C} := \{c_1, ...c_N\}$, where N is the number of clicks. Examples of click guidance signals are depicted in Fig. 7.

Disks. As disks and Gaussian heatmaps are computed independently for each click, they are defined for a single click c_i over voxels/pixels v in the image volume. Here, σ controls the radius of the disks in Eq. (1).

$$\mathrm{disk}(v, c_i, \sigma) = \begin{cases} 1, & \text{if } ||v - c_i||_2 \leq \sigma \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Gaussian Heatmaps apply Gaussian filters centered around each click c_i to create softer edges with an exponential decrease away from the click in Eq. (2).

$$\mathrm{heatmap}(v, c_i, \sigma) = \exp\left(-\frac{||v - c_i||_2}{2\sigma^2}\right) \tag{2}$$

Euclidean Distance Transform (EDT) is defined in Eq. (3) as the minimum Euclidean distance between a voxel/pixel v and the set of clicks $\mathcal{C}$. It is similar to the disk signal in Eq. (1), but instead of filling the sphere with a constant value it computes the distance of each voxel to the closest click point.

$$\mathrm{EDT}(v, \mathcal{C}) = \min_{c_i \in \mathcal{C}} ||v - c_i||_2 \tag{3}$$

Geodesic Distance Transform (GDT) is defined in Eq. (4) as the shortest geodesic path distance between each voxel in the volume and the closest click in the set $\mathcal{C}$ [181]. The shortest geodesic path in GDT also takes into account intensity differences between voxels along the path. The shortest path is denoted as Φ in Eq. (4) and can be computed with, e.g., the Fast Marching method [182].

$$\mathrm{GDT}(v, \mathcal{C}) = \min_{c_i \in \mathcal{C}} \Phi(v, c_i) \tag{4}$$

Exponentialized Geodesic distance (exp-GDT) proposed in MIDeepSeg [38] is defined in Eq. (5) as an exponentiation of GDT from Eq. (4):

$$\text{exp-GDT}(v, \mathcal{C}) = 1 - \exp(-\mathrm{GDT}(v, \mathcal{C})) \tag{5}$$

Location Prior (LP), as proposed by Sun et al. [3], incorporates both the Manhattan distance and the information about crossed edges detected by a Canny edge detector [123]. The LP assigns an initial intensity value of 255 to the center voxel, denoted as $c = (c_x, c_y)$, and decreases this value by 1 for each vertical or horizontal step taken. Furthermore, when a step crosses a detected edge the intensity value decreases by an additional 10. LP combines the notion of distance with the presence of edges to provide a comprehensive measure for location estimation.

$$\mathrm{LP}(v) = \left(0, 255 - \sum_{i=c_x}^{v_x} \sum_{j=c_y}^{v_y} \begin{cases} -10 & \text{if } \mathrm{Canny}(I)(x_i, y_i) == 1 \text{ and edge\_crossed} \\ -1 & \text{otherwise} \end{cases}\right)$$

Attraction Field Weight Map (AF), as introduced in [14], draws inspiration from the attraction field generated by punctual electric charges of opposite values. AF utilizes unitary gradient fields, denoted as $\nabla S_i(v)$, which are centered around two clicks, namely c_1 and c_2. These gradient fields exhibit higher values between the clicks, indicating their significance for the segmentation process. The hyperparameter $p \in \mathbb{R}$ controls the decay of the vectors' magnitude.

$$AF(v, c_1, c_2) = \frac{\nabla S_1(v)}{|\nabla S_1(v)|^p} - \frac{\nabla S_2(v)}{|\nabla S_2(v)|^p} \tag{6}$$

$$\nabla S_i(v) = \frac{2(v_x - c_{ix}) + 2(v_y - c_{iy}) + (v_z - c_{iz})}{2||v - c_i||} \tag{7}$$

Appendix B
Scribble Guidance Signals

Scribbles are defined as 3D or 2D sets of points $\mathcal{C}$, i.e., $\mathcal{C} := \{c_1, ...c_N\}$, where $c_i \in \mathbb{R}^3$ or $c_i \in \mathbb{R}^2$, depending on the dimensions of the input image. In a formal sense, scribbles can be seen as a set of clicks. However, conceptually, scribbles manifest as a diverse array of interactions, encompassing

This work has been submitted to the IEEE for possible publication. Copyright may be transferred without notice, after which this version may no longer be accessible.

The present contribution is supported by the Helmholtz Association under the joint research school "HIDSS4Health – Helmholtz Information and Data Science School for Health." *(*Zdravko Marinov and *Paul F. Jäger are co-first authors.) (Corresponding author: Zdravko Marinov.)*

Zdravko Marinov and Rainer Stiefelhagen are with the Computer Vision for Human-Computer Interaction Lab, Department of Informatics, Karlsruhe Institute of Technology, Adenauerring 10, 76131 Karlsruhe, Germany (e-mail: zdravko.marinov@kit.edu).

Jan Egger and Jens Kleesiek are with the Institute for Artificial Intelligence in Medicine (IKIM), University Hospital Essen (AöR), Girardetstraße 2, 45131 Essen, Germany.

Paul F. Jäger is with the German Cancer Research Center (DKFZ) Heidelberg, Interactive Machine Learning Group, Im Neuenheimer Feld 223, 69120 Heidelberg, Germany, and with the Helmholtz Imaging, DKFZ, Im Neuenheimer Feld 223, 69120 Heidelberg, Germany.

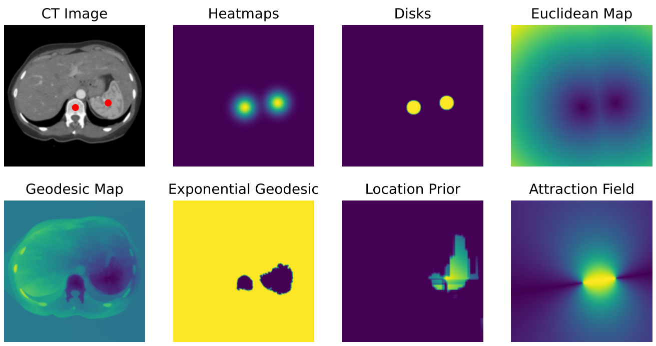

Fig. 7. Examples of click-based guidance signals.

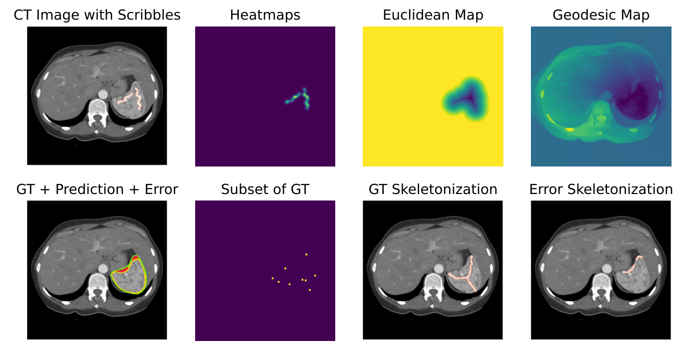

Fig. 8. Examples of scribble-based guidance signals. GT: Ground-truth mask. Bottom left image – green: GT , yellow: model prediction, red: error.

structured actions like deliberate line strokes, spontaneous unstructured marks such as random dabs, or a fusion of both. Examples of scribble guidance signals are shown in Fig. 8.

Gaussian Heatmaps for scribbles are derived from the click heatmaps in Eq. (2) by summing all click heatmaps into one guidance signal, resulting in Eq. (8).

$$\text{heatmap}(v, \mathcal{C}, \sigma) = \sum_{i=0}^{N} \text{heatmap}(v, c_i, \sigma) \tag{8}$$

The **Euclidean Distance Transform** (EDT) and the **Geodesic Distance Transform** (GDT) do not differ in any way from their click-based versions in Eq. (3) and (4) since those are already defined over a set of points $\mathcal{C}$.

Subset of Ground-Truth. One way to simulate scribbles with a robot user is to randomly sample a subset of the ground-truth mask $\mathcal{M}$. As scribbles do not inherently adhere to a specific structure, this typically manifests as a series of random clicks, resembling the illustration in Fig. 8.

$$\mathcal{C} = \{c_i\}_{i=1}^{N}, \text{ where } x_i \sim \mathcal{M} \text{ and } N \leq |\mathcal{M}| \tag{9}$$

Ground-truth Skeletonization is another way to simulate scribbles with a robot user by representing the morphological structure of the ground-truth mask $\mathcal{M}$ in the scribble $\mathcal{C}$. The skeleton$(\cdot)$ in Eq. (10) consists of the 1-pixel wide medial axes of the mask [184]. An example is depicted in Fig. 8.

$$\mathcal{C} = \text{skeleton}(\mathcal{M}) \tag{10}$$

Error Skeletonization is a way to simulate iterative scribbles, which are used to correct the previous prediction with a corrective stroke [27], [33], [53], [54]. The scribbles are computed the same way as in Eq. (10) but over the missegmented region $\mathcal{E}$ instead of the ground-truth mask $\mathcal{M}$.

$$\mathcal{C} = \text{skeleton}(\mathcal{E}) \tag{11}$$

Ground-truth Scribbles are a guidance signal where the raw scribble set $\mathcal{C}$ provided by a real human annotator is used directly as a representation of the interaction. This is often done to avoid information leaking into neighboring voxels, e.g., through applying a distance transform or a heatmap to the scribbles [75], [91].

Appendix C
Implicit Signals and Other Guidance Signals

Implicit signals subtly incorporate interactions into the model's training or inference, without using structured inputs like spherical heatmaps or skeletonized scribbles. Examples include weights in the loss function based on the distance to clicks/scribbles, or cropping inputs via bounding box interactions to selectively feed to the model. Implicit signals are represented by an *action*, such as loss function *weighting*, or input *cropping*. In contrast, explicit signals are conveyed through a defined *structure*, like Gaussian *heatmaps* or error *skeletons*.

Less common guidance signals encompass vertex polygons and B-splines, employed to outline the segmentation mask boundary [50], [70]. Users can adjust the boundary by manipulating vertices or control points of the spline. Another signal involves leveraging predictions from an auxiliary approach, such as GraphCut [131], which generates pseudolabels added to the input image. Additionally, methods utilizing the Segment Anything Model (SAM) [137] use positional encodings to represent bounding box or click coordinates.

Appendix D
Public Datasets and Public Code Links

Appendix E
Full List of Literature Databases and Venues in our Search Strategy

Appendix F
PRISMA 2020 Checklist

Tables VIII, IX, and X show the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 [139] checklist and where we have reported each item in our review. Certain items are marked with ”-” since they either do not apply to our review or are excluded due to the technical nature of our study, which diverges from the clinical emphasis of the PRISMA guidelines.

While our review predominantly centers on technical methodology rather than clinical outcomes, we make an effort to adhere to the definition of ”synthesis methods” within the PRISMA guidelines as closely as possible. In this review, we define synthesis methods as the systematic analysis and summarization of results from the reviewed studies to draw

TABLE III
PUBLIC DATASETS USED FOR INTERACTIVE SEGMENTATION

Abbreviation	Dataset	Link	Modality	Abbreviation	Dataset	Link	Modality
D1	ACDC	Link	MRI	D92	TN3K	Link	US
D2	NCI-ISBI-13	Link	MRI	D93	Carotid Artery	Link	US
D3	BraTS15	Link	MRI	D94	TN-SCUI	Link	US
D4	BraTS18	Link	MRI	D95	GlaS	Link	Microscopy
D5	MM WHS	Link	MRI	D96	CRAG	Link	Microscopy
D6	BraTS19	Link	MRI	D97	MonuSeg	Link	Microscopy
D7	BraTS20	Link	MRI	D98	CPM	Link	Microscopy
D8	PROMISE12	Link	MRI	D99	NuClick	Link	Microscopy
D9	Multi-Atlas MICCAI12	Link	MRI	D100	CRC	Link	Microscopy
D10	OAI-ZIB	Link	MRI	D101	PAIP19	Link	Microscopy
D11	SCGMSC	Link	MRI	D102	CAMELYON16	Link	Microscopy
D12	ICCVB	Link	MRI	D103	Amgad et al	Link	Microscopy
D13	Duke-Breast-Cancer-MRI	Link	MRI	D104	DSB 2018	Link	Microscopy
D14	WMHSC	Link	MRI	D105	ConSeP	Link	Microscopy
D15	Figshare	Link	MRI	D106	BACH	Link	Microscopy
D16	GammaKnife	Link	MRI	D107	NEPTUNE	Link	Microscopy
D17	CC-Tumor	Link	MRI	D108	Hubmap HPA	Link	Microscopy
D18	crossMoDa	Link	MRI	D109	Hubmap Kidney	Link	Microscopy
D19	FeTa	Link	MRI	D110	NeurIPS22	Link	Microscopy
D20	Han-Seg	Link	MRI	D111	HBC	Link	Microscopy
D21	ISLES	Link	MRI	D112	ssTEM	Link	Microscopy
D22	Meningioma-SEG	Link	MRI	D113	MouseColon	Link	Microscopy
D23	M&Ms	Link	MRI	D114	EPFL-EM	Link	Microscopy
D24	PI-CAI	Link	MRI	D115	MouseBrain	Link	Microscopy
D25	PP-MI	Link	MRI	D116	Mouse_4T1	Link	Microscopy
D26	Qin-Prostate	Link	MRI	D117	HPC	Link	Microscopy
D27	Qubiq	Link	MRI	D118	MouseBrain_FL	Link	Microscopy
D28	Spine	Link	MRI	D119	TCGA	Link	Microscopy
D29	ATLAS	Link	MRI	D120	CREMI	Link	Microscopy
D30	AtriaSeg	Link	MRI	D121	PH2	Link	Dermoscopy
D31	BrainPTM 2021	Link	MRI	D122	BCN-20000	Link	Dermoscopy
D32	iSeg2019	Link	MRI	D123	UWaterlooSkin	Link	Dermoscopy
D33	IXI	Link	MRI	D124	HAM-10000	Link	Dermoscopy
D34	I2CVB	Link	MRI	D125	MLD	Link	Dermoscopy
D35	LivScar	Link	MRI	D126	FUSC	Link	Dermoscopy
D36	MRSpineSeg	Link	MRI	D127	ISIC	Link	Dermoscopy
D37	ADNI	Link	MRI	D128	SIIM-ACR	Link	X-Ray
D38	SKI10	Link	MRI	D129	Xray-Chest	Link	X-Ray
D39	DeepLesion	Link	CT	D130	Xray-Hip	Link	X-Ray
D40	BTCV	Link	CT	D131	COVID-19 X-Ray	Link	X-Ray
D41	SegThor	Link	CT	D132	ChestXRay	Link	X-Ray
D42	LiTS	Link	CT	D133	Chest X-Ray-Montgomery	Link	X-Ray
D43	Gibson et al	Link	CT	D134	Chest Pneumothora	Link	X-Ray
D44	LIDC-IDRI	Link	CT	D135	COVID Radiography	Link	X-Ray
D45	IRCAD	Link	CT	D136	COVID-Qu	Link	X-Ray
D46	FUMPE	Link	CT	D137	JSRT	Link	X-Ray
D47	StructSeg2019	Link	CT	D138	Lung-CXR	Link	X-Ray
D48	KiTS 19	Link	CT	D139	CDD-CESM	Link	X-Ray
D49	Pancreas-CT	Link	CT	D140	Qata-COVID	Link	X-Ray
D50	CT-ORG	Link	CT	D141	CVC ClinicDB	Link	Colonoscopy
D51	COVID19-CT-Lung	Link	CT	D142	Pra-Net	Link	Colonoscopy
D52	COVID19-Lung-CT-Challenge	Link	CT	D143	kvasir-SEG	Link	Colonoscopy
D53	LCTSC	Link	CT	D144	BKAI-IGH NeoPolyp	Link	Colonoscopy
D54	NSCLC	Link	CT	D145	CholecSeg8k	Link	Colonoscopy
D55	UESTC-COVID-19	Link	CT	D146	m2caiseg	Link	Colonoscopy
D56	MSD COVID 19	Link	CT	D147	PolypGen	Link	Colonoscopy
D57	DeepMind CT	Link	CT	D148	RobTool	Link	Colonoscopy
D58	ProstateX	Link	CT	D149	sibvse	Link	Colonoscopy
D59	AbdomenCT-1k	Link	CT	D150	MICCAI Instrument Seg (EndoVis)	Link	Colonoscopy
D60	CIRDataset	Link	CT	D151	EndoTect 2020	Link	Colonoscopy
D61	COVID190CT-Seg	Link	CT	D152	ETIS-Larib	Link	Colonoscopy
D62	GLIS-RT	Link	CT	D153	AutoLaparo	Link	Colonoscopy
D63	HCC-TACE-Seg	Link	CT	D154	Kvasir-Instrument	Link	Colonoscopy
D64	INSTANCE	Link	CT	D155	CVC-ColonDB	Link	Colonoscopy
D65	KiPA	Link	CT	D156	CVC-300	Link	Colonoscopy
D66	LymphNodes	Link	CT	D157	IDRID	Link	Fundus
D67	NSCLC-PleThora	Link	CT	D158	PAPILA	Link	Fundus
D68	NSCLC-Radiogenomics	Link	CT	D159	EyePACSp	Link	Fundus
D69	TotalSegmentator	Link	CT	D160	Drishiti-GS	Link	Fundus
D70	WORD	Link	CT	D161	RIM-ONE-r3	Link	Fundus
D71	ChestCT	Link	CT	D162	REFUGE	Link	Fundus
D72	MALBCV	Link	CT	D163	FIVES	Link	Fundus
D73	Verse 2019	Link	CT	D164	CHASEDB	Link	Fundus
D74	Verse 2020	Link	CT	D165	DRIVE	Link	Fundus
D75	4C2021 C04 TLS01	Link	CT	D166	iChallengeAMD	Link	Fundus
D76	SLIVER07	Link	CT	D167	iChallengePALM	Link	Fundus
D77	AbdomenAtlas-8K	Link	CT	D168	STARE	Link	Fundus
D78	LUNA16	Link	CT	D169	Intercranial Cystoid Fluid	Link	OCT
D79	COVID-19 CT	Link	CT	D170	OCT-DME	Link	OCT
D80	CETUS	Link	US	D171	AROI	Link	OCT
D81	CAMUS	Link	US	D172	ROSE	Link	OCT
D82	Nerve	Link	US	D173	OCTA-500	Link	OCT
D83	HC18	Link	US	D174	CHAOS	Link	CT, MRI
D84	Breast US	Link	US	D175	AMOS	Link	CT, MRI
D85	CT2US	Link	US	D176	MSD	Link	CT, MRI
D86	US-Muscle	Link	US	D177	Lung-PETCT	Link	PET/CT
D87	Abdomen US	Link	US	D178	AutoPET	Link	PET/CT
D88	Breast Cancer US	Link	US	D179	HECKTOR	Link	PET/CT
D89	MMOTU	Link	US	D180	Tetteh et al	Link	Synthetic angiography
D90	FH-PS US	Link	US	D181	OASIS-3	Link	TOF-MRA
D91	ThyroidUS	Link	US	D182	RadImageNet	Link	CT, US, MRI

TABLE IV
LIST OF ALL REVIEWED INTERACTIVE METHODS WITH PUBLICLY AVAILABLE CODE

Paper	Code
DeepIGeoS [5]	https://github.com/HITLAB-DeepIGeoS/
Zhou et al. [11]	https://github.com/DLwbm123/OCMIST
iWNet [14]	https://github.com/gmaresta/iW-Net
UGIR [22]	https://github.com/HiLab-git/UGIR
NuClick [26]	https://github.com/navidstuv/NuClick
MIDeepSeg [38]	https://github.com/HiLab-git/MIDeepSeg
Sambaturu et al. [41]	https://tinyurl.com/ym4yhpr2
Zhou et al. 2 [42]	https://github.com/lingorX/Mem3D
Zhang et al. [47]	https://github.com/sunalbert/Sequential-patch-based-segmentation
Zheng et al. 2 [48]	https://github.com/ritmininglab/CLIS
DINs [49]	https://github.com/Jarvis73/DINs
Sun et al. 2 [60]	https://github.com/Tian-lab/IGMedSeg
iSegFormer [64]	https://github.com/uncbiag/iSegFormer
ECONet [65]	https://github.com/masadcv/ECONet-MONAILabel
i3Deep [66]	https://github.com/Karol-G/i3Deep
DeepEdit [67]	https://tinyurl.com/ycykt2uf
Liu et al. [68]	https://wtliu7.github.io/tis/
Shi et al. [69]	https://github.com/luyueshi/Hybrid-Propagation
AnatomySketch [70]	https://tinyurl.com/45tmh96n
Galisot et al. [71]	https://tinyurl.com/4ct77jsf
Zhou et al. 3 [81]	https://github.com/lingorX/Mem3D
Hallitschke et al. [82]	https://github.com/verena-hallitschke/pet-ct-annotate
Liu et al. 2 [83]	https://github.com/uncbiag/iSegFormer
Asad et al. [85]	https://github.com/masadcv/MONet-MONAILabel
Wei et al. [89]	https://tinyurl.com/3r7b4yw7
Zhuang et al. [90]	https://github.com/DlutMedimgGroup/Scribble-Guided-Segmentation
Zhuang et al. 2 [87]	https://tinyurl.com/yemvhnyh
GtG [91]	https://github.com/Zrrr1997/Guiding-The-Guidance/tree/main
Qu et al. [92]	https://github.com/MrGiovanni/AbdomenAtlas
SAM-MedIA [93]	https://github.com/mazurowski-lab/segment-anything-medical-evaluation
MedSAM [120]	https://github.com/bowang-lab/MedSAM
MedSAM-Adapter [99]	https://github.com/WuJunde/Medical-SAM-Adapter
SAM-Adapter [98]	https://tianrun-chen.github.io/SAM-Adaptor/
OpthamologySAM [100]	https://github.com/Qsingle/LearnablePromptSAM
GazeSAM [103]	https://github.com/ukaukaaaa/GazeSAM
Mattjie et al. [107]	https://github.com/Malta-Lab/SAM-zero-shot-in-Medical-Imaging
PolypSAM [108]	https://github.com/ricklisz/Polyp-SAM
PromptUNet [109]	https://github.com/WuJunde/PromptUNet
IAMSAM [111]	https://github.com/portrai-io/IAMSAM
DeSAM [112]	https://github.com/yifangao112/DeSAM
3DSAM [118]	https://github.com/med-air/3DSAM-adapter
MedLSAM [116]	https://github.com/openmedlab/MedLSAM

comprehensive conclusions and identify overarching patterns and trends. Our review's synthesis methods (rows 13a-13f in Table VIII) encompass the following elements:

TABLE V
LIST OF ALL LITERATURE DATABASES USED IN STEP 1 OF OUR SYSTEMATIC SEARCH

Literature Database	Link
Google Scholar	https://scholar.google.com/
PubMed	https://pubmed.ncbi.nlm.nih.gov/
IEEE Xplore	https://ieeexplore.ieee.org/Xplore/home.jsp
SpringerLink	https://link.springer.com/
arXiv	https://arxiv.org/

TABLE VI
LIST OF ALL CONFERENCES, JOURNALS, AND CONFERENCE WORKSHOPS USED IN STEP 4 OF OUR SYSTEMATIC SEARCH. ALL PROCEEDINGS OF THE VENUES IN THE TABLE ARE INSPECTED FOR ELIGIBLE STUDIES PUBLISHED BETWEEN 2016 AND 2023 FOR THE REVIEW

Venue	Abbreviation	Type	Link
Applied Sciences	Appl. Sci.	Journal	Link
Artificial Intelligence in Medicine	Artif Intell Med	Journal	Link
BioScience Trends	Biosci. Trends	Journal	Link
Biomedical Signal Processing and Control	Biomed Signal Process Control	Journal	Link
Cytometry Part A	Cytometry A	Journal	Link
Diagnostics	-	Journal	Link
Frontiers of Information Technology & Electronic Engineering	FITEE	Journal	Link
IEEE Journal of Biomedical and Health Informatics	J-BHI	Journal	Link
IEEE Transactions on Image Processing	TIP	Journal	Link
IEEE Transactions on Medical Imaging	TMI	Journal	Link
IEEE Transactions on Pattern Analysis and Machine Intelligence	TPAMI	Journal	Link
International Journal of Computer Assisted Radiology and Surgery	IJCARS	Journal	Link
Journal of Biomedical Semantics	J. Biomed. Semant.	Journal	Link
Journal of Digital Imaging	JDI	Journal	Link
Journal of Pathology Informatics	JPI	Journal	Link
Machine Learning and Knowledge Extraction	MAKE	Journal	Link
Machine Learning with Applications	MLWA	Journal	Link
Medical Image Analysis	MedIA	Journal	Link
Medical Physics	Med Phys	Journal	Link
Neurocomputing	-	Journal	Link
Physics and Imaging in Radiation Oncology	-	Journal	Link
Physics in Medicine & Biology	Phys. Med. Biol.	Journal	Link
Radiology: Artificial Intelligence	Radiol.: Artif. Intell.	Journal	Link
Scientific Reports	Sci. Rep.	Journal	Link
AAAI Conference on Artificial Intelligence	AAAI	Conference	Link
ACM International Conference on Multimedia	ACM-MM	Conference	Link
Annual International Conference of the IEEE Engineering in Medicine and Biology Society	EMBC	Conference	Link
Asian Conference on Pattern Recognition	ACPR	Conference	Link
IEEE Global Conference on Consumer Electronics	GCCE	Conference	Link
IEEE International Conference on Multimedia Big Data	BigMM	Conference	Link
IEEE International Conference on Research, Innovation and Vision for the Future	RIVF	Conference	Link
IEEE International Symposium on Biomedical Imaging	ISBI	Conference	Link
IEEE/CVF Conference on Computer Vision and Pattern Recognition	CVPR	Conference	Link
IEEE/CVF International Conference on Computer Vision	ICCV	Conference	Link
IEEE/RSJ International Conference on Intelligent Robots and Systems	IROS	Conference	Link
International Conference on Medical Image Computing and Computer-Assisted Intervention	MICCAI	Conference	Link
International Symposium on Image Computing and Digital Medicine	ISICDM	Conference	Link
Medical Imaging with Deep Learning	MIDL	Conference	Link
SPIE Medical Imaging	-	Conference	Link
Applications of Medical Artificial Intelligence	AMAI	Conference Workshop	Link
Eurographics Workshop on Visual Computing for Biology and Medicine	VCBM	Conference Workshop	Link
International MICCAI Brainlesion Workshop	BrainLes	Conference Workshop	Link
International Workshop on Deep Learning in Medical Image Analysis	DLMIA	Conference Workshop	Link
International Workshop on Graph Learning in Medical Imaging	GLMI	Conference Workshop	Link
International Workshop on Hardware Aware Learning for Medical Imaging and Computer Assisted Intervention	HAL-MICCAI	Conference Workshop	Link
International Workshop on Large-scale Annotation of Biomedical data and Expert Label Synthesis	LABELS	Conference Workshop	Link
International Workshop on Machine Learning in Medical Imaging	MLMI	Conference Workshop	Link
MICCAI Workshop on Data Augmentation, Labelling, and Imperfections	DALI	Conference Workshop	Link

TABLE VII
RETRIEVED STUDIES FOR EACH KEYWORD COMBINATION

Keywords	Interactive Segmentation Medical Deep	Interactive Delineation Medical Deep	Human-in-the-Loop Segmentation Medical Deep	Human-in-the-Loop Delineation Medical Deep
Google Scholar	296	19	29	13
PubMed	262	36	10	1
IEEEXplore	110	2	11	0
SpringerLink	318	2	2	0
arXiv	78	4	10	10
Total	1064	63	62	14

- Tabular representation of all studies: A structured arrangement of studies and their corresponding data items in a clear and accessible format. This information is presented in Table I and Table II, located on pages 4 and 5, respectively.

- Introduction of a taxonomy: A taxonomy tree, introduced in Section III, paragraphs 1-3, to offer a structured categorization of the reviewed studies.
- Visual rationale for study categorization: We utilize Fig. 4 to visually illustrate the rationale guiding the categorization within the taxonomy tree, ensuring transparency throughout the categorization process.
- Visualization and analysis of the data items of the reviewed studies: We analyze the distribution of data items to unveil patterns, visually presented in Fig. 5, and provide a comprehensive discussion of potential reasons for these patterns in Section V-A.
- Analysis of the cross-comparisons: We analyze the comparisons between reviewed studies in Fig. 7, and explore the underlying reasons for the absence of systematic comparisons within the field in Section V-D.

REFERENCES

[1] M. Rajchl, M. C. Lee, O. Oktay, K. Kamnitsas, J. Passerat-Palmbach, W. Bai, M. Damodaram, M. A. Rutherford, J. V. Hajnal, B. Kainz, *et al.*, "Deepcut: Object segmentation from bounding box annotations using convolutional neural networks," *IEEE transactions on medical imaging*, vol. 36, no. 2, pp. 674–683, 2016.

[2] M. Amrehn, S. Gaube, M. Unberath, F. Schebesch, T. Horz, M. Strumia, S. Steidl, M. Kowarschik, and A. Maier, "Ui-net: interactive artificial neural networks for iterative image segmentation based on a user model," in *Proceedings of the Eurographics Workshop on Visual Computing for Biology and Medicine*, pp. 143–147, 2017.

[3] J. Sun, Y. Shi, Y. Gao, and D. Shen, "A point says a lot: an interactive segmentation method for mr prostate via one-point labeling," in *Machine Learning in Medical Imaging: 8th International Workshop, MLMI 2017, Held in Conjunction with MICCAI 2017, Quebec City, QC, Canada, September 10, 2017, Proceedings 8*, pp. 220–228, Springer, 2017.

[4] Y. B. Can, K. Chaitanya, B. Mustafa, L. M. Koch, E. Konukoglu, and C. F. Baumgartner, "Learning to segment medical images with scribble-supervision alone," in *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support: 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 20, 2018, Proceedings 4*, pp. 236–244, Springer, 2018.

[5] G. Wang, M. A. Zuluaga, W. Li, R. Pratt, P. A. Patel, M. Aertsen, T. Doel, A. L. David, J. Deprest, S. Ourselin, *et al.*, "Deepigeos: a deep interactive geodesic framework for medical image segmentation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 41, no. 7, pp. 1559–1572, 2018.

[6] G. Wang, W. Li, M. A. Zuluaga, R. Pratt, P. A. Patel, M. Aertsen, T. Doel, A. L. David, J. Deprest, S. Ourselin, *et al.*, "Interactive medical image segmentation using deep learning with image-specific fine tuning," *IEEE transactions on medical imaging*, vol. 37, no. 7, pp. 1562–1573, 2018.

[7] G. Bredell, C. Tanner, and E. Konukoglu, "Iterative interaction training for segmentation editing networks," in *Machine Learning in Medical Imaging: 9th International Workshop, MLMI 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Proceedings 9*, pp. 363–370, Springer, 2018.

[8] A. K. Dhara, K. R. Ayyalasomayajula, E. Arvids, M. Fahlström, J. Wikström, E.-M. Larsson, and R. Strand, "Segmentation of post-operative glioblastoma in mri by u-net with patient-specific interactive refinement," in *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 4th International Workshop, BrainLes 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Revised Selected Papers, Part I 4*, pp. 115–122, Springer, 2019.

[9] Y. Tang, A. P. Harrison, M. Bagheri, J. Xiao, and R. M. Summers, "Semi-automatic recist labeling on ct scans with cascaded convolutional neural networks," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2018: 21st International Conference, Granada, Spain, September 16-20, 2018, Proceedings, Part IV 11*, pp. 405–413, Springer, 2018.

[10] T. Sakinis, F. Milletari, H. Roth, P. Korfiatis, P. Kostandy, K. Philbrick, Z. Akkus, Z. Xu, D. Xu, and B. J. Erickson, "Interactive segmentation of medical images through fully convolutional neural networks," *arXiv preprint arXiv:1903.08205*, 2019.

[11] B. Zhou, L. Chen, and Z. Wang, "Interactive deep editing framework for medical image segmentation," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part III 22*, pp. 329–337, Springer, 2019.

[12] S. Khan, A. H. Shahin, J. Villafruela, J. Shen, and L. Shao, "Extreme points derived confidence map as a cue for class-agnostic interactive segmentation using deep neural network," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part II 22*, pp. 66–73, Springer, 2019.

[13] W. Lei, H. Wang, R. Gu, S. Zhang, S. Zhang, and G. Wang, "Deepigeos-v2: deep interactive segmentation of multiple organs from head and neck images with lightweight cnns," in *Large-Scale Annotation of Biomedical Data and Expert Label Synthesis and Hardware Aware Learning for Medical Imaging and Computer Assisted Intervention: International Workshops, LABELS 2019, HAL-MICCAI 2019, and CuRIOUS 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 13 and 17, 2019, Proceedings 4*, pp. 61–69, Springer, 2019.

[14] G. Aresta, C. Jacobs, T. Araújo, A. Cunha, I. Ramos, B. van Ginneken, and A. Campilho, "iw-net: an automatic and minimalistic interactive lung nodule segmentation deep network," *Scientific reports*, vol. 9, no. 1, pp. 1–9, 2019.

[15] H. Roth, L. Zhang, D. Yang, F. Milletari, Z. Xu, X. Wang, and D. Xu, "Weakly supervised segmentation from extreme points," in *Large-Scale Annotation of Biomedical Data and Expert Label Synthesis and Hardware Aware Learning for Medical Imaging and Computer Assisted Intervention: International Workshops, LABELS 2019, HAL-MICCAI 2019, and CuRIOUS 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 13 and 17, 2019, Proceedings 4*, pp. 42–50, Springer, 2019.

[16] L. Cerrone, A. Zeilmann, and F. A. Hamprecht, "End-to-end learned random walker for seeded image segmentation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 12559–12568, 2019.

[17] H. Zheng, Y. Chen, X. Yue, and C. Ma, "Deep interactive segmentation of uncertain regions with shadowed sets," in *Proceedings of the Third International Symposium on Image Computing and Digital Medicine*, pp. 244–248, 2019.

[18] C.-H. Chao, Y.-C. Cheng, H.-T. Cheng, C.-W. Huang, T.-Y. Ho, C.-K. Tseng, L. Lu, and M. Sun, "Radiotherapy target contouring with convolutional gated graph neural network," *arXiv preprint arXiv:1904.03086*, 2019.

[19] M. Längkvist, J. Widell, P. Thunberg, A. Loutfi, and M. Lidén, "Interactive user interface based on convolutional auto-encoders for annotating ct-scans," *arXiv preprint arXiv:1904.11701*, 2019.

[20] X. Wang, L. Zhang, H. Roth, D. Xu, and Z. Xu, "Interactive 3d segmentation editing and refinement via gated graph neural networks," in *Graph Learning in Medical Imaging: First International Workshop, GLMI 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 17, 2019, Proceedings*, pp. 9–17, Springer, 2019.

[21] T. Boers, Y. Hu, E. Gibson, D. Barratt, E. Bonmati, J. Krdzalic, F. van der Heijden, J. Hermans, and H. Huisman, "Interactive 3d u-net for the segmentation of the pancreas in computed tomography scans," *Physics in Medicine & Biology*, vol. 65, no. 6, p. 065002, 2020.

[22] G. Wang, M. Aertsen, J. Deprest, S. Ourselin, T. Vercauteren, and S. Zhang, "Uncertainty-guided efficient interactive refinement of fetal brain segmentation from stacks of mri slices," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference, Lima, Peru, October 4–8, 2020, Proceedings, Part IV 23*, pp. 279–288, Springer, 2020.

[23] X. Liao, W. Li, Q. Xu, X. Wang, B. Jin, X. Zhang, Y. Wang, and Y. Zhang, "Iteratively-refined interactive 3d medical image segmentation with multi-agent reinforcement learning," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 9394–9402, 2020.

[24] A. Raju, Z. Ji, C. T. Cheng, J. Cai, J. Huang, J. Xiao, L. Lu, C. Liao, and A. P. Harrison, "User-guided domain adaptation for rapid annotation from user interactions: a study on pathological liver segmentation," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference, Lima, Peru, October 4–8, 2020, Proceedings, Part I*, pp. 457–467, Springer, 2020.

TABLE VIII
PRISMA 2020 CHECKLIST

Section and Topic	Item	Checklist Item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts Checklist.	Appendix F, Table X
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Page 1, Section I, paragraph 4
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Page 1, Section I, paragraph 5 (bulleted list)
METHODS			
Eligibility Criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses	Page 3, Section III, paragraph 1
Information sources	6	Specify all databases, registers, websites, organizations, reference lists, and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Page 2, Section III, paragraph 1
Search strategy	7	Present the full search strategies for all databases, registers, and websites, including any filters and limits used.	Page 2, Section III, paragraph 1; and page 3, Section III, paragraphs 1 and 3
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, and whether they worked independently.	Page 3, Section III, paragraph 2
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, and any processes for obtaining or confirming data from study investigators.	Page 3, Section III, paragraph 4
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Page 3, Section III, paragraph 4
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Page 3, Section III, paragraph 4
Study risk of bias assessment	11	Specify the methods used to assess the risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study, and whether they worked independently.	-
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results	-
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Page 3, Section IV, paragraphs 1-3; page 6, Fig. 3; and page 7, Fig. 4
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Page 3, Section IV, paragraphs 1-3
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Page 3, paragraphs 1-3; page 4, Table I; and page 5, Table II
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s).	Page 3, Section IV, paragraphs 1-3; and page 7, Fig. 7
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Page 15, Section V-D; and page 6, Fig. 6
	13f	Describe any sensitivity analyses conducted to assess the robustness of the synthesized results.	-
Reporting bias assessment	14	Describe any methods used to assess the risk of bias due to missing results in a synthesis (arising from reporting biases).	-
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	-

TABLE IX
PRISMA 2020 CHECKLIST, CONTINUED

Section and Topic	Item	Checklist Item	Location where item is reported
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Page 2, Fig. 2; page 3, paragraph 3; and Appendix F, Table VII
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Page 3, Section III, paragraph 5
Study Characteristics	17	Cite each included study and present its characteristics.	Pages 3-12, Sections IV-A, IV-B, and IV-C (all paragraphs each) cite and describe all studies in detail; page 4, Table I; page 5, Table II; and page 14, Fig. 6 contains citations to all studies
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	-
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	-
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies	-
	20b	Present results of all statistical syntheses conducted.	Pages 12-13, Section V-A (all paragraphs); and page 13 Fig. 5
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	-
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	-
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	-
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	-
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Page 15, Section VI, paragraph 1
	23b	Discuss any limitations of the evidence included in the review.	-
	23c	Discuss any limitations of the review processes used.	-
	23d	Discuss implications of the results for practice, policy, and future research.	Page 15, Section IV-B (all paragraphs)
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	The review was not registered
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	A protocol was not provided
	24c	Describe and explain any amendments to the information provided at registration or in the protocol.	A protocol was not provided
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	-
Competing interests	26	Declare any competing interests of review authors.	-
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	-

TABLE X
PRISMA 2020 ABSTRACT CHECKLIST

Section and Topic	Item	Checklist Item	Reported (Yes/No)
TITLE			
Title	1	Identify the report as a systematic review.	Yes
BACKGROUND			
Objectives	2	Provide an explicit statement of the main objective(s) or question(s) the review addresses.	Yes
METHODS			
Eligibility criteria	3	Specify the inclusion and exclusion criteria for the review.	No
Information sources	4	Specify the information sources (e.g. databases, registers) used to identify studies and the date when each was last searched.	No
Risk of bias	5	Specify the methods used to assess risk of bias in the included studies.	No
Synthesis of results	6	Specify the methods used to present and synthesize results.	Yes
RESULTS			
Included studies	7	Give the total number of included studies and participants and summarize relevant characteristics of studies.	Yes
Synthesis of results	8	Present results for main outcomes, preferably indicating the number of included studies and participants for each. If meta-analysis was done, report the summary estimate and confidence/credible interval.	No
DISCUSSION			
Limitations of evidence	9	Provide a brief summary of the limitations of the evidence included in the review (e.g. study risk of bias, inconsistency, and imprecision).	No
Interpretation	10	Provide a general interpretation of the results and important implications.	Yes
OTHER			
Funding	11	Specify the primary source of funding for the review.	No
Registration	12	Provide the register name and registration number.	No

[25] C. Ma, Q. Xu, X. Wang, B. Jin, X. Zhang, Y. Wang, and Y. Zhang, "Boundary-aware supervoxel-level iteratively refined interactive 3d image segmentation with multi-agent reinforcement learning," *IEEE Transactions on Medical Imaging*, vol. 40, no. 10, pp. 2563–2574, 2020.

[26] N. A. Koohbanani, M. Jahanifar, N. Z. Tajadin, and N. Rajpoot, "Nuclick: a deep learning framework for interactive segmentation of microscopic images," *Medical Image Analysis*, vol. 65, p. 101771, 2020.

[27] T. Kitrungrotsakul, I. Yutaro, L. Lin, R. Tong, J. Li, and Y.-W. Chen, "Interactive deep refinement network for medical image segmentation," *arXiv preprint arXiv:2006.15320*, 2020.

[28] A. Pepe, R. Schussnig, J. Li, C. Gsaxner, X. Chen, T.-P. Fries, and J. Egger, "Iris: interactive real-time feedback image segmentation with deep learning," in *Medical Imaging 2020: Biomedical Applications in Molecular, Structural, and Functional Imaging*, vol. 11317, pp. 181–186, SPIE, 2020.

[29] W. Hu, X. Yao, Z. Zheng, X. Zhang, Y. Zhong, X. Wang, Y. Zhang, and Y. Wang, "Error attention interactive segmentation of medical image through matting and fusion," in *Machine Learning in Medical Imaging: 11th International Workshop, MLMI 2020, Held in Conjunction with MICCAI 2020, Lima, Peru, October 4, 2020, Proceedings 11*, pp. 11–20, Springer, 2020.

[30] Z. Tian, X. Li, Y. Zheng, Z. Chen, Z. Shi, L. Liu, and B. Fei, "Graph-convolutional-network-based interactive prostate segmentation in mr images," *Medical physics*, vol. 47, no. 9, pp. 4164–4176, 2020.

[31] C.-H. Chao, H.-T. Cheng, T.-Y. Ho, L. Lu, and M. Sun, "Interactive radiotherapy target delineation with 3d-fused context propagation," *arXiv preprint arXiv:2012.06873*, 2020.

[32] Y. Tang, K. Yan, J. Xiao, and R. M. Summers, "One click lesion recist measurement and segmentation on ct scans," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference, Lima, Peru, October 4–8, 2020, Proceedings, Part IV 23*, pp. 573–583, Springer, 2020.

[33] H. Jinbo, T. Kitrungrotsaku, Y. Iwamoto, L. Lin, H. Hu, and Y.-W. Chen, "Development of an interactive semantic medical image segmentation system," in *2020 IEEE 9th Global Conference on Consumer Electronics (GCCE)*, pp. 678–681, IEEE, 2020.

[34] K. B. Girum, G. Créhange, R. Hussain, and A. Lalande, "Fast interactive medical image segmentation with weakly supervised deep learning method," *International Journal of Computer Assisted Radiology and Surgery*, vol. 15, pp. 1437–1444, 2020.

[35] D. J. Ho, N. P. Agaram, P. J. Schüffler, C. M. Vanderbilt, M.-H. Jean, M. R. Hameed, and T. J. Fuchs, "Deep interactive learning: an efficient labeling approach for deep learning-based osteosarcoma treatment response assessment," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference, Lima, Peru, October 4–8, 2020, Proceedings, Part V 23*, pp. 540–549, Springer, 2020.

[36] M. X.-L. Foo, S. T. Kim, M. Paschali, L. Goli, E. Burian, M. Makowski, R. Braren, N. Navab, and T. Wendler, "Interactive segmentation for covid-19 infection quantification on longitudinal ct scans," *arXiv preprint arXiv:2110.00948*, 2021.

[37] A. Menon, P. Singh, P. Vinod, and C. Jawahar, "Interactive learning for assisting whole slide image annotation," in *Asian Conference on Pattern Recognition*, pp. 504–517, Springer, 2021.

[38] X. Luo, G. Wang, T. Song, J. Zhang, M. Aertsen, J. Deprest, S. Ourselin, T. Vercauteren, and S. Zhang, "Mideepseg: Minimally interactive segmentation of unseen objects from medical images using deep learning," *Medical image analysis*, vol. 72, p. 102102, 2021.

[39] R. Feng, X. Zheng, T. Gao, J. Chen, W. Wang, D. Z. Chen, and J. Wu, "Interactive few-shot learning: Limited supervision, better medical image segmentation," *IEEE Transactions on Medical Imaging*, vol. 40, no. 10, pp. 2575–2588, 2021.

[40] H. R. Roth, D. Yang, Z. Xu, X. Wang, and D. Xu, "Going to extremes: weakly supervised medical image segmentation," *Machine Learning and Knowledge Extraction*, vol. 3, no. 2, pp. 507–524, 2021.

[41] B. Sambaturu, A. Gupta, C. Jawahar, and C. Arora, "Efficient and generic interactive segmentation framework to correct mispredictions during clinical evaluation of medical images," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part II 24*, pp. 625–635, Springer, 2021.

[42] T. Zhou, L. Li, G. Bredell, J. Li, and E. Konukoglu, "Quality-aware memory network for interactive volumetric image segmentation," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part II 24*, pp. 560–570,

Springer, 2021.

[43] H. Williams, J. Pedrosa, L. Cattani, S. Housmans, T. Vercauteren, J. Deprest, and J. D'hooge, "Interactive segmentation via deep learning and b-spline explicit active surfaces," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part I 24*, pp. 315–325, Springer, 2021.

[44] X. Li, M. Qiao, Y. Guo, J. Zhou, S. Zhou, C. Chang, and Y. Wang, "Wdtiseg: One-stage interactive segmentation for breast ultrasound image using weighted distance transform and shape-aware compound loss," *Applied Sciences*, vol. 11, no. 14, p. 6279, 2021.

[45] W. Li, Q. Xu, C. Shen, B. Hu, F. Zhu, Y. Li, B. Jin, and X. Wang, "Interactive medical image segmentation with self-adaptive confidence calibration," *arXiv preprint arXiv:2111.07716*, 2021.

[46] J. Deng and X. Xie, "3d interactive segmentation with semi-implicit representation and active learning," *IEEE Transactions on Image Processing*, vol. 30, pp. 9402–9417, 2021.

[47] J. Zhang, Y. Shi, J. Sun, L. Wang, L. Zhou, Y. Gao, and D. Shen, "Interactive medical image segmentation via a point-based interaction," *Artificial Intelligence in Medicine*, vol. 111, p. 101998, 2021.

[48] E. Zheng, Q. Yu, R. Li, P. Shi, and A. Haake, "A continual learning framework for uncertainty-aware interactive image segmentation," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 35, pp. 6030–6038, 2021.

[49] J.-W. Zhang, W. Chen, K. I. Ly, X. Zhang, F. Yan, J. Jordan, G. Harris, S. Plotkin, P. Hao, and W. Cai, "Dins: deep interactive networks for neurofibroma segmentation in neurofibromatosis type 1 on whole-body mri," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 2, pp. 786–797, 2021.

[50] Z. Tian, X. Li, Z. Chen, Y. Zheng, H. Fan, Z. Li, C. Li, and S. Du, "Interactive prostate mr image segmentation based on convlstms and ggnn," *Neurocomputing*, vol. 438, pp. 84–93, 2021.

[51] D. Jiang, Y. Wang, F. Zhou, H. Ma, W. Zhang, W. Fang, P. Zhao, and Z. Tong, "Residual refinement for interactive skin lesion segmentation," *Journal of Biomedical Semantics*, vol. 12, no. 1, p. 22, 2021.

[52] Y. Bai, G. Sun, Y. Li, L. Shen, and L. Zhang, "Progressive medical image annotation with convolutional neural network-based interactive segmentation method," in *Medical Imaging 2021: Image Processing*, vol. 11596, pp. 732–742, SPIE, 2021.

[53] S. Cho, H. Jang, J. W. Tan, and W.-K. Jeong, "Deepscribble: interactive pathology image segmentation using deep neural networks with scribbles," in *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, pp. 761–765, IEEE, 2021.

[54] T. Kitrungrotsakul, Q. Chen, H. Wu, Y. Iwamoto, H. Hu, W. Zhu, C. Chen, F. Xu, Y. Zhou, L. Lin, *et al.*, "Attention-refnet: Interactive attention refinement network for infected area segmentation of covid-19," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 7, pp. 2363–2373, 2021.

[55] R. Daulatabad, R. Vega, J. L. Jaremko, J. Kapur, A. R. Hareendranathan, and K. Punithakumar, "Integrating user-input into deep convolutional neural networks for thyroid nodule segmentation," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 2637–2640, IEEE, 2021.

[56] X. H. Manh, H. Vu, X. D. Nguyen, L. H. P. Tu, H. D. Viet, P. B. Nguyen, and M. H. Nguyen, "Interactive z-line segmentation tool for upper gastrointestinal endoscopy images using binary partition tree and u-net," in *2021 RIVF International Conference on Computing and Communication Technologies (RIVF)*, pp. 1–6, IEEE, 2021.

[57] M. J. Trimpl, D. Boukerroui, E. P. Stride, K. A. Vallis, and M. J. Gooding, "Interactive contouring through contextual deep learning," *Medical Physics*, vol. 48, no. 6, pp. 2951–2959, 2021.

[58] Y. Fang, D. Zhu, N. Zhou, L. Liu, and J. Yao, "Pipo-net: A semi-automatic and polygon-based annotation method for pathological images," in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 2978–2984, IEEE, 2021.

[59] M. Jahanifar, N. Z. Tajeddin, N. A. Koohbanani, and N. M. Rajpoot, "Robust interactive semantic segmentation of pathology images with minimal user input," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 674–683, 2021.

[60] L. Sun, Z. Tian, Z. Chen, W. Luo, and S. Du, "An efficient interactive segmentation framework for medical images without pre-training," *Medical Physics*, 2022.

[61] M. Shahedi, J. D. Dormer, M. Halicek, and B. Fei, "The effect of image annotation with minimal manual interaction for semiautomatic prostate segmentation in ct images using fully convolutional neural networks," *Medical physics*, vol. 49, no. 2, pp. 1153–1160, 2022.

[62] A. Atzeni, L. Peter, E. Robinson, E. Blackburn, J. Althonayan, D. C. Alexander, and J. E. Iglesias, "Deep active learning for suggestive segmentation of biomedical image stacks via optimisation of dice scores and traced boundary length," *Medical Image Analysis*, vol. 81, p. 102549, 2022.

[63] L. Bi, M. Fulham, and J. Kim, "Hyper-fusion network for semi-automatic segmentation of skin lesions," *Medical image analysis*, vol. 76, p. 102334, 2022.

[64] Q. Liu, Z. Xu, Y. Jiao, and M. Niethammer, "isegformer: Interactive segmentation via transformers with application to 3d knee mr images," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2022: 25th International Conference, Singapore, September 18–22, 2022, Proceedings, Part V*, pp. 464–474, Springer, 2022.

[65] M. Asad, L. Fidon, and T. Vercauteren, "Econet: Efficient convolutional online likelihood network for scribble-based interactive segmentation," in *International Conference on Medical Imaging with Deep Learning*, pp. 35–47, PMLR, 2022.

[66] K. Gotkowski, C. Gonzalez, I. Kaltenborn, R. Fischbach, A. Bucher, and A. Mukhopadhyay, "i3deep: Efficient 3d interactive segmentation with the nnu-net," in *International Conference on Medical Imaging with Deep Learning*, pp. 441–456, PMLR, 2022.

[67] A. Diaz-Pinto, P. Mehta, S. Alle, M. Asad, R. Brown, V. Nath, A. Ihsani, M. Antonelli, D. Palkovics, C. Pinter, *et al.*, "Deepedit: Deep editable learning for interactive segmentation of 3d medical images," in *Data Augmentation, Labelling, and Imperfections: Second MICCAI Workshop, DALI 2022, Held in Conjunction with MICCAI 2022, Singapore, September 22, 2022, Proceedings*, pp. 11–21, Springer, 2022.

[68] W. Liu, C. Ma, Y. Yang, W. Xie, and Y. Zhang, "Transforming the interactive segmentation for medical imaging," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2022: 25th International Conference, Singapore, September 18–22, 2022, Proceedings, Part IV*, pp. 704–713, Springer, 2022.

[69] L. Shi, X. Zhang, Y. Liu, and X. Han, "A hybrid propagation network for interactive volumetric image segmentation," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2022: 25th International Conference, Singapore, September 18–22, 2022, Proceedings, Part IV*, pp. 673–682, Springer, 2022.

[70] M. Zhuang, Z. Chen, H. Wang, H. Tang, J. He, B. Qin, Y. Yang, X. Jin, M. Yu, B. Jin, *et al.*, "Anatomysketch: An extensible open-source software platform for medical image analysis algorithm development," *Journal of Digital Imaging*, pp. 1–11, 2022.

[71] G. Galisot, J.-Y. Ramel, T. Brouard, E. Chaillou, and B. Serres, "Visual and structural feature combination in an interactive machine learning system for medical image segmentation," *Machine Learning with Applications*, vol. 8, p. 100294, 2022.

[72] Z. Lin, Z. Zhang, L.-H. Han, and S.-P. Lu, "Multi-mode interactive image segmentation," in *Proceedings of the 30th ACM International Conference on Multimedia*, pp. 905–914, 2022.

[73] R. Pirabaharan and N. Khan, "Interactive segmentation using u-net with weight map and dynamic user interactions," in *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 4754–4757, IEEE, 2022.

[74] I. Mikhailov, B. Chauveau, N. Bourdel, and A. Bartoli, "A deep learning-based interactive medical image segmentation framework," in *Applications of Medical Artificial Intelligence: First International Workshop, AMAI 2022, Held in Conjunction with MICCAI 2022, Singapore, September 18, 2022, Proceedings*, pp. 98–107, Springer, 2022.

[75] R. Pirabaharan and N. Khan, "Improving interactive segmentation using a novel weighted loss function with an adaptive click size and two-stream fusion," in *2022 IEEE Eighth International Conference on Multimedia Big Data (BigMM)*, pp. 7–12, IEEE, 2022.

[76] X. Chen, B. Zhou, L. Xiong, C. Zhao, L. Wang, Y. Zhang, and H. Xu, "Balancing regional and global information: An interactive segmentation framework for ultrasound breast lesion," *Biomedical Signal Processing and Control*, vol. 77, p. 103723, 2022.

[77] S. Liang, H. Lu, M. Zang, X. Wang, Y. Jiao, T. Zhao, E. Y. Xu, and J. Xu, "Deep sed-net with interactive learning for multiple testicular cell types segmentation and cell composition analysis in mouse seminiferous tubules," *Cytometry Part A*, vol. 101, no. 8, pp. 658–674, 2022.

[78] M. Ju, M. Lee, J. Lee, J. Yang, S. Yoon, and Y. Kim, "All you need is a few dots to label ct images for organ segmentation," *Applied Sciences*, vol. 12, no. 3, p. 1328, 2022.

[79] W. Ma, S. Zheng, L. Zhang, H. Zhang, and Q. Dou, "Rapid model transfer for medical image segmentation via iterative human-in-the-

loop update: from labelled public to unlabelled clinical datasets for multi-organ segmentation in ct," in *2022 IEEE 19th International Symposium on Biomedical Imaging (ISBI)*, pp. 1–5, IEEE, 2022.

[80] T. Bai, A. Balagopal, M. Dohopolski, H. E. Morgan, R. McBeth, J. Tan, M.-H. Lin, D. J. Sher, D. Nguyen, and S. Jiang, "A proof-of-concept study of artificial intelligence–assisted contour editing," *Radiology: Artificial Intelligence*, vol. 4, no. 5, p. e210214, 2022.

[81] T. Zhou, L. Li, G. Bredell, J. Li, J. Unkelbach, and E. Konukoglu, "Volumetric memory network for interactive medical image segmentation," *Medical Image Analysis*, vol. 83, p. 102599, 2023.

[82] V. J. Hallitschke, T. Schlumberger, P. Kataliakos, Z. Marinov, M. Kim, L. Heiliger, C. Seibold, J. Kleesiek, and R. Stiefelhagen, "Multimodal interactive lung lesion segmentation: A framework for annotating pet/ct images based on physiological and anatomical cues," *arXiv preprint arXiv:2301.09914*, 2023.

[83] Q. Liu, M. Zheng, B. Planche, Z. Gao, T. Chen, M. Niethammer, and Z. Wu, "Exploring cycle consistency learning in interactive volume segmentation," *arXiv preprint arXiv:2303.06493*, 2023.

[84] A. Bruzadin, M. Boaventura, M. Colnago, R. G. Negri, and W. Casaca, "Learning label diffusion maps for semi-automatic segmentation of lung ct images with covid-19," *Neurocomputing*, vol. 522, pp. 24–38, 2023.

[85] M. Asad, H. Williams, I. Mandal, S. Ather, J. Deprest, J. D'hooge, and T. Vercauteren, "Adaptive multi-scale online likelihood network for ai-assisted interactive segmentation," *arXiv preprint arXiv:2303.13696*, 2023.

[86] A. H. Shahin, Y. Zhuang, and N. El-Zehiry, "From sparse to precise: A practical editing approach for intracardiac echocardiography segmentation," *arXiv preprint arXiv:2303.11041*, 2023.

[87] M. Zhuang, Z. Chen, H. Wang, H. Tang, J. He, B. Qin, Y. Yang, X. Jin, M. Yu, B. Jin, *et al.*, "Efficient contour-based annotation by iterative deep learning for organ segmentation from volumetric medical images," *International Journal of Computer Assisted Radiology and Surgery*, vol. 18, no. 2, pp. 379–394, 2023.

[88] D. J. Ho, M. H. Chui, C. M. Vanderbilt, J. Jung, M. E. Robson, C.-S. Park, J. Roh, and T. J. Fuchs, "Deep interactive learning-based ovarian cancer segmentation of h&e-stained whole slide images to study morphological patterns of brca mutation," *Journal of Pathology Informatics*, vol. 14, p. 100160, 2023.

[89] Z. Wei, J. Ren, S. S. Korreman, and J. Nijkamp, "Towards interactive deep-learning for tumour segmentation in head and neck cancer radiotherapy," *Physics and Imaging in Radiation Oncology*, vol. 25, p. 100408, 2023.

[90] M. Zhuang, Z. Chen, Y. Yang, L. Kettunen, and H. Wang, "Annotation-efficient training of medical image segmentation network based on scribble guidance in difficult areas," *International Journal of Computer Assisted Radiology and Surgery*, pp. 1–10, 2023.

[91] Z. Marinov, R. Stiefelhagen, and J. Kleesiek, "Guiding the guidance: A comparative analysis of user guidance signals for interactive segmentation of volumetric images," *arXiv preprint arXiv:2303.06942*, 2023.

[92] C. Qu, T. Zhang, H. Qiao, J. Liu, Y. Tang, A. Yuille, and Z. Zhou, "Abdomenatlas-8k: Annotating 8,000 ct volumes for multi-organ segmentation in three weeks," in *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023.

[93] M. A. Mazurowski, H. Dong, H. Gu, J. Yang, N. Konz, and Y. Zhang, "Segment anything model for medical image analysis: an experimental study," *arXiv preprint arXiv:2304.10517*, 2023.

[94] R. Deng, C. Cui, Q. Liu, T. Yao, L. W. Remedios, S. Bao, B. A. Landman, L. E. Wheless, L. A. Coburn, K. T. Wilson, *et al.*, "Segment anything model (sam) for digital pathology: Assess zero-shot segmentation on whole slide imaging," *arXiv preprint arXiv:2304.04155*, 2023.

[95] S. Mohapatra, A. Gosai, and G. Schlaug, "Sam vs bet: A comparative study for brain extraction and segmentation of magnetic resonance images using deep learning," *arXiv preprint arXiv:2304.04738*, vol. 2, p. 4, 2023.

[96] F. Putz, J. Grigo, T. Weissmann, P. Schubert, D. Hoefler, A. Gomaa, H. B. Tkhayat, A. Hagag, S. Lettmaier, B. Frey, *et al.*, "The segment anything foundation model achieves favorable brain tumor autosegmentation accuracy on mri to support radiotherapy treatment planning," *arXiv preprint arXiv:2304.07875*, 2023.

[97] C. Hu and X. Li, "When sam meets medical images: An investigation of segment anything model (sam) on multi-phase liver tumor segmentation," *arXiv preprint arXiv:2304.08506*, 2023.

[98] T. Chen, L. Zhu, C. Ding, R. Cao, S. Zhang, Y. Wang, Z. Li, L. Sun, P. Mao, and Y. Zang, "Sam fails to segment anything?–sam-adapter: Adapting sam in underperformed scenes: Camouflage, shadow, and more," *arXiv preprint arXiv:2304.09148*, 2023.

[99] J. Wu, R. Fu, H. Fang, Y. Liu, Z. Wang, Y. Xu, Y. Jin, and T. Arbel, "Medical sam adapter: Adapting segment anything model for medical image segmentation," *arXiv preprint arXiv:2304.12620*, 2023.

[100] Z. Qiu, Y. Hu, H. Li, and J. Liu, "Learnable ophthalmology sam," *arXiv preprint arXiv:2304.13425*, 2023.

[101] S. He, R. Bao, J. Li, P. E. Grant, and Y. Ou, "Accuracy of segment-anything model (sam) in medical image segmentation tasks," *arXiv preprint arXiv:2304.09324*, 2023.

[102] P. Shi, J. Qiu, S. M. D. Abaxi, H. Wei, F. P.-W. Lo, and W. Yuan, "Generalist vision foundation models for medical imaging: A case study of segment anything model on zero-shot medical segmentation," *Diagnostics*, vol. 13, no. 11, p. 1947, 2023.

[103] B. Wang, A. Aboah, Z. Zhang, and U. Bagci, "Gazesam: What you see is what you segment," *arXiv preprint arXiv:2304.13844*, 2023.

[104] M. Hu, Y. Li, and X. Yang, "Skinsam: Empowering skin cancer segmentation with segment anything model," *arXiv preprint arXiv:2304.13973*, 2023.

[105] A. Wang, M. Islam, M. Xu, Y. Zhang, and H. Ren, "Sam meets robotic surgery: An empirical study in robustness perspective," *arXiv preprint arXiv:2304.14674*, 2023.

[106] D. Cheng, Z. Qin, Z. Jiang, S. Zhang, Q. Lao, and K. Li, "Sam on medical images: A comprehensive study on three prompt modes," *arXiv preprint arXiv:2305.00035*, 2023.

[107] C. Mattjie, L. V. de Moura, R. C. Ravazio, L. S. Kupssinskü, O. Parraga, M. M. Delucis, and R. C. Barros, "Exploring the zero-shot capabilities of the segment anything model (sam) in 2d medical imaging: A comprehensive evaluation and practical guideline," *arXiv preprint arXiv:2305.00109*, 2023.

[108] Y. Li, M. Hu, and X. Yang, "Polyp-sam: Transfer sam for polyp segmentation," *arXiv preprint arXiv:2305.00293*, 2023.

[109] J. Wu, "Promptunet: Toward interactive medical image segmentation," *arXiv preprint arXiv:2305.10300*, 2023.

[110] M. Hu, Y. Li, and X. Yang, "Breastsam: A study of segment anything model for breast tumor detection in ultrasound images," *arXiv preprint arXiv:2305.12447*, 2023.

[111] D. Lee, J. Park, S. Cook, s.-j. Yoo, D. Lee, and H. Choi, "Iamsam: Image-based analysis of molecular signatures using the segment-anything model," *bioRxiv*, pp. 2023–05, 2023.

[112] Y. Gao, W. Xia, D. Hu, and X. Gao, "Desam: Decoupling segment anything model for generalizable medical image segmentation," *arXiv preprint arXiv:2306.00499*, 2023.

[113] C. Shen, W. Li, Y. Zhang, and X. Wang, "Temporally-extended prompts optimization for sam in interactive medical image segmentation," *arXiv preprint arXiv:2306.08958*, 2023.

[114] G. Ning, H. Liang, Z. Jiang, H. Zhang, and H. Liao, "The potential of'segment anything'(sam) for universal intelligent ultrasound image guidance," *BioScience Trends*, 2023.

[115] L. Zhang, Z. Liu, L. Zhang, Z. Wu, X. Yu, J. Holmes, H. Feng, H. Dai, X. Li, Q. Li, *et al.*, "Segment anything model (sam) for radiation oncology," *arXiv preprint arXiv:2306.11730*, 2023.

[116] W. Lei, X. Wei, X. Zhang, K. Li, and S. Zhang, "Medlsam: Localize and segment anything model for 3d medical images," *arXiv preprint arXiv:2306.14752*, 2023.

[117] G. Deng, K. Zou, K. Ren, M. Wang, X. Yuan, S. Ying, and H. Fu, "Sam-u: Multi-box prompts triggered uncertainty estimation for reliable sam in medical image," *arXiv preprint arXiv:2307.04973*, 2023.

[118] S. Gong, Y. Zhong, W. Ma, J. Li, Z. Wang, J. Zhang, P.-A. Heng, and Q. Dou, "3dsam-adapter: Holistic adaptation of sam from 2d to 3d for promptable medical image segmentation," *arXiv preprint arXiv:2306.13465*, 2023.

[119] Y. Huang, X. Yang, L. Liu, H. Zhou, A. Chang, X. Zhou, R. Chen, J. Yu, J. Chen, C. Chen, *et al.*, "Segment anything model for medical images?," *arXiv preprint arXiv:2304.14660*, 2023.

[120] J. Ma and B. Wang, "Segment anything in medical images," *arXiv preprint arXiv:2304.12306*, 2023.

[121] S. Roy, T. Wald, G. Koehler, M. R. Rokuss, N. Disch, J. Holzschuh, D. Zimmerer, and K. H. Maier-Hein, "Sam. md: Zero-shot medical image segmentation capabilities of the segment anything model," *arXiv preprint arXiv:2304.05396*, 2023.

[122] H. Nickisch, C. Rother, P. Kohli, and C. Rhemann, "Learning an interactive segmentation system," in *Proceedings of the Seventh Indian Conference on Computer Vision, Graphics and Image Processing*, pp. 274–281, 2010.

[123] J. Canny, "A computational approach to edge detection," *IEEE Transactions on pattern analysis and machine intelligence*, no. 6, pp. 679–698, 1986.

[124] W. Pedrycz, "Shadowed sets: representing and processing fuzzy sets," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 28, no. 1, pp. 103–109, 1998.

[125] D. Barbosa, T. Dietenbeck, J. Schaerer, J. D'hooge, D. Friboulet, and O. Bernard, "B-spline explicit active surfaces: an efficient framework for real-time 3-d region-based segmentation," *IEEE transactions on image processing*, vol. 21, no. 1, pp. 241–251, 2011.

[126] A. Yezzi Jr, A. Tsai, and A. Willsky, "A fully global approach to image segmentation via coupled curve evolution equations," *Journal of Visual Communication and Image Representation*, vol. 13, no. 1-2, pp. 195–216, 2002.

[127] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*, pp. 234–241, Springer, 2015.

[128] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[129] Z.-H. Zhou, "A brief introduction to weakly supervised learning," *National science review*, vol. 5, no. 1, pp. 44–53, 2018.

[130] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132–7141, 2018.

[131] Y. Y. Boykov and M.-P. Jolly, "Interactive graph cuts for optimal boundary & region segmentation of objects in nd images," in *Proceedings eighth IEEE international conference on computer vision. ICCV 2001*, vol. 1, pp. 105–112, IEEE, 2001.

[132] P. Salembier and L. Garrido, "Binary partition tree as an efficient representation for image processing, segmentation, and information retrieval," *IEEE transactions on Image Processing*, vol. 9, no. 4, pp. 561–576, 2000.

[133] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Süsstrunk, "Slic superpixels compared to state-of-the-art superpixel methods," *IEEE transactions on pattern analysis and machine intelligence*, vol. 34, no. 11, pp. 2274–2282, 2012.

[134] M. Jenkinson, M. Pechaud, S. Smith, *et al.*, "Bet2: Mr-based estimation of brain, skull and scalp surfaces," in *Eleventh annual meeting of the organization for human brain mapping*, vol. 17, p. 167, Toronto., 2005.

[135] A. Hatamizadeh, V. Nath, Y. Tang, D. Yang, H. R. Roth, and D. Xu, "Swin unetr: Swin transformers for semantic segmentation of brain tumors in mri images," in *International MICCAI Brainlesion Workshop*, pp. 272–284, Springer, 2021.

[136] F. Isensee, P. F. Jaeger, S. A. Kohl, J. Petersen, and K. H. Maier-Hein, "nnu-net: a self-configuring method for deep learning-based biomedical image segmentation," *Nature methods*, vol. 18, no. 2, pp. 203–211, 2021.

[137] A. Kirillov, E. Mintun, N. Ravi, H. Mao, C. Rolland, L. Gustafson, T. Xiao, S. Whitehead, A. C. Berg, W.-Y. Lo, *et al.*, "Segment anything," *arXiv preprint arXiv:2304.02643*, 2023.

[138] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, *et al.*, "An image is worth 16x16 words: Transformers for image recognition at scale," *arXiv preprint arXiv:2010.11929*, 2020.

[139] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and P. Group*, "Preferred reporting items for systematic reviews and meta-analyses: the prisma statement," *Annals of internal medicine*, vol. 151, no. 4, pp. 264–269, 2009.

[140] N. Xu, B. Price, S. Cohen, J. Yang, and T. S. Huang, "Deep interactive object selection," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 373–381, 2016.

[141] C. Rother, V. Kolmogorov, and A. Blake, "" grabcut" interactive foreground extraction using iterated graph cuts," *ACM transactions on graphics (TOG)*, vol. 23, no. 3, pp. 309–314, 2004.

[142] F. Perazzi, J. Pont-Tuset, B. McWilliams, L. Van Gool, M. Gross, and A. Sorkine-Hornung, "A benchmark dataset and evaluation methodology for video object segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 724–732, 2016.

[143] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, "The pascal visual object classes (voc) challenge," *International journal of computer vision*, vol. 88, pp. 303–338, 2010.

[144] B. Hariharan, P. Arbeláez, L. Bourdev, S. Maji, and J. Malik, "Semantic contours from inverse detectors," in *2011 international conference on computer vision*, pp. 991–998, IEEE, 2011.

[145] K. McGuinness and N. E. O'connor, "A comparative evaluation of interactive segmentation algorithms," *Pattern Recognition*, vol. 43, no. 2, pp. 434–444, 2010.

[146] M. Eisenmann, A. Reinke, V. Weru, M. D. Tizabi, F. Isensee, T. J. Adler, S. Ali, V. Andrearczyk, M. Aubreville, U. Baid, *et al.*, "Why is the winner the best?," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 19955–19966, 2023.

[147] S. G. Hart and L. E. Staveland, "Development of nasa-tlx (task load index): Results of empirical and theoretical research," in *Advances in psychology*, vol. 52, pp. 139–183, Elsevier, 1988.

[148] J. Brooke, "Sus: a "quick and dirty'usability," *Usability evaluation in industry*, vol. 189, no. 3, pp. 189–194, 1996.

[149] A. Diaz-Pinto, S. Alle, V. Nath, Y. Tang, A. Ihsani, M. Asad, F. Pérez-García, P. Mehta, W. Li, M. Flores, *et al.*, "Monai label: A framework for ai-assisted interactive labeling of 3d medical images," *arXiv preprint arXiv:2203.12362*, 2022.

[150] K. A. Philbrick, A. D. Weston, Z. Akkus, T. L. Kline, P. Korfiatis, T. Sakinis, P. Kostandy, A. Boonrod, A. Zeinoddini, N. Takahashi, *et al.*, "Ril-contour: a medical imaging dataset annotation tool for and with deep learning," *Journal of digital imaging*, vol. 32, pp. 571–581, 2019.

[151] P. D. Lösel, T. van de Kamp, A. Jayme, A. Ershov, T. Faragó, O. Pichler, N. Tan Jerome, N. Aadepu, S. Bremer, S. A. Chilingaryan, *et al.*, "Introducing biomedisa as an open-source online platform for biomedical image segmentation," *Nature communications*, vol. 11, no. 1, p. 5577, 2020.

[152] S. Mahadevan, P. Voigtlaender, and B. Leibe, "Iteratively trained interactive segmentation," in *British Machine Vision Conference (BMVC)*, 2018.

[153] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *International journal of computer vision*, vol. 1, no. 4, pp. 321–331, 1988.

[154] S. Gatidis, M. Früh, M. Fabritius, S. Gu, K. Nikolaou, C. La Fougère, J. Ye, J. He, Y. Peng, L. Bi, *et al.*, "The autopet challenge: Towards fully automated lesion segmentation in oncologic pet/ct imaging," 2023.

[155] F. Zhao and X. Xie, "An overview of interactive medical image segmentation," *Annals of the BMVA*, vol. 2013, no. 7, pp. 1–22, 2013.

[156] S. D. Olabarriaga and A. W. Smeulders, "Interaction in the segmentation of medical images: A survey," *Medical image analysis*, vol. 5, no. 2, pp. 127–142, 2001.

[157] H. Ramadan, C. Lachqar, and H. Tairi, "A survey of recent interactive image segmentation methods," *Computational visual media*, vol. 6, pp. 355–384, 2020.

[158] Ç. Kaymak and A. Uçar, "A brief survey and an application of semantic image segmentation for autonomous driving," *Handbook of Deep Learning Applications*, pp. 161–200, 2019.

[159] D. Tabernik, S. Šela, J. Skvarč, and D. Skočaj, "Segmentation-based deep-learning approach for surface-defect detection," *Journal of Intelligent Manufacturing*, vol. 31, no. 3, pp. 759–776, 2020.

[160] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. Van Der Laak, B. Van Ginneken, and C. I. Sánchez, "A survey on deep learning in medical image analysis," *Medical image analysis*, vol. 42, pp. 60–88, 2017.

[161] M. Bakator and D. Radosav, "Deep learning and medical diagnosis: A review of literature," *Multimodal Technologies and Interaction*, vol. 2, no. 3, p. 47, 2018.

[162] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, Y. Burren, N. Porz, J. Slotboom, R. Wiest, *et al.*, "The multimodal brain tumor image segmentation benchmark (brats)," *IEEE transactions on medical imaging*, vol. 34, no. 10, pp. 1993–2024, 2014.

[163] M. Antonelli, A. Reinke, S. Bakas, K. Farahani, A. Kopp-Schneider, B. A. Landman, G. Litjens, B. Menze, O. Ronneberger, R. M. Summers, *et al.*, "The medical segmentation decathlon," *Nature communications*, vol. 13, no. 1, p. 4128, 2022.

[164] P. Bilic, P. Christ, H. B. Li, E. Vorontsov, A. Ben-Cohen, G. Kaissis, A. Szeskin, C. Jacobs, G. E. H. Mamani, G. Chartrand, *et al.*, "The liver tumor segmentation benchmark (lits)," *Medical Image Analysis*, vol. 84, p. 102680, 2023.

[165] L. Maier-Hein, B. Menze, *et al.*, "Metrics reloaded: Pitfalls and recommendations for image analysis validation," *arXiv. org*, no. 2206.01653, 2022.

[166] P. Krähenbühl and V. Koltun, "Efficient inference in fully connected crfs with gaussian edge potentials," *Advances in neural information processing systems*, vol. 24, 2011.

[167] A. E. Lefohn, J. E. Cates, and R. T. Whitaker, "Interactive, gpu-based level sets for 3d segmentation," in *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2003: 6th International Conference, Montréal, Canada, November 15-18, 2003. Proceedings 6*, pp. 564–572, Springer, 2003.

[168] C. Sommer, C. Straehle, U. Koethe, and F. A. Hamprecht, "Ilastik: Interactive learning and segmentation toolkit," in *2011 IEEE international symposium on biomedical imaging: From nano to macro*, pp. 230–233, IEEE, 2011.

[169] P. A. Yushkevich, Y. Gao, and G. Gerig, "Itk-snap: An interactive tool for semi-automatic segmentation of multi-modality biomedical images," in *2016 38th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, pp. 3342–3345, IEEE, 2016.

[170] A. Reinke, M. D. Tizabi, M. Baumgartner, M. Eisenmann, D. Heckmann-Nötzel, A. E. Kavur, T. Rädsch, C. H. Sudre, L. Acion, M. Antonelli, *et al.*, "Understanding metric-related pitfalls in image analysis validation," *ArXiv*, 2023.

[171] S. Nikolov, S. Blackwell, A. Zverovitch, R. Mendes, M. Livne, J. De Fauw, Y. Patel, C. Meyer, H. Askham, B. Romera-Paredes, *et al.*, "Clinically applicable segmentation of head and neck anatomy for radiotherapy: deep learning algorithm development and validation study," *Journal of medical Internet research*, vol. 23, no. 7, p. e26151, 2021.

[172] R. Li and X. Chen, "An efficient interactive multi-label segmentation tool for 2d and 3d medical images using fully connected conditional random field," *Computer Methods and Programs in Biomedicine*, vol. 213, p. 106534, 2022.

[173] I. Wolf, M. Vetter, I. Wegner, T. Böttger, M. Nolden, M. Schöbinger, M. Hastenteufel, T. Kunert, and H.-P. Meinzer, "The medical imaging interaction toolkit," *Medical image analysis*, vol. 9, no. 6, pp. 594–604, 2005.

[174] G. Wang, X. Luo, R. Gu, S. Yang, Y. Qu, S. Zhai, Q. Zhao, K. Li, and S. Zhang, "Pymic: A deep learning toolkit for annotation-efficient medical image segmentation," *Computer Methods and Programs in Biomedicine*, vol. 231, p. 107398, 2023.

[175] L. Castrejon, K. Kundu, R. Urtasun, and S. Fidler, "Annotating object instances with a polygon-rnn," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 5230–5238, 2017.

[176] K.-K. Maninis, S. Caelles, J. Pont-Tuset, and L. Van Gool, "Deep extreme cut: From extreme points to object segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 616–625, 2018.

[177] K. Sofiiuk, I. Petrov, O. Barinova, and A. Konushin, "f-brs: Rethinking backpropagating refinement for interactive segmentation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8623–8632, 2020.

[178] W.-D. Jang and C.-S. Kim, "Interactive image segmentation via backpropagating refinement scheme," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5297–5306, 2019.

[179] Z. Li, Q. Chen, and V. Koltun, "Interactive image segmentation with latent diversity," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 577–585, 2018.

[180] A. S. A. Khaizi, R. A. M. Rosidi, H.-S. Gan, and K. A. Sayuti, "A mini review on the design of interactive tool for medical image segmentation," in *2017 International Conference on Engineering Technology and Technopreneurship (ICE2T)*, pp. 1–5, 2017.

[181] A. Criminisi, T. Sharp, and A. Blake, "Geos: Geodesic image segmentation," in *Computer Vision–ECCV 2008: 10th European Conference on Computer Vision, Marseille, France, October 12-18, 2008, Proceedings, Part I 10*, pp. 99–112, Springer, 2008.

[182] P. J. Toivanen, "New geodosic distance transforms for gray-scale images," *Pattern Recognition Letters*, vol. 17, no. 5, pp. 437–450, 1996.

[183] L. Grady, "Random walks for image segmentation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 28, no. 11, pp. 1768–1783, 2006.

[184] S. Peleg and A. Rosenfeld, "A min-max medial axis transformation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, no. 2, pp. 208–210, 1981.