AutoSAM: Adapting SAM to Medical Images by Overloading the Prompt Encoder

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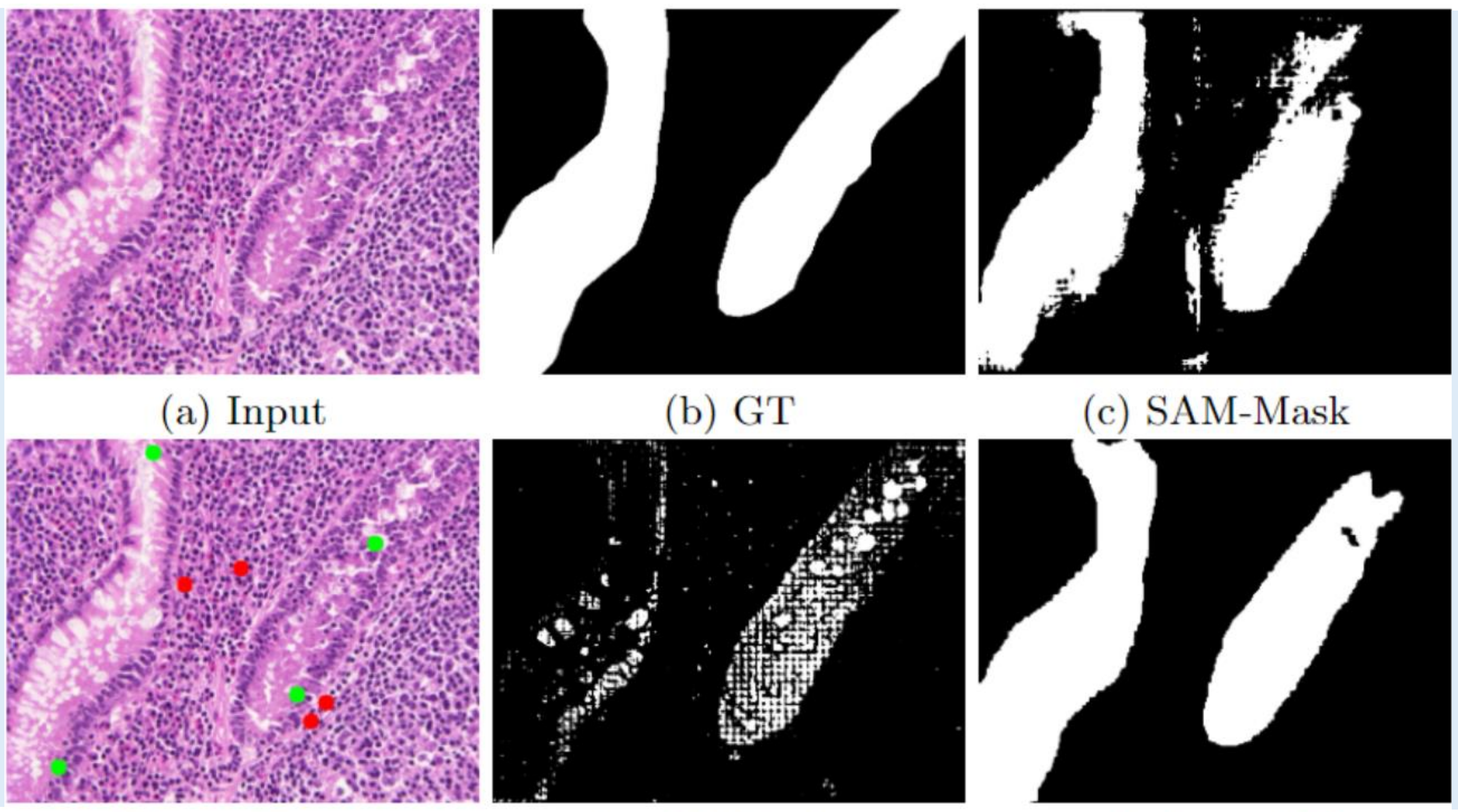
BMVC 2023

Introduction

Segment Anything Model

- *The promptable image segmentation model is an efficient and practical approach to real-world segmentation tasks that allows for flexibility in prompts, quick mask computation, and ambiguity awareness.*
- *However, SAM's performance may not be optimal on medical imaging datasets due to its pre-training on natural images.*



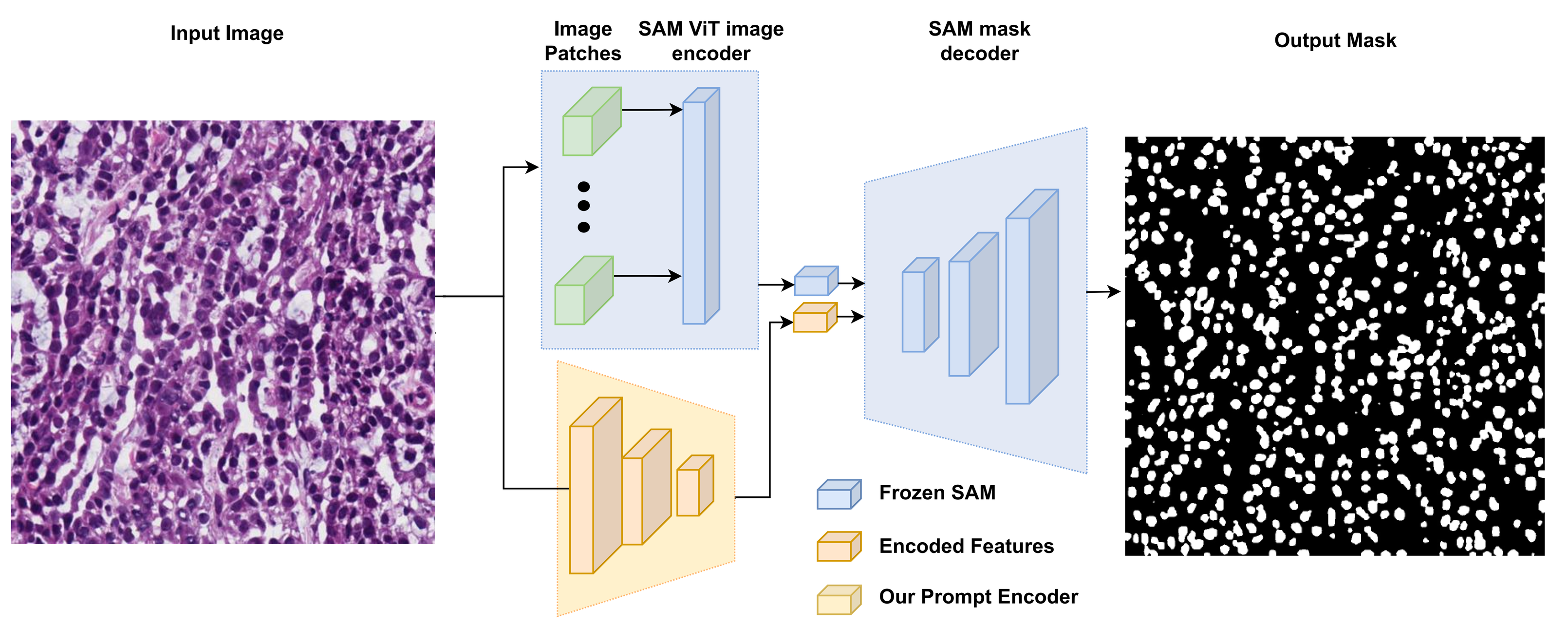
(a) Input (b) GT (c) SAM-Mask

(d) Point Prompt (e) SAM-Point (f) AutoSAM

Our Work

- *We propose an end-to-end approach to improve segmentation mask accuracy for medical images without fine-tuning the pretrained SAM network.*
- *Our solution involves the training of an auxiliary prompt encoder network, which generates a surrogate prompt for SAM given an input image.*
- *While the prompt encoder provided with SAM requires inputs such as a bounding box, a set of points, or a mask, the one we train has the image itself as its input.*

Method



The SAM network S produces an output segmentation mask M_z by taking the input image I and the prompts' embedding Z:

$$M_z = S(I, Z), \tag{1}$$

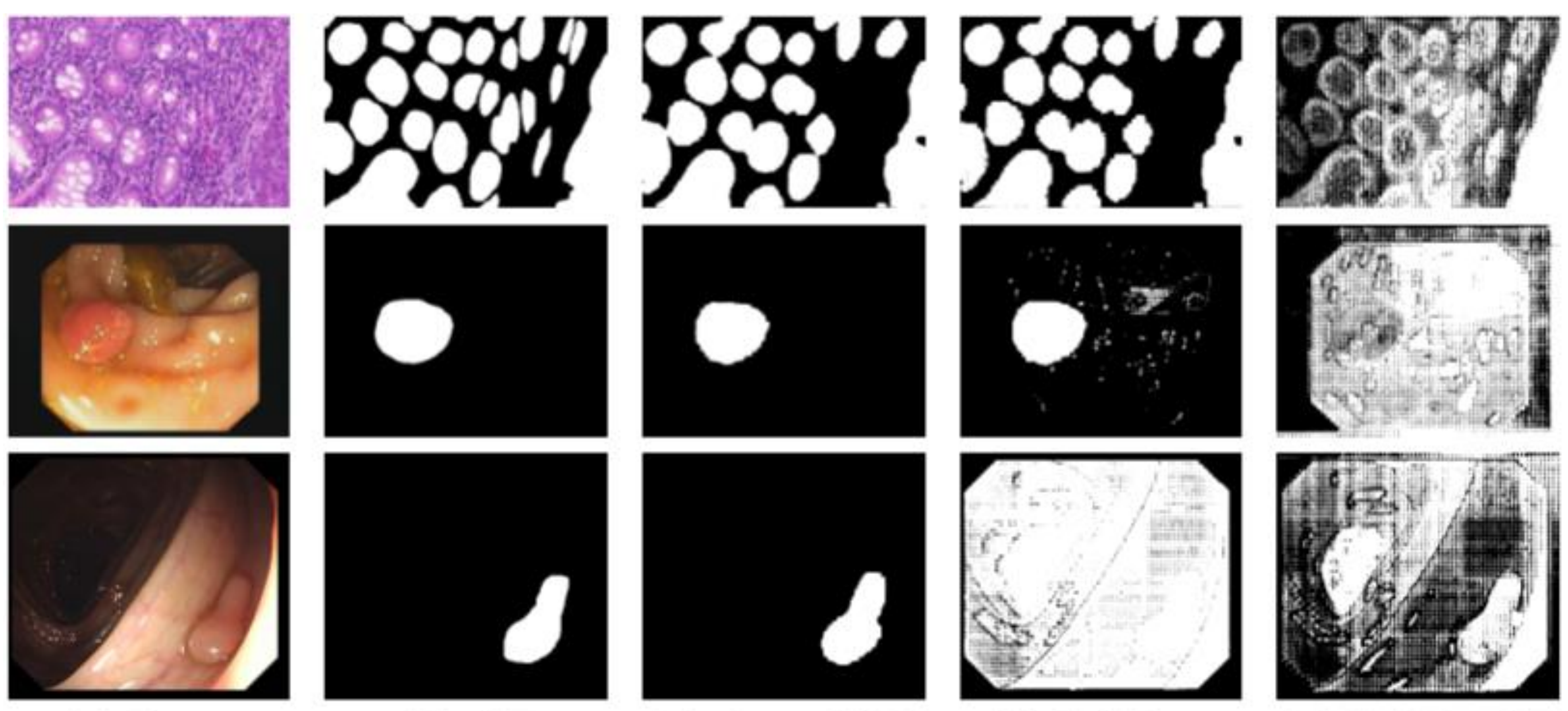
The prompts embedding Z can be any representation of different prompts, such as masks, boxes, and points.

Instead of using the original prompts encoder, we introduce a prompts generator network, denoted as g, that generates guidance prompts Z_I for SAM given an input image I. g is the only network trained by our method.

This prompts generator network g takes as input the image I and generates prompts $Z_I = g(I)$ for SAM to improve its segmentation mask output.

While training our method, the SAM network S propagates gradients to the prompts generator network g from two segmentation losses that we employ: the binary cross-entropy loss (BCE) and the Dice loss. The BCE loss is given by the negative log-likelihood of the ground truth mask M and the SAM output $S(I, Z_I)$, while the Dice loss measures the overlap between the predicted and ground truth masks. Formally, the losses are expressed as:

$$L_{seg}(I) = L_{BCE}(I, Z_I, M) + L_{dice}(I, Z_I, M), \tag{2}$$



(a) Input (b) GT (c) AutoSAM (d) SAM+g (e) SAM+GT

Conclusion

- *SAM is a powerful segmentation model for natural images.*
- *It has the potential to become a prominent foundation model, i.e., be effective for downstream tasks such as medical image analysis.*
- *We show that this may only require ``the right guidance'' in the form of a dedicated conditioning signal that is provided by an auxiliary network that replaces the prompt embedding.*
- *As no prompt is required, our method turns SAM into a fully automatic method.*

Results

Method	Monu		GlaS	
	Dice	IoU	Dice	IoU
FCN [2]	28.84	28.71	-	-
U-Net [35]	79.43	65.99	86.05	75.12
U-Net++ [58]	79.49	66.04	87.36	79.03
Res-UNet [53]	79.49	66.07	-	-
Axial Attention [50]	76.83	62.49	-	-
MedT [47]	79.55	66.17	88.85	78.93
FCN-Hardnet85 [5]	79.52	66.06	89.37	82.09
UCTransNet [49]	79.87	66.68	89.84	82.24
3P-SEG [37]	80.30	67.19	91.19	84.34
MedAdaptor-SAM [52] (conditioned on GT points)	80.34	67.33	92.02	85.88
AutoSAM (ours)	**82.43**	**70.17**	**92.82**	**87.08**
Lightweight decoder $h(g(I))$	76.75	62.32	91.51	84.80
SAM w/ GT point prompt	29.65	17.52	61.67	46.40
SAM w/ GT mask as prompt	30.24	18.21	58.46	42.81
SAM w/ AutoSAM output as the mask prompt	58.10	41.26	87.71	79.92

Method	Kvasir33 [19]		Clinic [3]		Colon [43]		ETIS [40]	
	Dice	IoU	Dice	IoU	Dice	IoU	Dice	IoU
U-Net [35]	81.8	74.6	82.3	75.5	51.2	44.4	39.8	33.5
U-Net++ [58]	82.1	74.3	79.4	72.9	48.3	41.0	40.1	34.4
SFA [14]	72.3	61.1	70.0	60.7	46.9	34.7	29.7	21.7
MSEG [18]	89.7	83.9	90.9	86.4	73.5	66.6	70.0	63.0
DCRNet [54]	88.6	82.5	89.6	84.4	70.4	63.1	55.6	49.6
ACSNet [56]	89.8	83.8	88.2	82.6	71.6	64.9	57.8	50.9
PraNet [12]	89.8	84.0	89.9	84.9	71.2	64.0	62.8	56.7
EU-Net [32]	90.8	85.4	90.2	84.6	75.6	68.1	68.7	60.9
SANet [51]	90.4	84.7	91.6	85.9	75.3	67.0	75.0	65.4
Polyp-PVT [8]	91.7	86.4	93.7	88.9	80.8	72.7	78.7	70.6
FCN-Hardnet85 [5]	90.0	84.9	92.0	86.9	77.3	70.2	76.9	69.5
3P-SEG [37]	**91.8**	86.5	**93.8**	89.0	80.9	73.4	79.1	71.4
Lightweight decoder $h(g(I))$	86.5	79.6	88.5	82.0	80.7	72.4	71.5	63.0
AutoSAM (ours)	91.0	**87.0**	92.8	**89.3**	**83.0**	**76.7**	**79.7**	**74.0**

	Method	SUN-SEG-Easy						SUN-SEG-Hard					
		S_α	E_ϕ^{mn}	F_β^w	F_β^{mn}	Dice	Sen	S_α	E_ϕ^{mn}	F_β^w	F_β^{mn}	Dice	Sen
Image-based	UNet [35]	0.669	0.677	0.459	0.528	0.530	0.420	0.670	0.679	0.457	0.527	0.542	0.429
	UNet++ [59]	0.684	0.687	0.491	0.553	0.559	0.457	0.685	0.697	0.480	0.544	0.554	0.467
	ACSNet [56]	0.782	0.779	0.642	0.688	0.713	0.601	0.783	0.787	0.636	0.684	0.708	0.618
	PraNet [11]	0.733	0.753	0.572	0.632	0.621	0.524	0.717	0.735	0.544	0.607	0.598	0.512
	SANet [51]	0.720	0.745	0.566	0.634	0.649	0.521	0.706	0.743	0.526	0.580	0.598	0.505
	AutoSAM(ours)	**0.815**	**0.855**	**0.716**	**0.774**	0.753	**0.672**	**0.822**	**0.866**	**0.714**	**0.764**	**0.759**	**0.726**
Video-based	COSNet [28]	0.654	0.600	0.431	0.496	0.596	0.359	0.670	0.627	0.443	0.506	0.606	0.380
	MAT [57]	0.770	0.737	0.575	0.641	0.710	0.542	0.785	0.755	0.578	0.645	0.712	0.579
	PCSA [16]	0.680	0.660	0.451	0.519	0.592	0.398	0.682	0.660	0.442	0.510	0.584	0.415
	2/3D [33]	0.786	0.777	0.652	0.708	0.722	0.603	0.786	0.775	0.634	0.688	0.706	0.607
	AMD [26]	0.474	0.533	0.133	0.146	0.266	0.222	0.472	0.527	0.128	0.141	0.252	0.213
	DCF [55]	0.523	0.514	0.270	0.312	0.325	0.340	0.514	0.522	0.263	0.303	0.317	0.364
	FSNet [21]	0.725	0.695	0.551	0.630	0.702	0.493	0.724	0.694	0.541	0.611	0.699	0.491
	PNSNet [20]	0.767	0.744	0.616	0.664	0.676	0.574	0.767	0.755	0.609	0.656	0.675	0.579
	VPS+ [22]	0.806	0.798	0.676	0.730	**0.756**	0.630	0.797	0.793	0.653	0.709	0.737	0.623