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Med-FastSAM: Improving Transfer Efficiency of SAM to Domain-Generalised Medical Image Segmentation

Yuxiang Luo
Qing Xu
Jinglei Feng
Guangwu Qian
Wenting Duan

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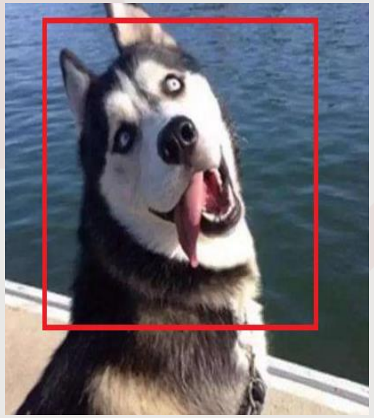
01 | Introduction

Why Segmentation matters: diagnosing diseases, planning treatments, even guiding surgeries.

Challenge: Varity of data between hospitals, equipment, and even patient groups

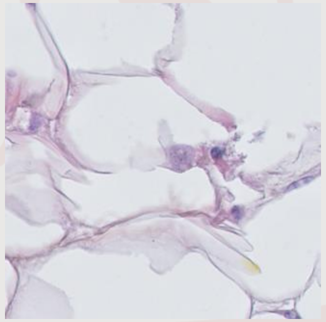
Goal: Making models that can adapt well to different types of medical data without needing extensive fine-tuning.

Train domain

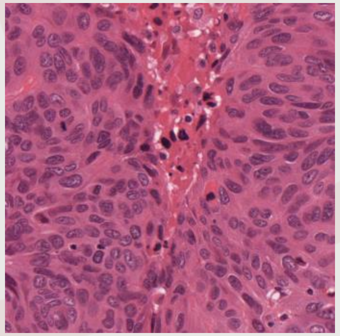


Test domain

Natural images: relatively low variability



Train domain



Test domain

Medical images: high variability

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02 Why Domain Generalization Matters in Medical Imaging

Diverse Data Sources: Medical images vary widely due to differences in hospitals, equipment, and imaging techniques.

Limited Data Availability: Medical datasets are often small and require expert labeling, making data collection costly and time-consuming

Need for Adaptability: Models must perform well on new data without frequent retraining, enabling faster deployment in clinical settings.

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03 Challenges with SAM and Related Models in Medical Imaging

SAM:

+High accuracy in natural image segmentation; +Adaptable across diverse image types.

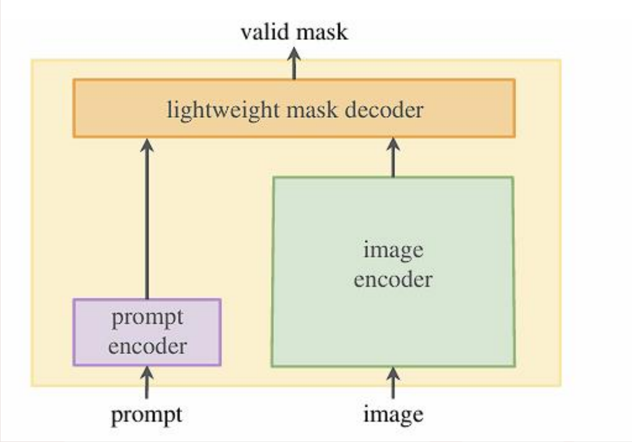
- High Computational Cost
- Manual Prompts
- Loss of Details

MedSAM, SAMed, Med-SA: Models developed to adapt SAM for medical images.

+ Improved Efficiency for medical images

- Still limited by model size and specific needs of manual prompts

SAM Structure



Segmentation Example in Natural Images

Kirillov, Alexander, et al. "Segment anything." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2023.

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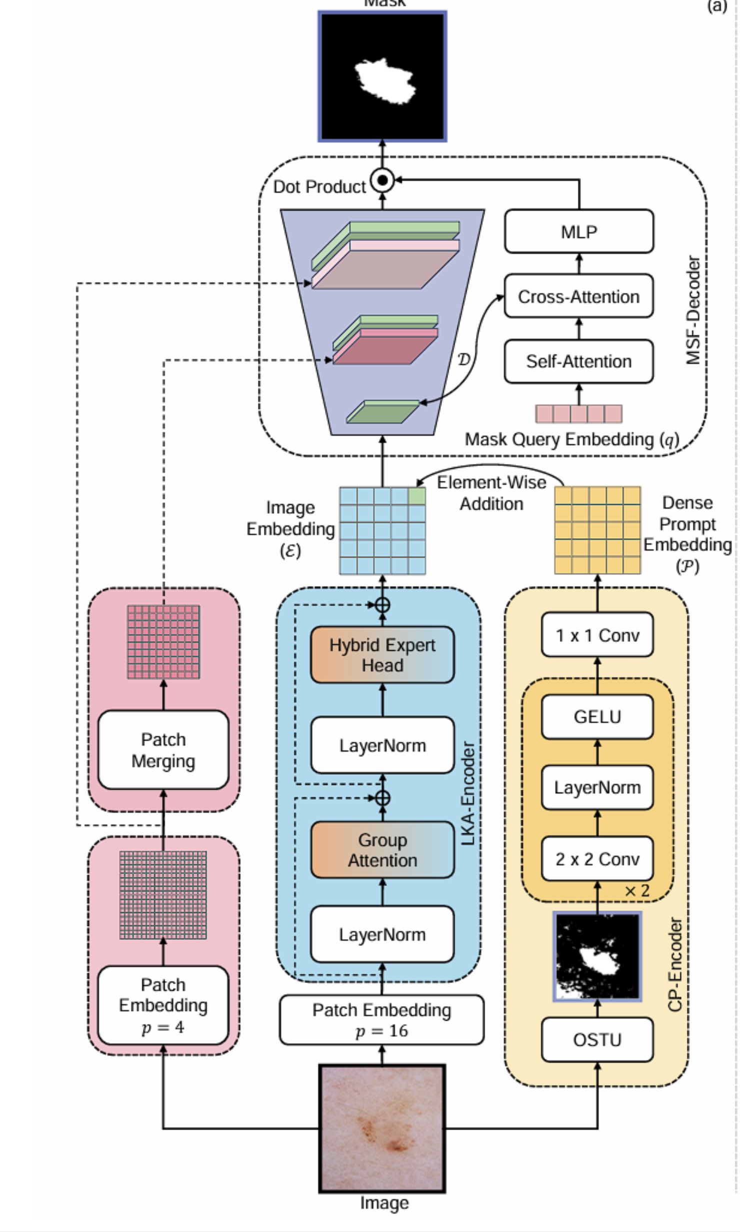

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04 | Med-FastSAM

To overcome these challenges, we introduce Med-FastSAM, a model designed specifically to adapt SAM for medical image segmentation. Med-FastSAM has three core components that address the limitations of SAM

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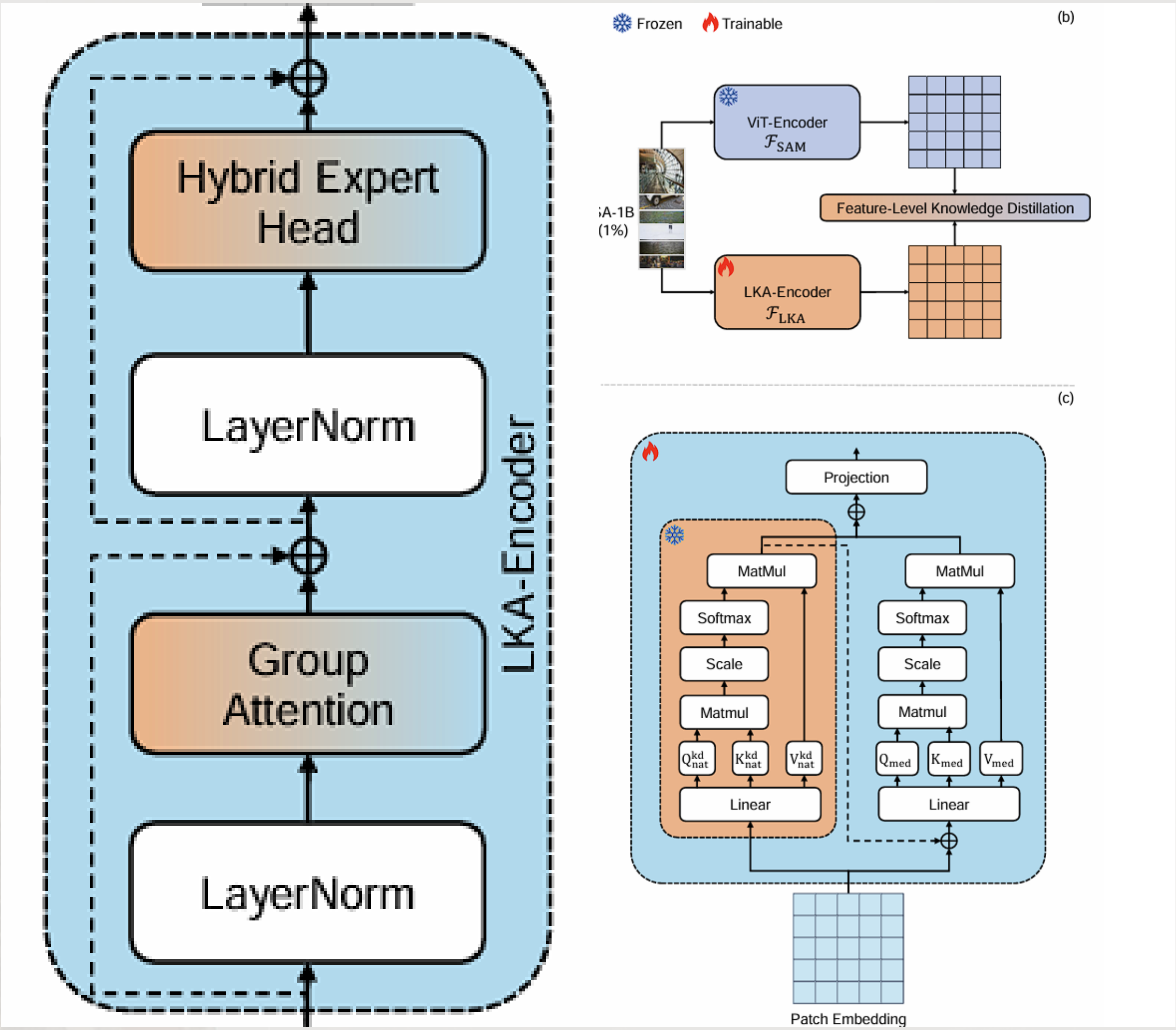
LKA-Encoder

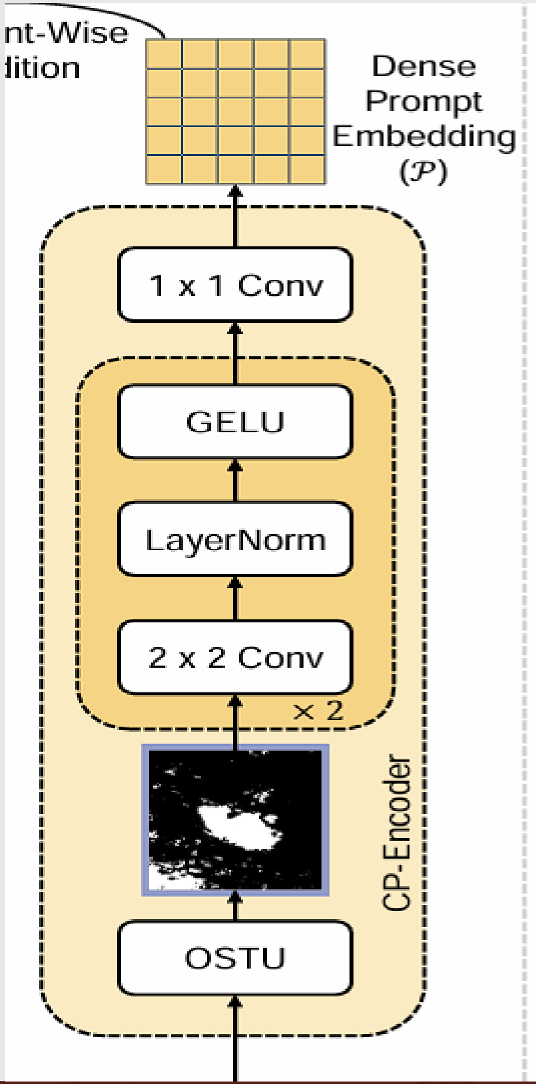
LKA-Encoder reduces computational costs by distilling essential knowledge from SAM and combining it with medical-specific features. This encoder not only makes the model lighter but also enhances its adaptability to medical images.



Coarse Prompt Encoder

CP-Encoder

CP-Encoder is introduced to eliminate the need for manual annotations. Instead of relying on expert-drawn points or boxes, it generates coarse masks automatically, making segmentation more efficient and accessible in clinical applications.



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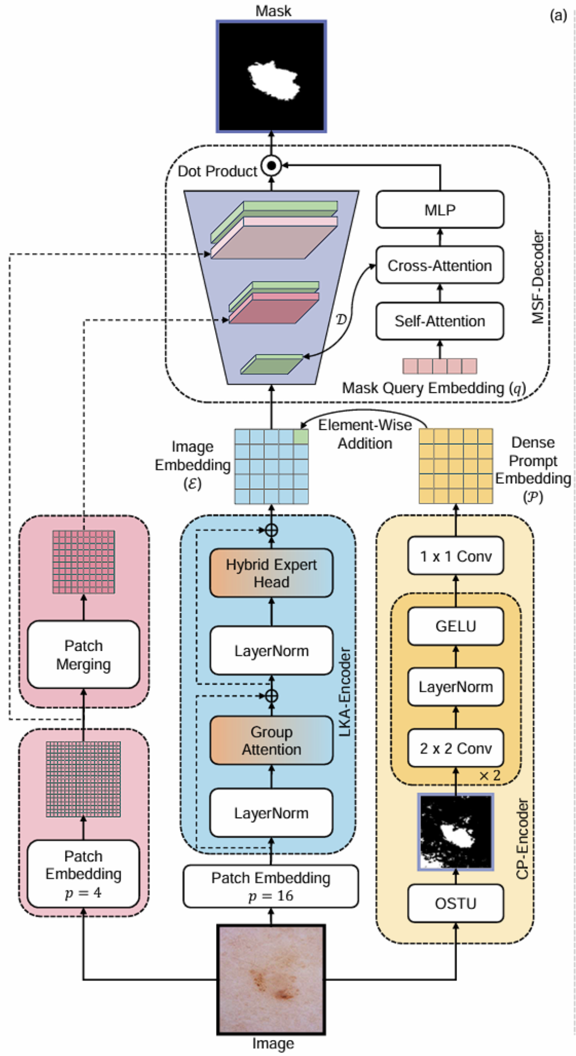
MSF-Decoder

Unlike SAM, which uses large patches and may overlook fine details, our MSF-Decoder integrates information at multiple scales to capture critical boundaries and details in medical images.



Med-FastSAM: Performance

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Table 1: Comparison with state-of-the-arts on two *source* domains.

Methods	Manual Prompt	Tuned/ Total (M)	ISIC-2018		MoNuSeg-2018	
			mIoU(%)	Dice(%)	mIoU(%)	Dice(%)
U-Net [24]	✘	13.40/13.40	74.66	83.26	60.12	74.53
ACC-UNet [10]	✘	16.68/16.68	75.89	84.72	64.06	77.76
nnU-Net [11]	✘	30.60/30.60	78.21	86.43	67.52	80.52
SAM [13]	Point	4.06/93.74	76.41	85.34	66.66	79.93
SAMMI [9]	Point	4.06/93.74	78.35	86.47	67.23	80.32
MedSAM [20]	Point	4.06/93.74	76.93	85.61	62.23	76.32
Med-SA [28]	Point	7.10/100.84	79.02	86.97	68.53	81.26
SAMed [33]	Point	4.21/93.88	78.98	86.93	68.00	80.88
MobileSAM [32]	Point	10.13/10.13	78.46	86.65	66.28	79.64
EfficientSAM [30]	Point	25.38/25.38	76.87	85.53	67.80	80.72
RepViT-SAM [27]	Point	9.98/9.98	77.01	85.72	64.40	78.29
Med-FastSAM	✘	8.62/14.48	**80.38**	**87.84**	**69.35**	**81.75**

Table 2: Comparison with state-of-the-arts on two *target* domains.

Methods	Manual Prompt	ISIC-2018 ⇒ PH2		MoNuSeg-2018 ⇒ TNBC	
		mIoU(%)	Dice(%)	mIoU(%)	Dice(%)
U-Net [24]	✘	77.56	86.70	36.19	50.02
ACC-UNet [10]	✘	78.12	86.99	39.34	52.43
nnU-Net [11]	✘	79.51	88.03	41.72	53.81
SAM [13]	Point	81.65	89.16	45.34	59.76
SAMMI [9]	Point	81.93	89.29	46.16	60.84
MedSAM [20]	Point	81.27	88.94	43.55	56.98
Med-SA [28]	Point	82.71	90.32	46.65	60.92
SAMed [33]	Point	82.54	90.10	46.28	60.73
MobileSAM [32]	Point	81.36	89.01	45.17	59.53
EfficientSAM [30]	Point	80.29	88.59	45.91	60.25
RepViT-SAM [27]	Point	81.15	88.87	44.93	59.31
Med-FastSAM	✘	**83.48**	**90.62**	**47.89**	**62.26**

We evaluated Med-FastSAM on benchmark datasets like ISIC-2018 for skin lesion segmentation and MoNuSeg for nuclei segmentation. Results show that Med-FastSAM outperforms other models without any manual prompts

Ablation Study

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Table 3: Ablation study of Med-FastSAM on the MoNuSeg dataset.

LKA-Encoder		CP-Encoder	MSF-Decoder	mIoU(%)	Dice(%)	Param(M)	FPS
HEH	GA						
				48.36	64.92	93.74	4.53
✓				52.06	67.94	11.32	26.68
✓	✓			68.36	80.82	14.46	24.19
✓	✓	✓		68.68	81.26	14.47	24.09
✓	✓	✓	✓	69.53	81.53	14.48	21.18

Additionally, Med-FastSAM is highly efficient, using only 15.45% of the parameters of the original SAM model, which makes it feasible in clinical settings with limited resources.

In summary, Med-FastSAM is not only accurate but also efficient and adaptable, making it practical for real-world medical imaging tasks."

Conclusion

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We propose Med-FastSAM to enhance SAM’ s transfer efficiency for domain-generalized medical image segmentation. It integrates three key modules: LKA-Encoder for improved feature representation and reduced computational costs; CP-Encoder for fully automated segmentation by eliminating manual annotations; and MSF-Decoder for capturing fine-grained details with multi-scale features. Experiments show Med-FastSAM outperforms existing SAM models, demonstrating superior generalization on unseen domains. Future work will focus on optimizing Med-FastSAM for diverse medical imaging modalities.