

Towards Diverse Binary Segmentation via A Simple yet General Gated Network

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Abstract

In many binary segmentation tasks, most CNNs-based methods use a U-shape encoder-decoder network as their basic structure. They ignore two key problems when the encoder exchanges information with the decoder: one is the lack of interference control mechanism between them, the other is without considering the disparity of the contributions from different encoder levels. In this work, we propose a simple yet general gated network (GateNet) to tackle them all at once. With the help of multi-level gate units, the valuable context information from the encoder can be selectively transmitted to the decoder. In addition, we design a gated dual branch structure to build the cooperation among the features of different levels and improve the discrimination ability of the network. Furthermore, we introduce a “Fold” operation to improve the atrous convolution and form a novel folded atrous convolution, which can be flexibly embedded in ASPP or DenseA-SPP to accurately localize foreground objects of various scales. GateNet can be easily generalized to many binary segmentation tasks, including general and specific object segmentation and multi-modal segmentation. Without bells and whistles, our network consistently performs favorably against the state-of-the-art methods under **10** metrics on **33** datasets of **10** binary segmentation tasks.

Keywords: Binary Segmentation, Gated Network, Gated Dual Branch, Folded Atrous Convolution.

1 Introduction

Image segmentation is the process of dividing a digital image into segments that simplify and/or change the representation of the image to something more meaningful and easier to analyze. From the perspective of pixel-level classification, image segmentation can be specifically divided into binary segmentation, semantic segmentation,

instance segmentation and panoramic segmentation. Compared with the others, segmentation problems considered in binary segmentation are more pure and focused, that is, accurately distinguishing the foreground and background. As shown in Fig. 1, binary segmentation has a wide range of applications in military, industrial, medical, etc.

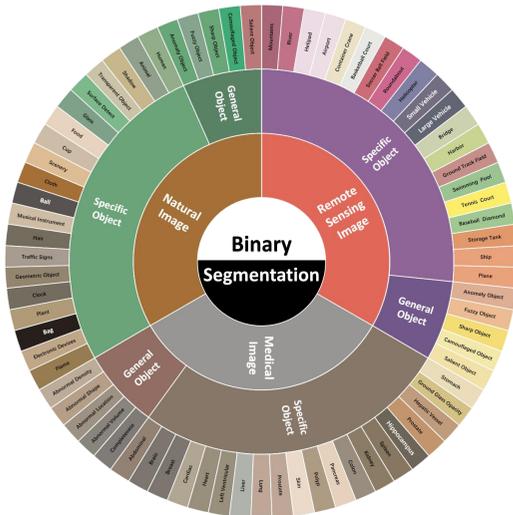


Fig. 1 Some meaningful binary segmentation tasks.

Rich foreground definitions prompt binary segmentation with numerous branches, such as salient object detection, camouflaged object detection, shadow detection and transparent object detection. In recent years, with the development of deep learning, there are many effective methods proposed and achieve good performance. Although each branch of binary segmentation is thriving and show a gratifying state, almost all methods focus on researching single one branch and ignore cross-branch comparison in experiments and techniques. As we know, each branch belongs to the binary segmentation trunk because they have a same mathematical definition. They face many same challenges in segmentation techniques. However, these task branches have become more and more independent, which will impede the development of the entire binary segmentation field. To this end, it is urgent to provide a general method for diverse binary segmentation branches.

There are three challenges in accurate binary segmentation: **Firstly**, most methods [41, 60, 113, 136, 146, 192, 212, 239, 248, 271] tend to adopt U-shape [110, 149] as the baseline and then combine multi-level features in either the encoder [146, 192, 212, 239, 248] or the decoder [60, 113, 212, 254, 285] to gradually reconstruct the high-resolution feature maps. In each convolutional block, they separately formulate the relationships of internal features during forward update. It is well known that the high-quality segmentation predicted in

the decoder relies heavily on the effective features provided by the encoder. Nevertheless, these methods directly use an all-pass skip-layer structure to concatenate the features of the encoder to the decoder in the isolated [41, 42, 116, 149, 239, 271] or nested [41, 136, 145, 259, 270, 285] manner. The effectiveness of feature aggregation at different levels is not quantified. This not only introduces misleading context information into the decoder but also causes that the typically useful features can not be adequately utilized. In cognitive science, Yang *et al.* [226] show that inhibitory neurons play an important role in how the human brain chooses to process the most important information from all the information presented to us. And inhibitory neurons ensure that humans respond appropriately to external stimuli by inhibiting other neurons and balancing excitatory neurons that stimulate neuronal activity. Inspired by this work, we think that it is necessary to set up an information screening unit between each pair of encoder and decoder blocks in binary prediction. It will help distinguish the most task-aware features of foreground regions and suppress background interference. **Secondly**, due to the limited receptive field, a single-scale convolutional kernel is difficult to capture context information of size-varying objects. This motivates many efforts [33, 44, 50, 75, 111, 115, 143, 237, 239] to investigate multi-scale feature extraction. These methods directly equip an atrous spatial pyramid pooling module [13] (ASPP) or DenseASPP [228] in their networks. However, when using a convolution with a large dilation rate, the information under the kernel seriously lacks correlation due to inserting too many zeros. This may be detrimental to the discrimination of subtle image structures. **Thirdly**, both body and boundary of the foreground need to accurately segmented. Most existing models either use progressive decoder [42, 87, 129, 131, 225, 263, 264, 270] or parallel decoder [33, 53, 75, 163, 173, 174, 213, 262]. The progressive structure begins with the top layer and gradually utilizes the output of the higher layer as prior knowledge to fuse the encoder features. This mechanism is not conducive to the recovery of details because the high-level features lack fine information. While the parallel structure easily results in inaccurate localization of objects since the low-level features without

semantic information directly interfere with the capture of global structure cues.

In this paper, we propose a simple yet general gated network (GateNet) for binary segmentation. Firstly, based on the feature pyramid network (FPN), we construct multi-level gate units to combine the features from the decoder and the encoder. We use convolution operation and nonlinear functions to calculate the correlations among features and assign gate values to different blocks. In this process, a partnership is established between different blocks by using weight distribution and the decoder can obtain more efficient information from the encoder and pay more attention to the target-aware regions. Secondly, we construct a folded atrous spatial pyramid pooling (Fold-ASPP) module to gather multi-scale high-level foreground cues. With the ‘‘Fold’’ operation, the atrous convolution is implemented on a group of local neighborhoods rather than a group of isolated sampling points, which can help generate more stable features and more adequately depict finer structure. Thirdly, we design a mix feature aggregation decoder that a parallel branch by concatenating the output of the progressive branch and the features of the gated encoder, so that the residual information complementary to the progressive branch is supplemented to generate the final prediction.

Our main contributions can be summarized as follows.

- We provide a unified perspective of binary segmentation by comprehensively analyzing many binary segmentation tasks.
 - We propose a simple gated network to adaptively control the amount of information that flows into the decoder from each encoder block. With multi-level gate units, the network can balance the contribution of each encoder block to the the decoder block and suppress the features of background regions.
 - We design a novel folded atrous convolution that can transfer existing multi-scale modules into our Fold style and enjoy more effective feature representation.
 - We build a dual branch architecture. They form a residual structure, complement each other through the gated processing and generate better results.
- We construct both single-stream and two-stream gated networks to adapt the binary segmentation required one or two input sources.
 - Extensive comparisons with 42 state-of-the-art methods on 33 challenging datasets of 10 binary segmentation tasks, including RGB, RGB-D and optical remote sensing image salient object detection, camouflaged object detection, defocus blur detection, shadow detection, transparent detection, glass detection, mirror detection and polyp segmentation in medical images, show that our method performs much better than other competitors under 10 metrics and possess strong generalization. Hence, it can be seen a strong baseline for the binary segmentation field.

Compared with the ECCV version [269] (Oral) of this work, the following extensions are made.

- I)** *We conduct a survey on the field of binary segmentation, covering 10 popular branches and 141 fully supervised methods, evaluation metrics and datasets.* **II)** *Deeper theoretical explanations of the proposed gate unit design are added and we improve the previous gate unit into a stronger version.* **III)** *Based on the overall structure of the original single-source input GateNet, we expand a two-stream version of GateNet suitable for two-source input tasks. Meanwhile, our multi-level gate units can further carry forward the spirit of suppress and balance between different sources.* **IV)** *We report much more extensive experimental results that demonstrate the superiority of both single-stream and dual-stream GateNet in 10 popular binary segmentation tasks.* **V)** *We further provide more implementation details and thorough ablation studies at qualitative and quantitative aspects.* **VI)** *We perform in-depth analyses and discussion for our gate unit.*

2 Retrospect

2.1 Diverse Binary Segmentation Tasks (DBS)

As shown in Fig. 1, there are many kinds of binary segmentation in real life. We select 10 currently well-developed and hot tasks that cover the requirements of general and specific object segmentation in natural images, remote sensing images, and medical images. According to the

rapid development of deep learning technology, we only review the research progress in recent five years in order to provide the latest and comprehensive content.

2.1.1 General Object Segmentation

- **RGB Salient Object Detection.** Salient object detection (SOD) aims to segment the most salient (judged by different consciousness) regions or objects in various scenes with or without the engineered cues, such as visual cues, geodesic cues, temporal cues, and human attention cues. Usually, it is adopted as a pre-processing step in many computer vision applications, such as scene classification [148], person re-identification [150] and image captioning [46].

- **RGB-D Salient Object Detection.** Although RGB SOD methods can achieve satisfactory performance in segmenting visually salient objects, some complex scenarios are still open to be resolved. For example, salient objects share similar appearance to the background or the other similar trivial objects. In recent years, various depth-assisted salient object detection (RGB-D SOD) methods [10, 143, 259] have been proposed, in which absorbing geodesic cues from the depth map is the hardcore.

- **Remote Sensing Image Salient Object Detection.** Remote sensing images (RSIs) are usually captured by sensors on an airplane as an aerial view under various viewing angle conditions. Although recent decades have witnessed the remarkable success of SOD for natural scene images, there is only a limited amount of researches focusing on SOD for optical remote sensing images (RSIs). Typically, optical RSIs cover a wide scope with complicated background and diverse noise interference.

- **Camouflaged Object Detection.** The study of camouflage has a long history in biology, and more details can be found in [162]. In the field of computer vision, research on camouflaged object detection (COD) is often associated with salient object detection task. In general, saliency models are designed for finding visually salient objects. They are not suitable for finding hidden objects. The local features of the camouflaged object are usually slightly different from the surrounding background. Recently, Fan *et al.* [41] make some attempts towards this direction. They first build

the largest COD dataset, which contains 10,000 images covering 78 camouflaged object categories.

2.1.2 Specific Object Segmentation

- **Defocus Blur Detection.** Defocus blur is a blurring degradation caused by defocusing and inappropriate depth of focus. Defocus blur is a common phenomenon in real life when the scene is beyond the focal distance of the camera. Defocus blur detection can be potentially used to many vision tasks (*e.g.*, autofocus, depth estimation).

- **Shadow Detection.** Shadow is the light effect caused by surface occlusion and are almost ubiquitous in our daily lives. On one hand, shadow can be used as auxiliary information due to rich depth and geometry visual cues. On the other hand, some important details of the object may be hidden when overlapping with shadows. Hence, shadow detection is important for shadow removal [65], scene geometry [81] and camera parameters [207].

- **Glass and Transparent Detection.** Transparent objects are widely present in the real world, such as glass, vitrines, and bottles. And most of them appear in indoor scenes, especially glass-like objects with brittle and smooth properties. Smart robot operates tasks in living rooms or offices, it needs to avoid fragile objects. Hence, it is essential for vision systems to be able to detect and segment transparent objects from input images.

- **Mirror Detection.** As a very important object in daily life, mirrors are ubiquitous. They can not only reflect light, but also present a similar mirror image of surrounding objects or scenes. As a result, once the computer vision system or robot encounters a scene with a mirror, the performance will drop significantly. To avoid this problem, it requires these systems to be able to detect and segment mirrors.

- **Polyp Detection.** According to GLOBOCAN 2020 data, colorectal cancer is the third most common cancer worldwide and the second most common cause of death. It usually begins as small, noncancerous (benign) clumps of cells called polyps that form on the inside of the colon. Over time some of these polyps can become colon cancers. Therefore, the best way of preventing colon cancer is to identify and remove polyps before they turn into cancer.

Table 1 Summary of essential characteristics for reviewed fully-supervised binary segmentation methods. The superscript “*” in the fifth column (code link) regards this repository does not provide pre-trained weights for re-evaluating performance publicly and “N/A” represents that the code is not available. **STL** is single task learning and **MTL** is multi-task learning.

No.	Year	Methods	Publication	Code Link	Backbone	Learning Paradigm	Training Dataset	#Training	
RGB Saliient Object Detection									
1	2018	R3Net[33]	IJCAI	Pytorch	ResNeXt-101 [219]	STL	MSRA10K [23]	10,000	
2		SFCN[247]	IJCAI	Caffe	VGG-16 [158]	STL	MSRA10K [23]	10,000	
3		BMPM[239]	CVPR	TensorFlow	VGG-16 [158]	STL	DUTS [188]	10,553	
4		PiCANet[114]	CVPR	Pytorch	ResNet-50 [59]/VGG-16 [158]	STL	DUTS [188]	10,553	
5		PAGRNet[254]	CVPR	N/A	VGG-19 [158]	STL	DUTS [188]	10,553	
6		DGRL[192]	CVPR	Caffe	ResNet-50 [59]	STL	DUTS [188]	10,553	
7		RAS[17]	ECCV	Pytorch	VGG-16 [158]	STL	MSRA-B [117]	2,500	
8	2019	DEF[293]	AAAI	N/A	ResNet-101 [59]/DenseNet-161 [68]/VGG-16 [158]	STL	DUTS [188]	10,553	
9		AFNet[49]	CVPR	Caffe	VGG-16 [158]	MTL	DUTS [188]	10,553	
10		BASNet[146]	CVPR	Pytorch	ResNet-34 [59]	STL	DUTS [188]	10,553	
11		CPD[212]	CVPR	Pytorch	ResNet-50 [59]/VGG-16 [158]	STL	DUTS [188]	10,553	
12		MLMSNet[208]	CVPR	Pytorch	VGG-16 [158]	STL	DUTS [188]	10,553	
13		CapSal[240]	CVPR	TensorFlow	ResNet-101 [59]	MTL	COCO-CapSal [240]/DUTS [188]	5,265/10,553	
14		PoolNet[111]	CVPR	Pytorch	ResNet-50 [59]/VGG-16 [158]	MTL/STL	BSD500 [4]+PASCAL VOC [37]+DUTS [188]/DUTS [188]	20,956/10,553	
15		PS[193]	CVPR	N/A	ResNet-50 [59]/VGG-16 [158]	STL	MSRA10K [23]	10,000	
16		PFA[262]	CVPR	TensorFlow*	VGG-16 [158]	STL	DUTS [188]	10,553	
17		SCRN[213]	ICCV	Pytorch	ResNet-50 [59]	MTL	DUTS [188]	10,553	
18		BANet[163]	ICCV	Caffe	ResNet-50 [59]/VGG-16 [158]	MTL	DUTS [188]	10,553	
19		HRSOD[232]	ICCV	Caffe	VGG-16 [158]	STL	HRSOD [232]+DUTS [188]/DUTS [188]	12,163/10,553	
20		EGNet[260]	ICCV	Pytorch	ResNet-50 [59]/VGG-16 [158]	MTL	DUTS [188]	10,553	
21		DUCRF[221]	ICCV	Caffe	VGG-16 [158]	STL	MSRA-B [117]	2,500	
22	TSPOANet[119]	ICCV	N/A	VGG-16 [158]	STL	DUTS [188]	10,553		
23	2020	PPFN[183]	AAAI	Pytorch	ResNet-101 [59]/VGG-16 [158]	STL	DUTS [188]	10,553	
24		GCPANet[119]	AAAI	Pytorch	ResNet-50 [59]	STL	DUTS [188]	10,553	
25		FBNet[202]	AAAI	Pytorch	ResNet-50 [59]	STL	DUTS [188]	10,553	
26		MSANet[284]	AAAI	N/A	VGG-16 [158]	STL	DUTS [188]	10,553	
27		MINet[136]	CVPR	Pytorch	ResNet-50 [59]/VGG-16 [158]	STL	DUTS [188]	10,553	
28		ITSD[278]	CVPR	Pytorch	ResNet-50 [59]/VGG-16 [158]	MTL	DUTS [188]	10,553	
29		LDF[203]	CVPR	Pytorch	ResNet-50 [59]	MTL	DUTS [188]	10,553	
30		CSNet[53]	ECCV	Pytorch	Res2Net-50 [52]/ResNet-50 [59]/CSNet [53]	STL	DUTS [188]	10,553	
31		GateNet[269]	ECCV	Pytorch	ResNeXt [219]/ResNet-101/ResNet-50 [59]/VGG-16 [158]	STL	DUTS [188]	10,553	
32		2021	PFS[126]	AAAI	N/A	ResNet-50 [59]	STL	DUTS [188]	10,553
33			KRN[220]	AAAI	Pytorch	ResNet-50 [59]	MTL	DUTS [188]	10,553
34	JSODCOD[91]		CVPR	Pytorch*	ResNet-50 [59]	MTL	COD10K [41]+CAMO [88]+DUTS [188]	14,593	
35	Auto-MSFNet[242]		ACM MM	Pytorch	ResNet-50 [59]/VGG-16 [158]	STL	DUTS [188]	10,553	
36	CTDNet[273]		ACM MM	Pytorch	ResNet-50/ResNet-18 [59]	MTL	DUTS [188]	10,553	
37	VST[116]		ICCV	Pytorch	T2T [231]	MTL	DUTS [188]	10,553	
38	HRRN[75]		ICCV	Pytorch	ResNet-50 [59]/VGG-16 [158]	MTL	HRSOD [232]+DUTS [188]/DUTS [188]	12,163/10,553	
39	INAS[54]		ICCV	Pytorch	NAS	STL	DUTS [188]	10,553	
40	SCA[159]		ICCV	Pytorch	ResNet-101 [59]	STL	SCAS [159]	5,534	
41	PoolNet+[112]		T-PAMI	N/A	ResNet-50 [59]/VGG-16 [158]/MobileNet-V2 [152]	STL	DUTS [188]	10,553	
42	CSNet[22]	T-PAMI	Pytorch	ResNet-50 [59]/Res2Net-50 [52]	STL	DUTS [188]	10,553		
43	EDN[211]	TIP	Pytorch	ResNet-50 [59]/VGG-16 [158]/MobileNet-V2 [152]	STL	DUTS [188]	10,553		
44	RCSBNet[83]	WACV	Pytorch	ResNet-50 [59]	MTL	DUTS [188]	10,553		
45	SHNet[253]	ECCV	N/A	ResNet-50 [59]/VGG-16 [158]	STL	DUTS [188]	10,553		
46	PGNet[215]	CVPR	Pytorch	ResNet-18 [59] + Swin-B [120]	MTL	DUTS [188]	10,553		
47	BBRF[127]	TIP	Pytorch*	Swin-T/B [120]	STL	DUTS [188]	10,553		
48	RMFormer[32]	ACM MM	Pytorch	Swin-B [120]	STL	DUTS [188]	10,553		
49	MENet[198]	CVPR	Pytorch	ResNet-50 [59]	MTL	DUTS [188]	10,553		
RGB-D Saliient Object Detection									
50	2018-2019	PDNet[286]	ICME	TensorFlow	VGG-16 [158]	STL	MSRA10K [23]+DUTS [188]+NJUD [80]+NLPR [141]	22,553	
51		PCA[10]	CVPR	N/A	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
52		AF[190]	Access	TensorFlow	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
53		cmSalGAN[77]	TMM	Pytorch	VGG-16 [158]	MTL	NJUD [80]+NLPR [141]	2,050	
54		MMCH[12]	PR	N/A	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
55		TAFNet[11]	TIP	N/A	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
56		DFP[259]	CVPR	Caffe	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
57		DMRA[143]	ICCV	Pytorch	VGG-19 [158]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985	
58		D3Net[43]	TNNLS	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,185	
59		ICNet[97]	TIP	Caffe	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
60		DisenFuse[9]	TIP	N/A	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
61		TDESDF[7]	TIP	N/A	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050	
62		DPANet[18]	TIP	Pytorch	ResNet-50 [59]	MTL	NJUD [80]+NLPR [141]	2,050	
63		JL-DCF[51]	CVPR	Caffe/Pytorch	ResNet-101 [59]/VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,200	
64	UCNet[237]	CVPR	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,200		
65	A2dele[144]	CVPR	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
66	SFF[243]	CVPR	Pytorch	VGG-16 [158]	MTL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
67	SZMA[115]	CVPR	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,050/2,850		
68	CoNet[75]	ECCV	Pytorch	ResNet-101 [59]	MTL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
69	CMWNet[98]	ECCV	Caffe	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050		
70	BBSNet[98]	ECCV	Pytorch	ResNet-50 [59]/VGG-19/VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050		
71	HDFNet[134]	ECCV	Pytorch	ResNet-50 [59]/VGG-19/VGG-16 [158]	STL	NJUD [80]+NLPR [141]/DUTLF-D [143]	2,185/800		
72	DANet[271]	ECCV	Pytorch	VGG-19/VGG-16 [158]	STL	NJUD [80]+NLPR [141]/DUTLF-D [143]	2,050/800		
73	PGAR[16]	ECCV	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,185/2,985		
74	CMMS[94]	ECCV	TensorFlow	VGG-16 [158]	MTL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
75	CAS-GNN[124]	ECCV	N/A	VGG-16 [158]	STL	NJUD [80]+NLPR [141]	2,050		
76	ATSA[241]	ECCV	Pytorch	VGG-19 [158]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
77	DASNet[261]	ACM MM	Pytorch*	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]	2,200		
78	FRDT[246]	ACM MM	Pytorch	VGG-19 [158]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
79	MMNet[106]	ACM MM	Pytorch	Res2Net-50 [52]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
80	HAINet[95]	TIP	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,050/2,850		
81	CDNet[79]	TIP	Pytorch	VGG-16 [158]	MTL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,050/2,850		
82	UTA[272]	TIP	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]	2,200		
83	DSNet[204]	TIP	Pytorch	ResNet-50 [59]	MTL	NJUD [80]+NLPR [141]	2,185		
84	RD3D[15]	AAAI	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,185/2,985		
85	DSA2F[165]	CVPR	Pytorch*	VGG-19 [158]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
86	DCF[74]	CVPR	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
87	CMINet[238]	ICCV	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,185/2,985		
88	SPNet[280]	ICCV	Pytorch	Res2Net-50 [52]	STL	NJUD [80]+NLPR [141]	2,185		
89	DFM-Net[252]	ACM MM	Pytorch	ResNet-34 [59]/MobileNet-v2 [152]	STL	NJUD [80]+NLPR [141]	2,200		
90	TriTransNet[121]	ACM MM	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,185/2,985		
91	CDINet[235]	ACM MM	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
92	DCMP[184]	TIP	N/A	VGG-16 [158]	STL	NJUD [80]+NLPR [141]/DUTLF-D [143]	2,185/800		
93	MAD[161]	TIP	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]	2,185		
94	CIR-Net[27]	TIP	Pytorch	ResNet-50 [59]/VGG-16 [158]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
95	DIGR-Net[24]	TMM	Pytorch	ResNet-50 [59]/VGG-16 [158]	MTL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
96	C2DFNet[245]	TMM	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]+DUTLF-D [143]	2,985		
97	MobileSal[210]	T-PAMI	Pytorch	MobileNet-v2 [152]	STL	NJUD [80]+NLPR [141]/DUTLF-D [143]	2,185/800		
98	DCBF[101]	ICCV	Pytorch	ResNet-50 [59]	MTL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,185/2,985		
99	MVSALNet[279]	ECCV	Pytorch	ResNet-50 [59]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,185/2,985		
100	SPSN[90]	ECCV	Pytorch	VGG-16 [158]	STL	NJUD [80]+NLPR [141]/NJUD [80]+NLPR [141]+DUTLF-D [143]	2,185/2,985		
101	HRTransNet[170]	TCSTP	Pytorch	ResNet-18 [59]	STL	NJUD [80]+NLPR [141] + DUTLF-D [143]	2,985		
102	CAVER[137]	TIP	Pytorch	ResNet-50/101 [59]	STL	NJUD [80]+NLPR [141] + DUTLF-D [143]	2,985		
103	PopNet[214]	ICCV	Pytorch	ResNet-18 [59]	MTL	NJUD [80]+NLPR [141] + DUTLF-D [143]	2,985		
104	CATNet[164]	TMM	Pytorch	Swin-B [120]	MTL	NJUD [80]+NLPR [141] + DUTLF-D [143]	2,985		

No.	Year	Methods	Publication	Code Link	Backbone	Learning Paradigm	Training Dataset	# Training	
Salient Object Detection in Optical Remote Sensing Images									
105	2019-2023	LV-Net ^[93]	TGRS	N/A	N/A	STL	ORSSD ^[93]	600	
106		DAFNet ^[249]	TIP	Pytorch*	VGG-16 ^[158]	MTL	ORSSD ^[93] /EORSSD ^[249]	600/1,400	
107		PDF-Net ^[92]	NC	N/A	VGG-16 ^[158]	STL	ORSSD ^[93]	600	
108		MFI-Net ^[283]	TGRS	N/A	ResNet-34 ^[59] /VGG-16 ^[158]	MTL	ORSSD ^[93] /EORSSD ^[249]	600/1,400	
109		RRNet ^[29]	TGRS	Pytorch	Res2Net-50 ^[52]	STL	ORSSD ^[93] /EORSSD ^[249]	600/1,400	
110		GGRNet ^[118]	PRCV	N/A	ResNet-50 ^[59]	STL	ORSSD ^[93] /EORSSD ^[249]	600/1,400	
111		MJRBNet ^[178]	TGRS	Pytorch	ResNet-50 ^[59] /VGG-16 ^[158]	STL	ORSSD ^[93] /EORSSD ^[249] /ORSI-4199 ^[178]	600/1,400/2,000	
112		CorrNet ^[99]	TGRS	Pytorch	VGG-16 ^[158]	STL	ORSSD ^[93] /EORSSD ^[249]	600/1,400	
113		MICNet ^[96]	TGRS	Pytorch	VGG-16 ^[158]	STL	ORSSD ^[93] /EORSSD ^[249]	600/1,400	
114		HFAcNet ^[191]	TGRS	N/A	ResNet-50 ^[59] /VGG-16 ^[158]	STL	ORSSD ^[93] /EORSSD ^[249] /ORSI-4199 ^[178]	600/1,400/2,000	
115		CIFNet ^[274]	GRSL	Pytorch	Res2Net-50 ^[52]	MTL	ORSSD ^[93] /EORSSD ^[249]	600/1,400	
116	BAFS-Net ^[55]	TGRS	Pytorch	ResNet-50 ^[59]	STL	ORSSD ^[93] /EORSSD ^[249]	600/1,400		
Camouflaged Object Detection									
117	2020-2021	SINet ^[41]	CVPR	Pytorch	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040	
118		PFNet ^[130]	CVPR	Pytorch	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040	
119		Rank-Net ^[255]	CVPR	Pytorch	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040	
120		MGL ^[233]	CVPR	Pytorch	ResNet-50 ^[59]	MTL	COD10K ^[41] +CAMO ^[88]	4,040	
121		JSODCOD ^[220]	CVPR	Pytorch	ResNet-50 ^[59]	MTL	COD10K ^[41] +CAMO ^[88] +DUTS ^[188]	14,593	
122		UGTR ^[225]	ICCV	Pytorch	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040	
123		MirrorNet ^[222]	Access	N/A	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040	
124		TANet ^[147]	TCSVT	N/A	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040	
125		ERRNet ^[73]	PR	N/A	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040	
126		PreyNet ^[244]	ACM MM	Pytorch	ResNet-50 ^[59]	MTL	COD10K ^[41] +CAMO ^[88]	4,040	
127		BGNNet ^[166]	LJCAI	Pytorch	Res2Net-50 ^[52]	MTL	COD10K ^[41] +CAMO ^[88]	4,040	
128	SegMaR ^[77]	CVPR	Pytorch	ResNet-50 ^[59]	MTL	COD10K ^[41] +CAMO ^[88]	4,040		
129	FM ^[276]	CVPR	N/A	Res2Net-50 ^[52] /ResNet-50 ^[59]	MTL	COD10K ^[41] +CAMO ^[88]	4,040		
130	ZoomNet ^[135]	CVPR	Pytorch	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040		
131	SINet-v2 ^[40]	T-PAMI	Pytorch	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040		
132	FAPNet ^[281]	TIP	Pytorch	Res2Net-50 ^[52]	MTL	COD10K ^[41] +CAMO ^[88]	4,040		
133	FindNet ^[104]	TIP	N/A	ResNet-50 ^[59]	STL	COD10K ^[41] +CAMO ^[88]	4,040		
134	R-MGL-v2 ^[234]	TIP	Pytorch	ResNet-50 ^[59]	MTL	COD10K ^[41] +CAMO ^[88]	4,040		
135	FPNet ^[28]	ACM MM	N/A	PVT ^[195]	STL	COD10K ^[41] +CAMO ^[88]	4,040		
136	FSPNet ^[69]	CVPR	Pytorch	ViT-B ^[35]	STL	COD10K ^[41] +CAMO ^[88]	4,040		
137	FEDER ^[57]	CVPR	Pytorch	Res2Net-50 ^[52] /ResNet-50 ^[59]	MTL	COD10K ^[41] +CAMO ^[88]	4,040		
138	HitNet ^[63]	AAAI	N/A	PVT ^[195]	STL	COD10K ^[41] +CAMO ^[88]	4,040		
Defocus Blur Detection									
139	2018-2023	BTBNet ^[267]	CVPR	N/A	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
140		DeFusionNet ^[174]	CVPR	N/A	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
141		CENet ^[268]	CVPR	Caffe	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
142		R2MRF ^[173]	AAAI	N/A	DenseNet-161 ^[68] /VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
143		BR2Net ^[171]	TMM	N/A	ResNeXt ^[219] /VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
144		Depth-Distill ^[31]	ECCV	Pytorch	ResNeXt-101 ^[219] /VGG-19 ^[158]	MTL	CUHK ^[66] +DUT ^[267]	1,204	
145		IS2CNet ^[256]	TCSVT	Caffe	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
146		SG ^[264]	CVPR	Pytorch	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
147		DEnets ^[263]	TIP	Pytorch	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
148		APL ^[265]	ECCV	Pytorch	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
149		MA-GANet ^[78]	TIP	N/A	VGG-16 ^[158]	STL	CTCUG ^[172] +DUT ^[267]	1,204	
150		M2CS ^[102]	TIP	Pytorch	VGG-16 ^[158]	STL	CUHK ^[66] /DUT ^[267]	704/60	
151		MLDBD ^[266]	TMM	Pytorch	VGG-16 ^[158]	STL	CUHK ^[66] +DUT ^[267]	1,204	
Shadow Detection									
152		2018-2023	ST-CGAN ^[185]	CVPR	N/A	ResNeXt-101 ^[219]	MTL	ISTD ^[185] /SBU ^[182]	1,330/4,089
153			DSC ^[87]	CVPR	Caffe	VGG-16 ^[158]	STL	SBU ^[182]	4,089
154			ADNet ^[87]	ECCV	Pytorch	N/A	STL	SBU ^[182]	4,089
155	BDRAR ^[289]		ECCV	Pytorch	ResNeXt-101 ^[219]	STL	SBU ^[182]	4,089	
156	ARGAN ^[34]		ICCV	N/A	VGG-16 ^[158]	STL	ISTD ^[185] /SBU ^[182]	1,330/4,089	
157	DSdNet ^[275]		CVPR	Pytorch	ResNeXt-101 ^[219]	STL	ISTD ^[185] /SBU ^[182]	1,330/4,089	
158	AFFPN ^[84]		SPL	Pytorch	ResNeXt-101 ^[219]	STL	ISTD ^[185] /SBU ^[182]	1,330/4,089	
159	RCMPNet ^[107]		ACM MM	N/A	ResNet ^[59]	STL	SBU ^[182]	4,089	
160	MIB ^[290]		ICCV	N/A	EfficientNet-B3 ^[169] /ResNeXt-101 ^[219]	STL	ISTD ^[185] /SBU ^[182]	1,330/4,089	
161	FSDNet ^[66]		TIP	Pytorch	MobileNet-v2 ^[152]	STL	CUHK-Shadow ^[66]	7,350	
162	ECA ^[47]		ACM MM	N/A	ResNet-101 ^[50]	STL	ISTD ^[185] /SBU ^[182] /CUHK-Shadow ^[66]	1,330/4,089/7,350	
163	SILT ^[227]	ICCV	Pytorch	PVT-v2-B5 ^[196]	STL	ISTD ^[185] /SBU ^[182] /CUHK-Shadow ^[66]	1,330/4,089/7,350		
Transparent Object Detection									
164	2018-2023	TOM-Net ^[8]	CVPR	Torch	VGG-16 ^[158]	MTL	TOM-Net ^[8]	178,000	
165		TransLab ^[217]	ECCV	Pytorch	ResNet-50 ^[59]	MTL	Trans10K ^[217]	5,000	
166		Trans2Seg ^[218]	LJCAI	Pytorch	ResNet-50 ^[59]	STL	Trans10K-v2 ^[218]	5,000	
167		Transfusion ^[291]	ICCV	N/A	ResNet-50 ^[59]	MTL	Trans10K ^[217]	5,000	
Glass Object Detection									
168	2020-2023	GDNet ^[131]	CVPR	Pytorch	ResNeXt-101 ^[219]	STL	GDD ^[131]	2,980	
169		RCARP ^[108]	CVPR	N/A	ResNeXt-101 ^[219]	STL	GSD ^[108]	3,202	
170		EBLNet ^[58]	ICCV	Pytorch	ResNeXt-101 ^[219]	MTL	GDD ^[131]	2,980	
171		PGSNet ^[230]	TIP	N/A	ResNeXt-101 ^[219]	STL	GDD ^[131] /HSO ^[?]	2,980/3,070	
172		RFENet ^[45]	LJCAI	Pytorch	ResNeXt-101 ^[219]	MTL	GDD ^[131]	2,980	
Mirror Object Detection									
173	2019-2023	MirrorNet ^[229]	ICCV	Pytorch	ResNeXt-101 ^[219]	STL	MSD ^[229]	3,063	
174		PMD ^[109]	CVPR	Pytorch*	ResNeXt-101 ^[219]	MTL	MSD ^[229] /PMD ^[109]	3,063/5,095	
175		PDNet ^[129]	CVPR	Pytorch	ResNet-50 ^[59]	STL	RGBD-Mirror ^[129]	2,000	
176		LSA ^[56]	CVPR	Pytorch	ResNeXt-101 ^[219]	STL	MSD ^[229] /PMD ^[109]	3,063/5,095	
Polyp Segmentation (Medical Image)									
177	2020-2023	ACSNet ^[251]	MICCAI	Pytorch*	ResNet-34 ^[59]	STL	Kvasir-SEG ^[72] /EndoScene ^[180]	600/547	
178		PraNet ^[42]	MICCAI	Pytorch	Res2Net-50 ^[52]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
179		ResUNet++ ^[71]	JBHI	TensorFlow*	ResNet ^[59]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
180		TransFuse ^[255]	MICCAI	N/A	VIT ^[35] /DeiT ^[176] /Res2Net ^[52] /ResNet ^[59]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
181		MSNet ^[270]	MICCAI	Pytorch	Res2Net-50 ^[52]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
182		EMS-Net ^[189]	EMBC	N/A	Res2Net-50 ^[52]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
183		APRNet ^[154]	EMBC	N/A	ResNet-34 ^[59]	STL	Kvasir-SEG ^[72] /EndoScene ^[180]	600/547	
184		UACANet ^[85]	ACM MM	Pytorch	Res2Net-50 ^[52]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
185		SANet ^[201]	MICCAI	Pytorch	Res2Net-50 ^[52]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
186		LOD-Net ^[21]	MICCAI	Pytorch*	ResNet-101 ^[59]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
187		CCBANet ^[132]	MICCAI	Pytorch*	ResNet-34 ^[59]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
188		HRENet ^[153]	MICCAI	N/A	ResNet-34 ^[59]	MTL	Kvasir-SEG ^[72] /Kvasir ^[72] +CVC-ClinicDB ^[5]	600/1,450	
189		SCR-Net ^[206]	AAAI	N/A	N/A	STL	Kvasir-SEG ^[72]	700	
190		TRFR-Net ^[155]	MICCAI	N/A	ResNet-34 ^[59]	STL	Kvasir-SEG ^[72] /ETIS-Larib ^[157] /CVC-ClinicDB ^[5]	700/137/210	
191		LDNet ^[250]	MICCAI	Pytorch*	Res2Net-50 ^[52]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
192		BoxPolyp ^[200]	MICCAI	N/A	Res2Net-50 ^[52] + PVT ^[195]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
193		PPFormer ^[6]	MICCAI	N/A	VGG-16 ^[158] + CVT ^[205]	STL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
194		CFANet ^[282]	PR	Pytorch	Res2Net-50 ^[52]	MTL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	
195		EMS-Net ^[189]	JBHI	N/A	Res2Net-50 ^[52]	MTL	Kvasir ^[72] +CVC-ClinicDB ^[5]	1,450	

Table 2 Summary of essential characteristics for reviewed fully-supervised binary segmentation methods. The superscript “*” in the fifth column (code link) regards this repository does not provide pre-trained weights for re-evaluating performance publicly and “N/A” represents that the code is not available.

No.	Year	Methods	Publication	Code Link	Core Components	Framework Style	CRF	Deep Supervision	Targeted Loss				
RGB Salient Object Detection													
1	2018	R3Net	[33]	IJCAI	Pytorch	Recurrent residual refinement network; Residual refinement block Symmetrical fully convolutional network; Structural loss	Parallel	✓	✓				
2		SFCN	[247]	IJCAI	Caffe								
3		BMPM	[239]	CVPR	TensorFlow					Multi-scale context-aware feature extraction module; Gated bi-directional message passing module			
4		PiCANet	[114]	CVPR	Pytorch						Pixel-wise contextual attention network; Bidirectional LSTM		
5		PAGRN	[254]	CVPR	N/A							Progressive attention; Multi-path recurrent feedback	
6		DGRL	[192]	ECCV	Caffe					Localization-to-Refinement network; Recurrent localization network	Progressive	✓/X	✓
7		RAS	[17]	ECCV	Pytorch					Residual learning; Reverse attention	Progressive		
8	2019	DEF	[293]	AAAI	N/A	Deep embedding features; Recursive feature integration network; Guided filter refinement network	Progressive	✓	✓				
9		AFNet	[49]	CVPR	Caffe					Attentive feedback network; Boundary-enhanced loss	Progressive		
10		BASNet	[146]	CVPR	Pytorch	Boundary-aware network; Hybrid loss (pixel-level, patch-level and map-level)	Progressive	✓	✓				
11		CPD	[212]	CVPR	Pytorch					Cascaded partial decoder	Progressive		
12		MLMSNet	[208]	CVPR	Pytorch	Multi-task intertwined supervision; Mutual learning module	Progressive	✓	✓				
13		CapSal	[240]	CVPR	TensorFlow					Leverage caption source; New dataset	Progressive		
14		PoolNet	[111]	CVPR	Pytorch	Pooling-based modules; Edge detection branch	Progressive	✓	✓				
15		PS	[193]	CVPR	N/A					Iterative top-down and bottom-up inference network	Progressive		
16		PFA	[262]	CVPR	TensorFlow*	Pyramid feature attention (SA&CA); Edge preservation loss	Parallel	✓	✓				
17		SCRN	[213]	ICCV	Pytorch					Cross refinement unit; Edge-Aware models	Parallel		
18		BANet	[163]	ICCV	Caffe	Selectivity-invariance; Boundary-aware network; Integrated successive dilation module	Parallel	✓	✓				
19		HRSO	[232]	ICCV	Caffe					New dataset; Global&Local network; Attended patch sampling	Progressive		
20		EGNet	[260]	ICCV	Pytorch	Edge guidance network; Complementary information modeling	Progressive	✓	✓				
21		DUCRF	[221]	ICCV	Caffe	Deep unified CRF Saliency Model	Progressive						
22	TSPONet	[119]	ICCV	N/A	CapsulNet-based model; Explore the part-object relationships	Progressive	✓	✓					
23	PFPP	[183]	AAAI	Pytorch	Feature polishing module	Progressive							
24	GCPANet	[19]	AAAI	Pytorch	Feature interweaved aggregation; Self refinement; Head attention; Global context flow	Progressive	✓	✓					
25	F3Net	[202]	AAAI	Pytorch					Cross feature module; Cascaded feedback decode; Pixel position aware loss	Progressive			
26	MSANet	[284]	AAAI	N/A	Attention transfer learning; Multi-type self-attention;	Progressive	✓	✓					
27	MINet	[136]	CVPR	Pytorch	Aggregate interaction module; Self-interaction module; Consistency-enhanced loss	Progressive							
28	ITSD	[278]	CVPR	Pytorch	Lightweight interactive two-stream decoder (Saliency&Contour); Adaptive contour loss	Progressive	✓	✓					
29	LDF	[203]	CVPR	Pytorch					Body&Detail supervision; Iterative feature interaction network	Progressive			
30	CSNet	[53]	ECCV	Pytorch	A flexible convolutional module (gOConv); light-weighted SOD model (100K parameters)	Parallel	✓	✓					
31	GateNet	[269]	ECCV	Pytorch					Gate Unit; Folded atrous convolution; Dual branch architecture	Progressive&Parallel			
32	PSF	[129]	AAAI	N/A	Pyramid shrinking decoder; Adjacent fusion module; Scale-aware enrichment module	Progressive	✓	✓					
33	KFDNet	[290]	AAAI	Pytorch	Coarse locating module; Attention-based sampler; Fine segmenting module				Progressive				
34	JSODC	[91]	CVPR	Pytorch*	Adversarial learning; Similarity measure module; Data interaction strategy	Progressive	✓	✓					
35	Auto-MSFNet	[242]	ACM MM	Pytorch	NAS-based model; Progressive polishing loss	Progressive							
36	CTDN	[273]	ACM MM	Pytorch	Complementary trilateral decoder	Progressive	✓	✓					
37	VST	[116]	ICCV	Pytorch	Transformer-based model; New token upsampling method	Progressive							
38	HRRN	[175]	ICCV	Pytorch	Low-resolution saliency classification network; High-resolution refinement network	Progressive	✓	✓					
39	iNAS	[54]	ICCV	Pytorch	NAS-based network; Device-aware search scheme; Latency group sampling	Progressive							
40	SCA	[159]	ICCV	Pytorch	New dataset; Semantic scene context-aware framework	Progressive	✓	✓					
41	PoolNet	+ [112]	T-PAMI	N/A	Global guidance module; Feature aggregation module	Progressive							
42	CSNet	[22]	T-PAMI	Pytorch	Light-weight holistic model; Dynamic weight decay scheme	Parallel	✓	✓					
43	EDN	[211]	TIP	Pytorch	Extreme downsampling; Scale-correlated pyramid convolution	Progressive							
44	RCSBNet	[83]	WACV	Pytorch	Stage-wise feature extraction module; New loss functions	Progressive	✓	✓					
45	SHNet	[253]	ECCV	N/A	Saliency hierarchy modules; Hyper kernel generator; Transformer decoder	Progressive							
46	QFNet	[170]	CVPR	Pytorch	One-stage framework for HRSO and cross-modal grading module; New dataset	Progressive	✓	✓					
47	BBRF	[127]	TIP	Pytorch*	Bilateral extreme stripping encoder; Dynamic complementary attention module; Loop compensation strategy	Progressive							
48	RMFormer	[32]	ACM MM	Pytorch	New dataset; Recurrent multi-scale transformer	Progressive	✓	✓					
49	MENet	[198]	CVPR	Pytorch	Multiscale feature enhancement module; Iterative training strategy	Progressive							
RGB-D Salient Object Detection													
50	2018-2019	PDNet	[286]	ICME	TensorFlow	RGB-based prior-model; Independent depth encoder	Progressive	✓	✓				
51		PCA	[10]	CVPR	N/A	Multi-level cross-modal fusion; Complementarity-aware fusion module	Progressive						
52		AF	[190]	Access	TensorFlow	Switch map; Weighted RGB and Depth stream output	Progressive	✓	✓				
53		cmSalGAN	[77]	TMM	Pytorch	Cross-modality generative adversarial network	Progressive						
54		MMCI	[12]	PR	N/A	Multi-path multi-modal fusion; Global&Local cross-modal fusion	Progressive	✓	✓				
55		TANet	[11]	TIP	N/A	Three-stream multi-modal fusion; Cross-modal distillation; Channel-wise attention	Progressive						
56		CPFP	[259]	CVPR	Caffe	Contrast loss; Contrast prior; Fluid pyramid integration strategy	Progressive	✓	✓				
57	DMRA	[143]	ICCV	Pytorch	Depth refinement block; Depth-induced multi-scale weighting module; Recurrent attention	Progressive							
58	2020	D3Net	[43]	TNNLS	Pytorch	New dataset; Depth deblur unit	Progressive	✓	✓				
59		ICNet	[97]	TIP	Caffe	Information conversion module; Cross-modal depth-weighted combination block	Progressive						
60		DisenFuse	[9]	TIP	N/A	Disentangled cross-modal fusion	Progressive	✓	✓				
61		TDESDF	[7]	TIP	N/A	Two-stage network; Depth estimation; Deep selective saliency fusion network	Progressive						
62		DPANet	[18]	TIP	Pytorch	Depth potentiality perception; Gated multi-modality attention module	Progressive	✓	✓				
63		JL-DCF	[51]	CVPR	Caffe/Pytorch	Joint learning (JL) and cross-modality fusion (DCF)	Progressive						
64		UCNet	[237]	CVPR	Pytorch	Conditional probabilistic model; Saliency consensus; Depth correction network	Progressive	✓	✓				
65		Ad2ele	[144]	CVPR	Pytorch	Depth distiller; Lightweight architecture	Progressive						
66		SSF	[243]	CVPR	Pytorch	Complimentary interaction module; Compensation-aware loss	Progressive	✓	✓				
67		S2MA	[115]	CVPR	Pytorch	Self-Mutual Attention	Progressive						
68		CoNet	[75]	ECCV	Pytorch	Collaborative learning framework	Parallel	✓	✓				
69		CMWNet	[98]	ECCV	Caffe	Cross-modal weighting network; RGB-depth interaction modules	Progressive						
70		BBSNet	[98]	ECCV	Pytorch	Bifurcated backbone strategy; Depth-enhanced module	Progressive	✓	✓				
71		HDFNet	[134]	ECCV	Pytorch	Hierarchical dynamic filtering network; Hybrid enhanced loss	Progressive						
72	DANet	[271]	ECCV	Pytorch	Single stream network; Depth-enhanced dual attention; Pyramidally attended module	Progressive	✓	✓					
73	PGAR	[16]	ECCV	Pytorch	Lightweight depth stream; Alternate refinement strategy; Guided residual block	Progressive							
74	CMMS	[94]	ECCV	TensorFlow	Cross-modality feature modulation module; Adaptive feature selection module	Progressive	✓	✓					
75	CAS-G3N	[124]	ECCV	N/A	Graph-based reasoning module	Progressive							
76	ATSA	[241]	ECCV	Pytorch	Flow ladder module; Depth attention module	Progressive	✓	✓					
77	DASNet	[261]	ACM MM	Pytorch*	Channel-aware fusion model; Depth awareness module; Depth-aware error loss	Progressive							
78	FRDT	[246]	ACM MM	Pytorch	Interweave fusion module; Gated select fusion module; Adaptive fusion module	Progressive	✓	✓					
79	MMNet	[106]	ACM MM	Pytorch	Cross-modal multi-stage fusion; Bi-directional multi-scale decoder	Progressive							
80	2021	HAINet	[95]	TIP	Pytorch	Hierarchical alternate interaction module	Progressive	✓	✓				
81		CDNet	[79]	TIP	Pytorch	Depth estimation; Two-stage cross-modal fusion	Progressive						
82		UTA	[272]	TIP	Pytorch	Gated multi-scale predictor Channel-aware fusion model; Depth-aware error loss	Progressive	✓	✓				
83		DSNet	[204]	TIP	Pytorch	Dynamic selective module; Cross-modal context module	Progressive						
84		RD3D	[15]	AAAI	Pytorch	3D encoder-decoder; Rich back projection paths	Progressive	✓	✓				
85		DSA2F	[165]	CVPR	Pytorch*	NAS-based model; Depth-sensitive attention	Progressive						
86		DCF	[74]	CVPR	Pytorch	Cross reference module; Depth calibration	Progressive	✓	✓				
87		CMINet	[238]	ICCV	Pytorch	Multi-stage cascaded learning; Mutual information minimization regularizer; New dataset	Progressive						
88		SPNet	[289]	ICCV	Pytorch	Specificity-preserving network; Cross-enhanced integration module; Multi-modal feature aggregation module	Progressive	✓	✓				
89		DFM	[252]	ACM MM	Pytorch	Depth quality-inspired feature manipulation	Progressive						
90	TriTransNet	[121]	ACM MM	Pytorch	Triplet transformer embedding module; Spatial&Channel attention	Progressive	✓	✓					
91	CDNet	[235]	ACM MM	Pytorch	RGB-induced detail enhancement; Depth-induced semantic enhancement; Dense decoding reconstruction	Progressive							
92	DCMF	[184]	TIP	N/A	Cross-modality long-range context information gathering module; Relation-based feature refinement module	Progressive	✓	✓					
93	MAD	[161]	TIP	Pytorch	Modality-aware Decoder	Progressive							
94	CIR-Net	[27]	TIP	Pytorch	Progressive attention guided integration unit; Importance gated fusion unit; Refinement middleware structure	Progressive	✓	✓					
95	DIGR-Net	[24]	TMM	Pytorch	Interference degree mechanism; Cross-modality integration block; Mutually guided cross-level fusion module	Progressive							
96	C2DFNet	[245]	TMM	Pytorch	Model-specific dynamic enhanced module; Scene-aware dynamic fusion module	Progressive	✓	✓					
97	MobileSal	[210]	T-PAMI	Pytorch	Compact pyramid refinement module; Implicit depth restoration	Progressive							
98	DCBF	[101]	IJCV	Pytorch	Boundary-aware multimodal fusion module; New dataset	Progressive	✓	✓					
99	MVSsalNet	[279]	ECCV	Pytorch	Multi-view augmentation; Dynamic filtering module	Progressive							
100	SPSN	[90]	ECCV	Pytorch	Supersample prototype sampling; Reliance selection module	Progressive	✓	✓					
101	HRTTransNet	[170]	TCSVT	Pytorch	Coordinate-wise spatial position; Dual-direction short connection fusion module	Progressive							
102	CAVER	[137]	TIP	Pytorch	Transformer-based information propagation path; Intra-Modal/Cross-Scale self-attention; Inter-Modal cross-attention	Progressive	✓	✓					
103	PopNet	[214]	ICCV	Pytorch	Structure Preserving; Local depth smoothing; Depth edge sharpening	Progressive							
104	CATNet	[164]	TMM	Pytorch	Attention feature enhancement module; Cross-modalfusion module	Progressive	✓	✓					

No. Year	Methods	Publication	Code Link	Core Components	Framework Style	CRF	Deep Supervision	Targeted Loss
Salient Object Detection in Optical Remote Sensing Images								
105	LV-Net[93]	TGRS	N/A	New dataset; L-shaped module; V-shaped module	Progressive			
106	DAFNet[249]	TIP	Pytorch*	New dataset; Dense attention fluid; Global context-aware attention	Progressive		✓	✓
107	PDF-Net[92]	NC	N/A	parallel down-up fusion network; Dense connection	Progressive		✓	✓
108	MFI-Net[283]	TGRS	N/A	Multi-scale feature integration under the explicit and implicit assistance of salient edge cues	Progressive		✓	✓
109	RRNet[29]	TGRS	Pytorch	Parallel multi-scale attention; Relational reasoning module	Progressive		✓	✓
110	GGRNet[118]	PRCV	N/A	Global graph reasoning module	Progressive		✓	✓
111	MJRRM[178]	TGRS	Pytorch	New dataset; Multi-scale joint boundary and region model	Progressive		✓	✓
112	CorrNet[99]	TGRS	Pytorch	Lightweight model; Correlation module; Dense lightweight refinement block	Progressive		✓	✓
113	MCCNet[96]	TGRS	Pytorch	Multi-Content complementation module	Progressive		✓	✓
114	HFA-Net[191]	TGRS	N/A	Hybrid encoder; Gated Fold-ASPP; Adjacent feature aligned module	Progressive		✓	✓
115	CIFNet[274]	GISL	Pytorch	Furcate skip-connection module; Expansion-integration module; Global leading attention module	Progressive		✓	✓
116	BAFS-Net[55]	TGRS	Pytorch	Bidimensional attention modules; semantic-guided fusion modules	Progressive		✓	✓
Camouflaged Object Detection								
117	SINet[41]	CVPR	Pytorch	New dataset; Search and identification net	Progressive		✓	✓
118	PFNet[130]	CVPR	Pytorch	Distraction mining strategy; Positioning and focus network	Progressive		✓	✓
119	Rank-Net[125]	CVPR	Pytorch	Camouflaged object ranking/localization; New dataset; Triplet tasks learning model	Progressive		✓	✓
120	MGL[233]	CVPR	Pytorch	Mutual guidance knowledge; Graph-based interaction module	Progressive		✓	✓
121	JSODCOD[220]	CVPR	Pytorch	Adversarial learning; Similarity measure module; Data interaction strategy	Progressive		✓	✓
122	UGTR[225]	ICCV	Pytorch	Bayesian learning into Transformer-based reasoning; Uncertainty-guided transformer reasoning model	Progressive		✓	✓
123	MirrorNet[222]	Access	N/A	Object proposal; Bio-inspired attack stream	Progressive		✓	✓
124	TANet[147]	TCSVT	N/A	Texture-aware refinement module; Boundary-consistency loss	Progressive		✓	✓
125	ERRNet[73]	PR	N/A	Selective edge aggregation; Reversible re-calibration unit	Progressive		✓	✓
126	PreyNet[244]	ACM MM	Pytorch	Bidirectional bridging interaction module; Predator learning	Progressive		✓	✓
127	BGNet[166]	LICAI	Pytorch	Boundary-related edge semantics; Edge-guidance feature module; Context aggregation module	Progressive		✓	✓
128	SegMaR[76]	CVPR	Pytorch	Hex-refinement framework; Fixation and edge regions	Progressive		✓	✓
129	FMI[277]	CVPR	N/A	Frequency clues; Frequency enhancement module; High-order relation module	Progressive		✓	✓
130	ZoomNet[135]	CVPR	Pytorch	Mixed-scale semantics; Scale integration unit; Hierarchical mixed-scale unit; Uncertainty-aware loss	Progressive		✓	✓
131	SINet-v2[40]	T-PAMI	Pytorch	Texture enhanced module; Neighbor connection decoder; Group-reversal attention	Progressive		✓	✓
132	FAPNet[281]	TIP	Pytorch	Boundary guidance module; Multi-scale feature aggregation module; Cross-level fusion and propagation module	Progressive		✓	✓
133	FindNet[104]	TIP	N/A	Boundary enhancement module; Texture enhancement module	Progressive		✓	✓
134	R-MGL-V2[234]	TIP	Pytorch	Graph-based mutual learning; Multi-source attention contextual recovery module	Progressive		✓	✓
135	FPNet[28]	ACM MM	N/A	RGB and frequency domains; Fully frequency-perception module; Progressive refinement mechanism	Progressive		✓	✓
136	FSPNet[69]	CVPR	Pytorch	Non-local token enhancement module; Feature shrinkage decoder; Adjacent interaction module	Progressive		✓	✓
137	FEDER[57]	CVPR	Pytorch	Frequency attention module; Guidance-based feature aggregation module	Progressive		✓	✓
138	HicNet[63]	AAAI	Pytorch	Recursive operation; Iteration weight scheme	Progressive		✓	✓
Defocus Blur Detection								
139	BTBNet[267]	CVPR	N/A	New dataset; Fully convolutional; Multi-stream network	Progressive		✓	✓
140	DeFusionNet[174]	CVPR	N/A	Multi-scale deep features	Parallel		✓	✓
141	CENet[268]	CVPR	Caffe	Cross-ensemble network	Progressive		✓	✓
142	R2MRF[173]	AAAI	N/A	Residual refinement modules	Parallel		✓	✓
143	BR2Net[171]	TMM	N/A	New dataset; Residual learning and refining module	Progressive		✓	✓
144	Depth-Distill[31]	ICCV	Pytorch	Depth information; Depth Distillation; Selective reception fields block	Progressive		✓	✓
145	IS2CNet[256]	TCSVT	Caffe	Hierarchical feature integration and bi-directional delivering mechanism	Progressive		✓	✓
146	SG[264]	CVPR	Pytorch	New dataset; Dual adversarial discriminators; Unsupervised learning	Progressive		✓	✓
147	DENNets[263]	TIP	Pytorch	Deep ensemble networks; Self-negative correlation and error function	Progressive		✓	✓
148	APL[265]	ECCV	Pytorch	Joint learning of defocus detection and defocus deblurring; Adversarial promoting learning framework	Progressive		✓	✓
149	MA-GANet[78]	TIP	N/A	Generative adversarial training strategy	Parallel		✓	✓
150	MKSNet[102]	TIP	Pytorch	Global similarity discriminator; Local similarity discriminators	Progressive		✓	✓
151	MLDBD[266]	TMM	Pytorch	Isomeric distillation mechanism; New dataset	Progressive		✓	✓
Shadow Detection								
152	ST-CGAN [185]	CVPR	N/A	Shadow detection and shadow removal; Stacked conditional generative adversarial network; New dataset	Progressive		✓	✓
153	DSC [67]	CVPR	Caffe	Spatial recurrent neural network; Direction-aware spatial context	Progressive		✓	✓
154	ADNet [87]	ECCV	Pytorch	GAN-based framework; Shadow detection/kattenuation network	Progressive		✓	✓
155	BDRAR [289]	ECCV	Pytorch	Recurrent attention residual module; Bidirectional feature pyramid network	Progressive	✓	✓	✓
156	ARGAN [34]	ICCV	N/A	Attentive recurrent generative adversarial network	Progressive	✓	✓	✓
157	DSDNet [275]	CVPR	Pytorch	Distraction-aware shadow module	Progressive	✓	✓	✓
158	AFFPN[84]	SPL	Pytorch	Attentive feedback feature pyramid network	Progressive	✓	✓	✓
159	RCMPNet[107]	ACM MM	N/A	Relative confidence map prediction network	Progressive	✓	✓	✓
160	MB[290]	ICCV	N/A	Feature decomposition and reweighting; Self-supervised	Progressive	✓	✓	✓
161	FSDNet[66]	TIP	Pytorch	New dataset; Detail enhancement module	Progressive		✓	✓
162	ECA[47]	ACM MM	N/A	Effective-Context augmentation	Progressive		✓	✓
163	SILT[227]	ICCV	Pytorch	Global-local fusion; Shadow-aware filter	Progressive		✓	✓
Transparent Object Detection								
164	TOM-Net [8]	CVPR	Torch	The first CNN-based model for transparent object detection; New dataset	Progressive		✓	✓
165	TransLab [217]	ECCV	Pytorch	New dataset; Boundary attention module	Progressive		✓	✓
166	Trans2Seg [218]	LICAI	Pytorch	New dataset; Transformer-based network	Progressive		✓	✓
167	Transfusion [291]	ICCV	N/A	New dataset; RGB-D SLAM approach	Progressive		✓	✓
Glass Object Detection								
168	GDNet [131]	CVPR	Pytorch	New dataset; Large-field contextual feature integration module	Progressive		✓	✓
169	RCARP [108]	CVPR	N/A	New dataset; Rich context aggregation module; Reflection-based refinement module	Progressive	✓	✓	✓
170	EBLNet [58]	ICCV	Pytorch	Refined differential module; Point-based graph convolution network	Progressive		✓	✓
171	PGSNet[230]	TIP	N/A	Discriminability enhancement module; Focus-and-exploration based fusion module; New dataset	Progressive		✓	✓
172	RFENet[45]	LICAI	Pytorch	Selective multi evolution module; Structurally attentive refinement	Progressive		✓	✓
Mirror Object Detection								
173	MirrorNet [229]	ICCV	Pytorch	New dataset; Contextual contrasted feature extraction module	Progressive	✓	✓	✓
174	PMD [109]	CVPR	Pytorch*	New dataset; Relational contextual contrasted local module; Edge detection and fusion module	Progressive	✓	✓	✓
175	PDNet [129]	CVPR	Pytorch	New dataset; Depth information; Dynamic weighting scheme	Progressive		✓	✓
176	LSA[56]	CVPR	Pytorch	Associations exploration module; Quadruple-Graph module	Progressive		✓	✓
Polyp Segmentation (Medical Image)								
177	ACSNNet[251]	MICCAI	Pytorch*	Local context attention; Global context Module; Adaptive selection module	Progressive		✓	✓
178	FraNet[42]	MICCAI	Pytorch	Parallel partial decoder; Recurrent reverse attention	Progressive		✓	✓
179	ResU-Net+ [71]	JBIH	TensorFlow*	Parallel partial decoder; Recurrent reverse attention	Progressive	✓	✓	✓
180	TransFuse[255]	MICCAI	N/A	combines Transformers and CNNs in a parallel style; BiFusion module	Progressive		✓	✓
181	MSNet[270]	MICCAI	Pytorch	Multi-scale subtraction module; LossNet	Progressive		✓	✓
182	EMS-Net[189]	EMBC	N/A	Receptive field block; Local context attention	Progressive		✓	✓
183	APRNet[154]	EMBC	N/A	Alternative prediction refinement network; Prediction residual refinement modules	Progressive		✓	✓
184	UACANet[85]	ACM MM	Pytorch	Parallel axial attention; Uncertainty augmented context attention	Progressive		✓	✓
185	SANet[201]	MICCAI	Pytorch	Shallow attention; Color exchange operation; Probability correction strategy	Progressive		✓	✓
186	LOD-Net[21]	MICCAI	Pytorch*	Oriented-derivatives feature	Progressive		✓	✓
187	CCBANet[132]	MICCAI	Pytorch*	Cascading Context module; Attention balance module	Progressive		✓	✓
188	HRENNet[153]	MICCAI	N/A	Context enhancement module; Adaptive feature aggregation module; Structure consistency aware loss	Progressive		✓	✓
189	SCR-Net[206]	AAAI	N/A	Semantic calibration module; Semantic refinement module	Progressive		✓	✓
190	TRFR-Net[155]	MICCAI	N/A	Domain-invariant feature decomposition module; Task-relevant feature replenishment module; Polyp-aware adversarial learning module	Progressive		✓	✓
191	LDNet[250]	MICCAI	Pytorch*	Dynamic kernel generation and updating scheme; Lesion-aware cross-attention module; Efficient self-attention module	Progressive		✓	✓
192	BoxPolyp[200]	MICCAI	N/A	Consistency loss; Fusion filter sampling module	Progressive		✓	✓
193	PPFormer[6]	MICCAI	N/A	PP-guided self-attention; Local-to-Global mechanism	Progressive		✓	✓
194	CFANet[282]	PR	Pytorch	Cross-level feature fusion module; Boundary aggregated module	Parallel		✓	✓
195	EMS-Net[189]	JBIH	N/A	Random multi-scale training strategy; Offline dynamic class activation mapping	Progressive		✓	✓

2.2 Fully Supervised Binary Segmentation Models

We first formulate the image-based binary segmentation problem. Formally, let \mathcal{X} and \mathcal{Y} denote the input space and output segmentation space, respectively. Fully supervised learning-based models generally seek to learn an *ideal* image-to-segment mapping $f^* : \mathcal{X} \mapsto \mathcal{Y}$ through directly utilizing ground truth masks as supervision signal.

In Tab. 1 and Tab. 2, we categorize recent fully supervised models. Through the analyses of 141 methods in 10 branches, we summarize some instructive findings: **I)** Single task learning (STL) is still the main learning paradigm in binary segmentation. Compared with STL, the proportion of MTL-based methods is only 34/141 and they finish MTL via cooperating with boundary prediction or depth estimation usually. It is worth noting that MTL-based RGB SOD methods have reached the 6/9 scale in 2021. We believe that the potential of MTL is huge, and more effective and richer strategies will emerge in the future under the continuous efforts of researchers. **II)** Our GateNet is the only one mixes both progress and parallel structures among 141 methods, thereby enjoying the advantages of both. Most methods still adopt the single progressive style. **III)** Conditional random field (CRF) gradually disappear in many models. Only some shadow and mirror detection methods adopt the CRF as post-processing. **IV)** Deep supervision becomes a popular supervision approach. 73/141 methods build the network with side outs to perform deep supervision. On one hand, deep supervision [89] is originally designed to speed up network convergence. On the other hand, it may bring extra performance gain for most models. **V)** Targeted loss function is conducive to performance improvement. 72/141 models directly adopt previous or re-design a new targeted loss, such as the hybrid loss [146], consistency-enhanced loss [136], pixel position aware loss [202], etc. It is clear that there is increasing competition in the research of targeted loss.

2.3 Multi-scale Feature Extraction

The multi-scale paradigm is mainly inspired by the scale-space theory that has been widely validated as an effective and theoretically sound

framework. It is well suited for addressing naturally occurring scale variations. Common forms in the field of computer vision mainly include the image pyramid [2] and the feature pyramid [110, 149]. Although the former has shown good performance, its application is limited by high computational and latency costs associated with the multi-input parallel processing paradigm, which makes it gradually give way to the more efficient latter in the era of deep learning. The feature pyramid can be roughly divided into two categories according to the form, namely, the inter-layer pyramid and the intra-layer pyramid. The former is based on features with different scales extracted by the feature encoder, such as the U-shape [110, 136, 140, 145, 149, 254] architecture. In this way, the internal cross-layer information propagation path progressively integrates semantic context and texture details from diverse scale representations. The intra-layer pyramid [13, 228, 239, 257, 271] can enhance the diversity of semantic content by constructing the multi-path structure within a layer to obtain a rich combination of receptive fields. Its good pluggability has also made it an important component in the architecture design of modern segmentation methods. Recently, the atrous spatial pyramid pooling module (ASPP) [13] and its variants [138, 151, 168, 199, 209, 228, 271, 294], which typify this structure, are widely applied in many segmentation tasks and networks. Some methods [84, 108, 130, 237, 239, 289] insert several ASPP modules into the encoder/decoder blocks of different levels, while some ones [33, 49, 58, 75, 125, 143] install it on the highest-level encoder block. As a basic component of ASPP, atrous convolution has the advantage of enlarging the receptive field to obtain large-scale features without increasing the computational cost compared to the vanilla convolution. Nevertheless, the repeated stride and pooling operations already make the top-layer features lose much fine information. With the increase of atrous rate, the correlation of sampling points further degrades, which leads to difficulties in capturing the changes of image details (*e.g.*, lathy background regions between adjacent objects or spindly parts of objects). In this work, we propose a folded atrous convolution to alleviate these issues and achieve a *local-in-local* effect. The folded atrous convolution can seamlessly replace the original atrous convolution in ASPP and other

variants (*e.g.*, DenseASPP [228], PAFE [271]), thus significantly improving performance.

2.4 Gated Mechanisms

The gated mechanism plays an important role in controlling the flow of information and is widely used in the long short term memory (LSTM). In [3], the gate unit combines two consecutive feature maps of different resolutions from the encoder to generate rich contextual information. And the gated mechanism is also integrated into the block feedback mechanism to bridge multiple iterations in the recurrent architecture [82]. Zhang *et al.* [239] adopt gate function to control the message passing when combining feature maps at all levels of the encoder. Chen *et al.* [18] propose a gate function controller to focus on regulating the fusion rate of the cross-modal information. Zhang *et al.* [246] utilize the gated select fusion module to selectively process the useful information from two modal features in low-levels. Due to the ability to filter information, the gated mechanism can also be seen as a special kind of attention mechanism. Wang *et al.* [194] exploit the pyramid attention module to enhance saliency representations for each layer in the encoder and enlarge the receptive field. Chen *et al.* [19] propose a head attention module to reduce information redundancy and enhance the top layers features by leveraging both spatial and channel-wise attention. Zhang *et al.* [254] apply both spatial and channel attention to each layer of the decoder. Liu *et al.* [115] construct both self-attention and mutual-attention in a non-local [197] style for extracting the complementary information between the different modalities. Zhu *et al.* [289] design the recurrent attention residual module to combine and process spatial contexts in two adjacent CNN layers. Zhang *et al.* [251] apply both the local context attention and SE-like [62] channel-wise attention for context selection. Taehun *et al.* [85] propose the uncertainty augmented context attention module to incorporate uncertain area for rich semantic feature extraction. More description about attention-based methods can be found in Tab. 2. In general, the above methods unilaterally consider the information interaction between different layers or intra-layer in the encoder or decoder. We integrate the features from the encoder and the decoder to formulate gate

function, which has the function of **block-wise attention** and models the overall distribution of all blocks in the network from the global perspective. However, while previous methods utilize the block-specific features to compute dense attention weights for the corresponding block, they directly feed the encoder features into the decoder and do not consider their mutual interference. Our proposed gate unit can naturally balance their contributions, thereby suppressing the response of the encoder to background regions. Experimental results in Fig. 8 and Fig. 9 intuitively demonstrate the effect of multi-level gate units on the above two aspects, respectively.

3 Proposed Method

The gated network architecture is shown in Fig. 2, in which encoder blocks, transition layers, decoder blocks and gate units are denoted as \mathbf{E}^i , \mathbf{T}^i , \mathbf{D}^i and \mathbf{G}^i , respectively ($i \in \{1, 2, 3, 4, 5\}$ indexes different levels). Their output feature maps are denoted as E^i , T^i , D^i and G^i , respectively. The final prediction is obtained by combining the FPN branch and the parallel branch.

3.1 Network Overview

Encoder Network. In our model, the encoder is based on a common pretrained backbone network, *e.g.*, the VGG [158], ResNet [59] or ResNeXt [219]. We take the VGG-16 network as an example, which contains thirteen Conv layers, five max-pooling layers and two fully connected layers. In order to fit saliency detection task, similar to most previous approaches [60, 239, 248, 254], we cast away all the fully-connected layers of the VGG-16 and remove the last pooling layer to retain details of last convolutional layer.

Decoder Network. The decoder comprises three main components: i) the FPN branch, which continually fuses different level features from $T^1 \sim T^5$ by element-wise addition; ii) the parallel branch, which combines the saliency map of the FPN branch and the feature maps of transition layers by cross-channel concatenation (At the same time, multi-level gate units ($\mathbf{G}^1 \sim \mathbf{G}^5$) are inserted between the transition layer and the decoder layer); iii) the Fold-ASPP module, which improves the original atrous spatial pyramid pooling (ASPP) by using a “Fold” operation. It can

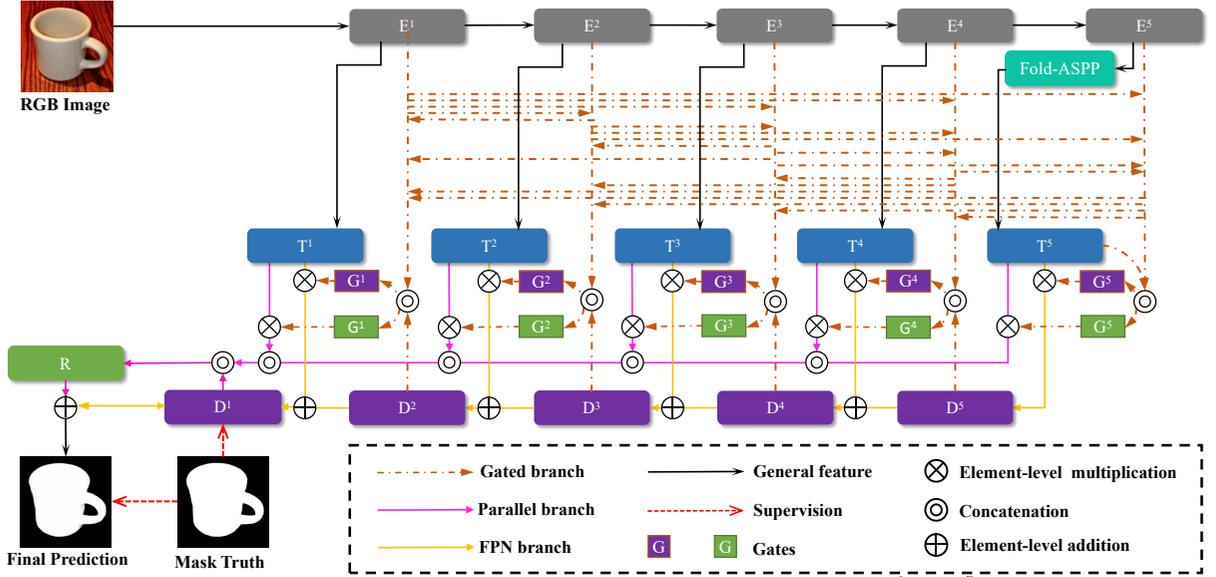


Fig. 2 Overall architecture of the gated network. It consists of five encoder blocks ($E^1 \sim E^5$), five transition layers ($T^1 \sim T^5$), five gate units ($G^1 \sim G^5$), five decoder blocks ($D^1 \sim D^5$) and the Fold-ASPP module. We employ twice supervision in this network. One acts at the end of the FPN branch D^1 . The other is used to guide the fusion of the two branches.

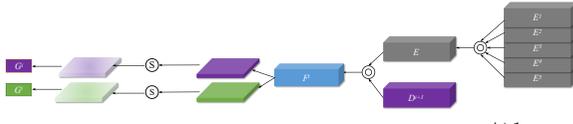


Fig. 3 Detailed illustration of the gate unit. D^{i+1} indicates feature maps of the previous decoder block. S is sigmoid function.

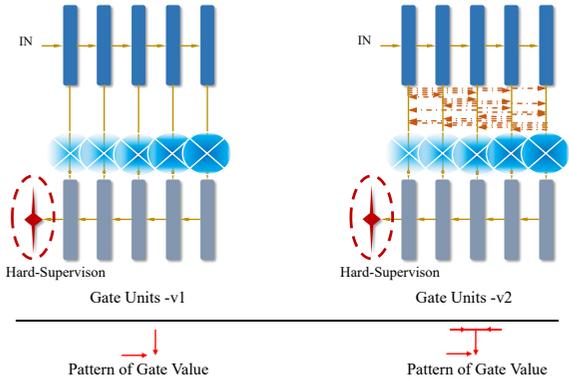


Fig. 4 Architecture comparison between the Gated FPN with gate units-v1 and gate units-v2.

take advantage of semantic features learned from E^5 to provide multi-scale information to the decoder.

3.2 Gated Dual Branch

The gate unit can control the message passing between scale-matching encoder and decoder blocks. By combining the feature maps of the previous decoder block, the gate value also characterizes the contribution that the current block of the encoder can provide. Fig. 3 shows the internal structure of the proposed gate unit. In particular, the aggregated encoder feature E and decoder feature D^{i+1} are integrated to obtain feature F^i , and then the output is fed into two branches, which includes a series of convolution, activation and pooling operations, to compute a pair of gate values G^i . The entire gated process can be formulated as,

$$E = \text{Conv}(\text{Cat}(E^1, E^2, E^3, E^4, E^5)), \quad (1)$$

$$G^i = \begin{cases} P(S(\text{Conv}(\text{Cat}(E, D^{i+1})))) & \text{if } i = 1, 2, 3, 4 \\ P(S(\text{Conv}(\text{Cat}(E, T^i)))) & \text{if } i = 5 \end{cases} \quad (2)$$

where $\text{Cat}(\cdot)$ is the concatenation operation among channel axis, $\text{Conv}(\cdot)$ is the convolution layer, $S(\cdot)$ is the element-wise sigmoid function, and $P(\cdot)$ is the global average pooling. The output channel of $\text{Conv}(\cdot)$ in Eq. 2 is 2. The resulted gate vector G^i has two different elements which correspond to two gate values in Fig. 3. Given the gate

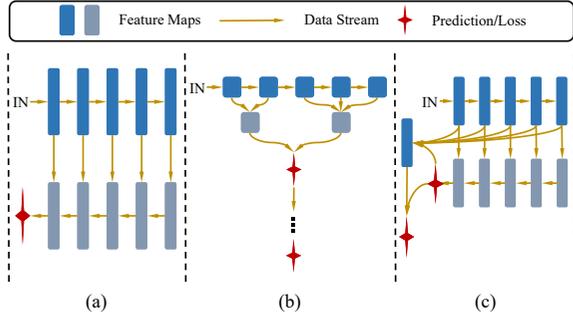


Fig. 5 Illustration of different decoder architectures. (a) Progressive structure. (b) Parallel structure. (c) Dual branch structure.

values, we can apply them to the FPN branch and the parallel branch to weight the transition-layer features $T^1 \sim T^5$, which are generated by exploiting 3×3 convolution to reduce the dimension of $E^1 \sim E^4$ and the Fold-ASPP to finely process E^5 (See Fig. 2 for details). Through multi-level gate units, we can suppress and balance the information flowing from different encoder blocks to the decoder.

Compared to the ECCV version [269] of Gate Units-v1, we modify the input feature maps of the current encoder block E^i to the all-level aggregated feature maps E . As shown in Fig. 4, the Gated FPN with Gate Units-v2 enjoys bidirectional soft supervision, which motivates the gating values of each layer to consider their corresponding contributions from a global perspective, rather than the local perspective in Gate Unit-v1. In this way, the cooperation among the various layers is closer, thereby, making the optimization of the network more efficient.

Generally, binary segmentation methods usually adopt the progressive or parallel structure as decoder architecture, as shown in Fig. 5(a, b). Progressive style is more conducive to the localization of the objects through the high-level feature guidance, while the parallel style is easier to restore details by making full use of low-level features. As can be seen from Tab. 2, previous methods only adopt either progressive or parallel mode and ignore the advantages brought by the other. In this work, we mix the two structures to build a dual branch decoder to overcome the above restrictions. We briefly describe the FPN branch. Taking D^i as an example, we firstly apply bilinear interpolation to upsample the higher-level feature D^{i+1} to

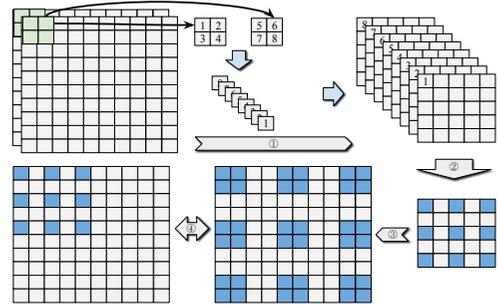


Fig. 6 Illustration of the folded atrous convolution. We use ①, ② and ③ to respectively indicate “Fold” operation, atrous convolution and “Unfold” operation. ④ shows the comparison between atrous convolution (Left) and the folded atrous convolution (Right).

the same size as T^i . Next, to decrease the number of parameters, T^i is reduced to 32 channels and fed into gate unit G^i . Lastly, the gated feature is fused with the upsampled feature of D^{i+1} by element-wise addition and convolutional layers. This process can be formulated as:

$$D^i = \begin{cases} Conv(G_1^i \cdot T^i + Up(D^{i+1})) & \text{if } i = 1, 2, 3, 4 \\ Conv(G_1^i \cdot T^i), & \text{if } i = 5, \end{cases} \quad (3)$$

where D^1 is a single-channel feature map with the same size as the input image.

In the parallel branch, we firstly upsample $T^1 \sim T^5$ to the same size of D^1 . Next, the multi-level gate units are followed to weight the corresponding transition-layer features. Lastly, we combine D^1 and the gated features by cross-channel concatenation. The whole process is written as:

$$F_{Cat} = Cat(D^1, Up(G_2^1 \cdot T^1), Up(G_2^2 \cdot T^2), Up(G_2^3 \cdot T^3), Up(G_2^4 \cdot T^4), Up(G_2^5 \cdot T^5)). \quad (4)$$

The final saliency map S^F is generated by integrating the predictions of the two branches with a residual connection as shown in Fig. 5(c),

$$S^F = S(Conv(F_{Cat}) + D^1), \quad (5)$$

where $S(\cdot)$ is the element-wise sigmoid function.

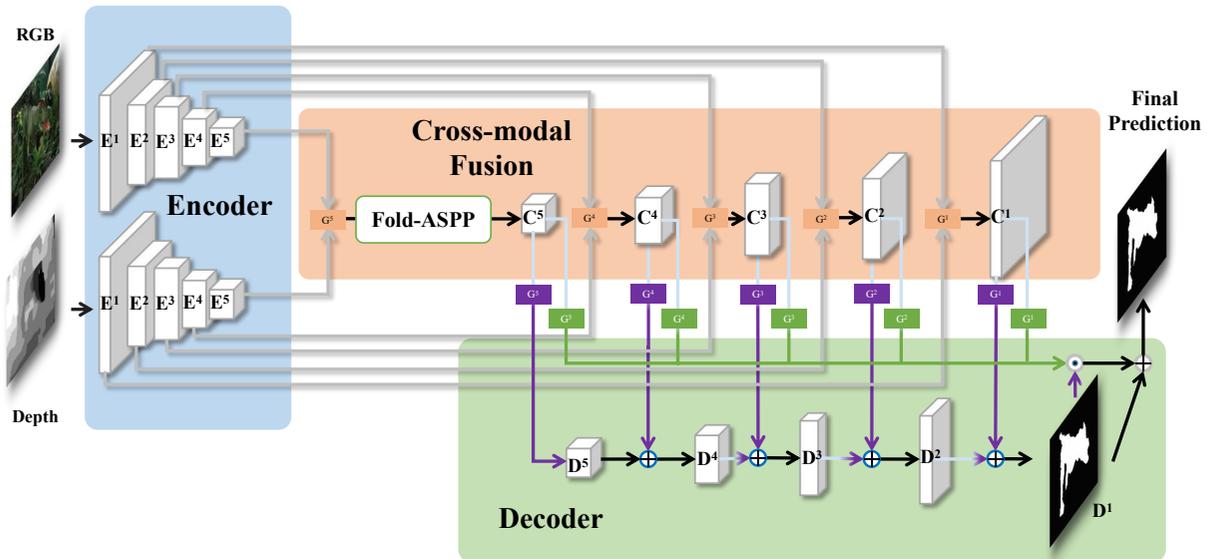


Fig. 7 Overall pipeline of the two-stream gated network. Firstly, we use two independent encoders to extract features for each modality separately. Fold-ASPP is followed and embedded in the top layer of the encoder. And then, we utilize multi-level gate units to control both cross-modal fusion and fused information transmitted to the decoder. The final prediction is yielded by the gated dual branch.

3.3 Folded Atrous Convolution

In order to obtain robust segmentation results by integrating multi-scale information, atrous spatial pyramid pooling (ASPP) is proposed in Deeplab [13]. And many works [58, 75, 84, 108, 125, 130, 143, 237, 239, 289] also show its effectiveness in different binary segmentation branches. The ASPP uses multiple parallel atrous convolutional layers with different dilation rates. The sparsity of atrous convolution kernel, especially when using a large dilation rate, results in that the association relationships among sampling points are too weak to extract stable features. In this paper, we apply a simple “Fold” operation to effectively relieve this issue. We visualize the folded atrous convolution structure in Fig. 6, which not only further enlarges the receptive field but also extends each valid sampling position from an isolate point to a 2×2 connected region.

Let \mathbf{X} represent feature maps with the size of $N \times N \times C$ (C is the channel number). We slide a 2×2 window on \mathbf{X} in stride 2 and then conduct atrous convolution with kernel size $K \times K$ in different dilation rates. Fig. 6 shows the computational process when $K = 3$ and dilation rate is 2. Firstly, we collect $2 \times 2 \times C$ feature points in each window from \mathbf{X} and then it is stacked by

channel direction, we call this operation “Fold”, which is shown in Fig. 6①. After the fold operation, we can get new feature maps with the size of $N/2 \times N/2 \times 4C$. A point on the new feature maps corresponds to a 2×2 area on the original feature maps. Secondly, we adopt an atrous convolution with a kernel size of 3×3 and dilation rate is 2. Followed by the reverse process of “Fold” which is called “Unfold” operation, the final feature maps are obtained. By using the folded atrous convolution, in the process of information transfer across convolution layers, more contexts are merged and the certain local correlation is also preserved, which provides the fault-tolerance capability for subsequent operations.

The Fold-ASPP is only equipped on the top of the encoder network, which consists of three folded atrous convolutional layers with dilation rates [2, 4, 6] to fit the size of feature maps. Just as group convolution [219] is a trade-off between depthwise convolution [26, 61] and vanilla convolution in the channel dimension, the proposed folded atrous convolution is a trade-off between atrous convolution and vanilla convolution in the spatial dimension.

3.4 Supervision

We use the pixel position aware loss L_{ppa} [202] which have been widely adopted in segmentation tasks. We use the same definitions as in [42, 202, 237, 270, 280]. As shown in Fig. 2, we apply supervision for both the intermediate prediction from the FPN branch and the final prediction from the dual branch. In the dual branch decoder, since the FPN branch gradually combines all-level gated encoding and decoding features, it has very powerful prediction ability. We expect that it can predict salient objects as accurately as possible under the supervision of ground truth. While the parallel branch only combines the gated encoding features, which is helpful to remedy the ignored details with the design of residual structure. Moreover, the supervision on D^1 can drive gate units to learn the weight of the contribution of each encoder block to the final prediction. The total loss L could be written as:

$$L = L_{ppa}^{s1} + L_{ppa}^{sf}, \quad (6)$$

where L_{ppa}^{s1} and L_{ppa}^{sf} are respectively used to regularize the output of the FPN branch and the final prediction.

3.5 Two-Stream Network

To finish some two-source input tasks, *e.g.*, RGB-D salient object detection, we extend the GateNet to a two-stream architecture to further demonstrate its effectiveness. The proposed two-stream GateNet is shown in Fig. 7. Compared with the single-stream network for single source input tasks, there are two main differences: (1) We add an extra encoder to extract features of other modals. (2) We convey the output features from the encoding blocks of two modalities to the gate unit to achieve cross-modal fusion at each level. The motivation of embedding gate units when performing cross-modal fusion is straightforward, that is, different modalities present different characteristics in each layer of the encoder, and low-quality modal features can interfere with the other one, leading to build a poor decoder. The form and composition of all gate units are the same as Fig. 3 and Eq. 2 except that the input features are different.

4 Experiments

4.1 Datasets

For the training and test dataset, we follow the settings of the most state-of-the-art methods [85, 116, 121, 131, 178, 217, 225, 229, 263, 275] in Tab. 1 on each binary segmentation task. And the details about these datasets can find in Tab. 3.

4.2 Evaluation Metrics

There are ten popular metrics used in different binary segmentation branches. F-measure [1] (F_{β}^{max} , F_{β}^{mean}), weighted F-measure [128] (F_{β}^{ω}), S-measure [38] (S_m), E-measure [39] (E_m) and MAE [142] (\mathcal{M}) are widely used in salient object detection, camouflaged object detection and defocus blur detection tasks. IOU and Dice scores are popular with medical image segmentation. BER [181] and Pixel Accuracy (PA) are more commonly used for shadow, mirror, glass and transparent detection. The lower value is better for the BER and MAE, and higher is better for others.

• **Pixel Accuracy (PA)** is calculated based on the binarized prediction mask and ground-truth:

$$PA = \frac{TP + TN}{TP + TN + FP + FN}, \quad (7)$$

where TP, TN, FP, FN denote true-positive, true-negative, false-positive, and false-negative, respectively.

• **F-measure (F_{β})** [1] is a metric that comprehensively considers both precision and recall:

$$F_{\beta} = \frac{(1 + \beta^2)\text{Precision} \times \text{Recall}}{\beta^2\text{Precision} + \text{Recall}}, \quad (8)$$

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad (9)$$

where β^2 is set to 0.3 as suggested in [1] to emphasize the precision. Some methods report the maximum F-measure (F_{β}^{max}) across the binary maps of different thresholds or the mean F-measure (F_{β}^{mean}) score by an adaptive threshold.

• **weighted F-measure (F_{β}^{ω})** [128] is proposed to improve the metric F-measure. It assigns different weights (ω) to precision and recall across different errors at different locations, considering the neighborhood information:

$$F_{\beta}^{\omega} = \frac{(1 + \beta^2)\text{Precision}^{\omega} \times \text{Recall}^{\omega}}{\beta^2\text{Precision}^{\omega} + \text{Recall}^{\omega}}. \quad (10)$$

Table 3 Summary of essential characteristics about popular binary segmentation datasets.

Dataset	Year	Publication	#Image	Core Description	Role
RGB Salient Object Detection					
MSRA10K [23]	2015	TPMAI	10,000	Large scale; Multi-object	Train
ECSSD [223]	2015	CVPR	1,000	Semantically meaningful but structurally complex natural contents	Test
HKU-IS [100]	2015	CVPR	4,447	Multiple disconnected salient objects; Overlapping the image boundary	Test
PASCAL-S [105]	2014	CVPR	850	Selected from the PASCAL VOC2010 val set	Test
DUT-OMRON [224]	2013	CVPR	5,168	Complicated background and diverse content	Train&Test
DUTS [188]	2017	CVPR	15,572	Large-scale; Complex scenarios with high-diversity contents; Most SOD models are typically trained on it	Train&Test
RGB-D Salient Object Detection					
NJUD [80]	2014	ICFP	1,985	Complex objects and challenging scenarios; Selected from 3D movies, the Internet, and photographs taken by a Fuji W3 stereo camera	Train&Test
NLPR [441]	2014	ECCV	1,000	There may exist multiple salient objects in each image; Captured by Kinect	Train&Test
DUTLF-D [143]	2019	ICCV	1,200	Contains 800 indoor and 400 outdoor scenes paired with the depth map and binary ground truth	Train&Test
STERE [133]	2012	CVPR	1,000	The first stereoscopic photo collection; Images downloaded from the Internet	Test
SIP [43]	2021	TNNLS	929	High-resolution images; Contain multiple salient persons per image	Test
SSD [287]	2017	ICCVW	80	Collected from three stereo movies	Test
RGBD135 [25]	2014	ICMCS	135	Consists of seven indoor scenes; Captured by Kinect	Test
LFSD [103]	2014	CVPR	100	Mainly built for saliency detection on the light filed	Test
ORSI Salient Object Detection					
ORSSD [93]	2019	TGRS	800	Diverse spatial resolution; Background is cluttered and complicated; Type of salient objects is various; The number and size of salient objects are variable	Train&Test
FORSSD [49]	2021	TIP	2,000	Multiple salient objects in one image; A number of small objects; More abundant scenarios; Imaging interferences; Specific circumstances	Train&Test
ORSI-4199 [178]	2021	TGRS	4,199	Large-scale; More challenges with background interference samples	Train&Test
Camouflaged Object Detection					
CHAMELEON [160]	2018	Unpublished Manuscript	76	The images were collected from the Internet via the Google search engine	Test
CAMO [88]	2019	CVIU	2,500	Eight categories	Train&Test
COD10K [41]	2020	CVPR	10,000	Large-scale; Broader size distribution; Global/Local contrast; Rich sub-classes; A large number of Full HD 1080p images	Train&Test
NC4K [125]	2021	CVPR	4,121	Large-scale; Evaluate the generalization ability of existing models	Test
Defocus Blur Detection					
CUHK [156]	2014	CVPR	704	Cluttered backgrounds and various scenes	Train&Test
DUT [267]	2018	CVPR	1,100	Multi-scale focused areas	Train&Test
Shadow Detection					
UCF [288]	2010	CVPR	245	Cluttered backgrounds and various scenes	Test
ISTD [186]	2018	CVPR	1,870	Both shadow detection and removal; Only 135 background scenes	Train&Test
SBU [182]	2016	ECCV	4,727	The largest shadow dataset covering general scenes; A wider variety of scenes	Train&Test
Transparent Object Detection					
Trans10K [217]	2020	ECCV	10,428	Two categories (stuff and things); Large-scale realworld images; Complex scenarios	Train&Test
Trans10K-v2 [218]	2021	LICAI	10,428	Semantic Segmentation; 11 fine-grained glass image categories with a diverse scenario and high resolution	Train&Test
Glass Detection					
GDD [131]	2020	CVPR	3,916	Large-scale; Both indoor and outdoor scenes; Various types of common glass; Glass located at different positions of an image	Train&Test
Mirror Detection					
MSD [229]	2019	ICCV	4,018	Large-scale; Both indoor and outdoor scenes; Different mirror shapes and multiple mirrors; Low global color contrast	Train&Test
Polyp Segmentation					
CVC-ColonDB [167]	2015	TMI	380	Colonoscopy images each with a polyp inside; Selected from 15 short colonoscopy videos	Test
CVC-ClinicDB [5]	2015	CMIG	612	Images from 31 colonoscopy clip; Images of size 576 × 768	Train&Test
EndoScene [180]	2017	JHE	912	Images from CVC-ColonDB and CVC-ClinicDB and are reannotated; Extend the old annotations to account for lumen, and specular highlights	Train&Test
ETIS [157]	2014	LICARS	196	An early established dataset for early diagnosis of colorectal cancer	Test
Kvasir [72]	2020	MMM	1,000	Existing largest-scale dataset	Train&Test

• **S-measure** (S_m) [38] evaluates the spatial structure similarity by combining the region-aware structural similarity S_r and the object-aware structural similarity S_o :

$$S_m = \alpha \times S_o + (1 - \alpha) \times S_r, \quad (11)$$

where α is empirically set to 0.5.

• **E-measure** (E_m) [39] can jointly capture image level statistics and local pixel matching information:

$$Q_S = \frac{1}{W \times H} \sum_{i=1}^W \sum_{j=1}^H \phi_S(i, j), \quad (12)$$

where ϕ_S is the enhanced alignment matrix, reflecting the correlation between prediction \mathbf{S} and the ground truth \mathbf{G} after subtracting their global means, respectively.

• **IOU** is the most common metric for evaluating classification accuracy:

$$IOU = \frac{TP}{TP + FP + FN}. \quad (13)$$

• **Dice** is a statistic used to gauge the similarity of two samples and become the most used metric

in validating medical image segmentation:

$$Dice = \frac{2TP}{FP + 2TP + FN}. \quad (14)$$

• **Balanced error rate (BER)** [181] is a common metric to evaluate shadow detection performance, where shadow and non-shadow regions contribute equally to the overall performance without considering their relative areas:

$$BER = (1 - \frac{1}{2}(\frac{TP}{TP + FN} + \frac{TN}{TN + FP})). \quad (15)$$

• **MAE** (\mathcal{M}) [142] measures the average absolute difference between the prediction $\mathbf{S} \in [0, 1]^{W \times H}$ and the ground truth $\mathbf{G} \in \{0, 1\}^{W \times H}$ pixel by pixel:

$$MAE = \frac{1}{W \times H} \sum_{i=1}^W \sum_{j=1}^H |\mathbf{G}(i, j) - \mathbf{S}(i, j)|. \quad (16)$$

In fact, all above metrics can be used for any binary segmentation sub-task. In this paper, we are the first to introduce all ten metrics into the quantitative comparison to provide a comprehensive performance evaluation.

4.3 Implementation Details

We use the PyTorch framework to implement our models on one RTX 3090 GPU for 100 epochs. The input resolutions of images are resized to 352×352 and we employ a general multi-scale training strategy as most methods [19, 42, 125, 202, 270, 280]. We adopt some image augmentation techniques to avoid overfitting, including random flipping, rotating, and border clipping. For the optimizer, we use the Adam [86]. For the learning rate, initial learning rate is set to 0.0001. We adopt the “step” learning rate decay policy, and set the decay size as 30 and decay rate as 0.9. For any sub-tasks, the above training strategy is used for all the gated network models involved in this paper. The difference among these models is only in the mini-batch size due to adopting different backbones. Specifically, the mini-batch size settings in the gatenet using VGG-16, ResNet-50, Res2Net-50, and ResNeXt-101 as the backbone are 8, 24, 24 and 16, respectively. The source code can be available at <https://github.com/Xiaoqi-Zhao-DLUT/GateNet-RGB-Saliency>.

4.4 Performance

We compare our models with state-of-the-art approaches in terms of ten metrics on all test sets corresponding for each binary segmentation task in Tab. 4 - Tab. 11. Since there are many test sets for RGB SOD, RGB-D SOD and polyp segmentation, we not only compare the performance under each metric, but also count the proportion of top 3 and top 1 performance to get an overall evaluation. Some quantitative analyses are as follows:

- In Tab. 4, among 50 scores of all **RGB SOD** datasets, our GateNet achieves significant performance improvement compared to the second best method CTDNet [273] in terms of top 3 (49/50 vs. 37/50) and top 1 (40/50 vs. 1/50), respectively. And, we still consistently outperform the VST [231] model even if it is equipped with a stronger transformer backbone T2T [231].
- Tab. 5 shows performance comparisons on five **polyp segmentation** datasets. Our GateNet consistently outperforms the second best approach UACANet [85] under top 3 (49/50 vs. 39/50) and top 1 (30/50 vs. 13/50), respectively. In particular, GateNet achieves a predominant performance

Table 4 Quantitative comparison of different RGB SOD methods. Top 3 and Top 1 scores are highlighted in **blue** and **red**, respectively.

Metric	F3Net	ITSd	MINet	KRN	Auto-MSF	LDf	VST	CTDNet	GateNet
	[202] AAAI 2020 Res-50	[278] CVPR 2021 Res-50	[136] CVPR 2021 Res-50	[220] AAAI 2021 Res-50	[242] ACMMM Res-50	[203] CVPR 2021 Res-50	[116] ICCV T2T Res-50	[273] ACMMM T2T Res-50	- - Res-50
DUTS [188]	$F_A \uparrow$	0.966	0.962	0.965	0.966	0.968	0.968	0.967	0.972
	$F_{mean}^{\max} \uparrow$	0.891	0.883	0.884	0.877	0.898	0.898	0.897	0.911
	$F_{\beta}^{\max} \uparrow$	0.840	0.804	0.828	0.856	0.851	0.855	0.818	0.857
	$F_{\beta}^{\text{opt}} \uparrow$	0.835	0.824	0.825	0.841	0.847	0.845	0.828	0.847
	$S_m \uparrow$	0.887	0.883	0.883	0.876	0.891	0.891	0.895	0.891
	$E_m \uparrow$	0.918	0.898	0.917	0.931	0.926	0.929	0.916	0.928
	$IOU \uparrow$	0.793	0.783	0.782	0.779	0.799	0.799	0.802	0.828
	$Dice \uparrow$	0.854	0.844	0.845	0.855	0.864	0.861	0.848	0.864
	$BER \downarrow$	0.062	0.065	0.069	0.072	0.064	0.064	0.060	0.052
	$M \downarrow$	0.035	0.041	0.037	0.034	0.034	0.034	0.037	0.034
DUT-OMRON [224]	$F_A \uparrow$	0.949	0.942	0.946	0.951	0.953	0.950	0.946	0.952
	$F_{mean}^{\max} \uparrow$	0.813	0.821	0.810	0.798	0.827	0.820	0.825	0.826
	$F_{\beta}^{\max} \uparrow$	0.766	0.756	0.756	0.778	0.783	0.774	0.756	0.779
	$F_{\beta}^{\text{opt}} \uparrow$	0.747	0.750	0.738	0.757	0.765	0.752	0.755	0.762
	$S_m \uparrow$	0.837	0.839	0.832	0.831	0.845	0.838	0.849	0.847
	$E_m \uparrow$	0.876	0.867	0.873	0.876	0.889	0.881	0.872	0.884
	$IOU \uparrow$	0.710	0.715	0.699	0.705	0.723	0.711	0.731	0.720
	$Dice \uparrow$	0.772	0.778	0.764	0.776	0.786	0.775	0.783	0.787
	$BER \downarrow$	0.101	0.091	0.106	0.107	0.098	0.102	0.088	0.095
	$M \downarrow$	0.053	0.056	0.050	0.049	0.049	0.052	0.058	0.052
ECSSD [203]	$F_A \uparrow$	0.969	0.969	0.969	0.967	0.967	0.988	0.973	0.969
	$F_{mean}^{\max} \uparrow$	0.945	0.947	0.948	0.941	0.946	0.950	0.951	0.950
	$F_{\beta}^{\max} \uparrow$	0.925	0.895	0.924	0.929	0.922	0.930	0.920	0.927
	$F_{\beta}^{\text{opt}} \uparrow$	0.912	0.892	0.914	0.917	0.910	0.915	0.910	0.915
	$S_m \uparrow$	0.924	0.925	0.925	0.914	0.923	0.924	0.932	0.925
	$E_m \uparrow$	0.946	0.932	0.953	0.954	0.942	0.951	0.957	0.949
	$IOU \uparrow$	0.879	0.879	0.879	0.871	0.876	0.880	0.893	0.881
	$Dice \uparrow$	0.923	0.919	0.922	0.923	0.919	0.923	0.922	0.940
	$BER \downarrow$	0.045	0.044	0.043	0.048	0.047	0.045	0.036	0.044
	$M \downarrow$	0.033	0.035	0.034	0.033	0.036	0.034	0.033	0.032
HKU-IS [100]	$F_A \uparrow$	0.937	0.932	0.934	0.937	0.937	0.947	0.936	0.937
	$F_{mean}^{\max} \uparrow$	0.937	0.933	0.935	0.928	0.937	0.940	0.942	0.941
	$F_{\beta}^{\max} \uparrow$	0.910	0.898	0.908	0.914	0.915	0.915	0.901	0.918
	$F_{\beta}^{\text{opt}} \uparrow$	0.900	0.893	0.899	0.904	0.902	0.905	0.898	0.908
	$S_m \uparrow$	0.916	0.916	0.919	0.908	0.918	0.920	0.928	0.920
	$E_m \uparrow$	0.923	0.923	0.923	0.960	0.960	0.962	0.962	0.965
	$IOU \uparrow$	0.862	0.857	0.862	0.853	0.863	0.867	0.877	0.869
	$Dice \uparrow$	0.911	0.904	0.910	0.912	0.911	0.915	0.911	0.917
	$BER \downarrow$	0.045	0.048	0.047	0.051	0.048	0.045	0.038	0.045
	$M \downarrow$	0.028	0.031	0.028	0.027	0.029	0.027	0.029	0.025
PASCAL3S [100]	$F_A \uparrow$	0.938	0.937	0.936	0.937	0.932	0.939	0.943	0.938
	$F_{mean}^{\max} \uparrow$	0.882	0.882	0.880	0.874	0.886	0.887	0.890	0.889
	$F_{\beta}^{\max} \uparrow$	0.844	0.797	0.840	0.854	0.842	0.853	0.842	0.851
	$F_{\beta}^{\text{opt}} \uparrow$	0.823	0.823	0.818	0.830	0.823	0.829	0.827	0.829
	$S_m \uparrow$	0.857	0.859	0.854	0.849	0.854	0.859	0.871	0.859
	$E_m \uparrow$	0.892	0.866	0.897	0.902	0.881	0.903	0.905	0.898
	$IOU \uparrow$	0.780	0.782	0.773	0.775	0.773	0.783	0.801	0.783
	$Dice \uparrow$	0.848	0.849	0.843	0.850	0.844	0.852	0.858	0.853
	$BER \downarrow$	0.080	0.078	0.084	0.084	0.085	0.081	0.066	0.078
	$M \downarrow$	0.064	0.066	0.066	0.063	0.070	0.062	0.062	0.064
Top 3	5/50	5/50	6/50	15/50	18/50	28/50	30/50	37/50	49/50
Top 1	0/50	0/50	0/50	1/50	5/50	0/50	3/50	1/50	40/50

on the CVC-ClinicDB [5] in terms of all ten metrics.

- For fair comparison with other **RGB-D SOD** methods, we show the performance of GateNet with ResNet-50 and Res2Net-50 as backbone. In Tab. 6, we can see that GateNet-Res-50 and GateNet-Res2-50 achieve the top 1 performance of 43/80 and 32/80 while the TriTransNet [121] and SPNet [280] only reach 11/80 and 10/70, respectively. Further, the comparison of GateNet-Res-50 + GateNet-Res2-50 and the TriTransNet + SPNet is 62/80 vs. 19/80.
- Tab. 7 - Tab. 11 show performance comparisons with **camouflaged, defocus blur, shadow, transparent, glass, mirror and ORSI SOD** methods, respectively. Without too much claim, our models achieve the best performance in terms of all ten metrics across 16 out of 17 different datasets.
- Tab. 12 lists the **model sizes, parameters, FLOPs and speed** of different methods with superior performance in Tab. 4 - Tab. 11 in detail. It can be seen that both two-stream and

Table 5 Quantitative comparison of different polyp segmentation methods. Top 3 and Top 1 scores are highlighted in **blue** and **red**, respectively.

Metric	UNet	UNet++	SFA	PrNet	SA-Net	MSNet	UACANet	GateNet
	[149] MICCAI 2015 Res2-50	[285] TMI 2019 Res2-50	[919] MICCAI 2020 Res2-50	[48] MICCAI 2020 Res2-50	[42] MICCAI 2021 Res2-50	[201] MICCAI 2021 Res2-50	[85] ACMMM 2021 Res2-50	- - Res2-50
Endosome [180]	PA \uparrow	0.979	0.984	0.936	0.990	0.993	0.990	0.993
	F $_{\beta}^{max}$ \uparrow	0.805	0.817	0.558	0.905	0.881	0.899	0.889
	F $_{\beta}^{mean}$ \uparrow	0.703	0.706	0.353	0.824	0.823	0.829	0.885
	F $_{\beta}^{w}$ \uparrow	0.684	0.687	0.341	0.843	0.859	0.848	0.886
	Em \uparrow	0.842	0.838	0.640	0.924	0.927	0.926	0.933
	IoU \uparrow	0.867	0.884	0.604	0.938	0.948	0.942	0.976
CVC-ColonDB [187]	PA \uparrow	0.625	0.622	0.565	0.765	0.808	0.807	0.836
	F $_{\beta}^{max}$ \uparrow	0.569	0.560	0.407	0.718	0.731	0.759	0.798
	F $_{\beta}^{mean}$ \uparrow	0.498	0.467	0.379	0.699	0.726	0.736	0.772
	F $_{\beta}^{w}$ \uparrow	0.711	0.691	0.634	0.820	0.836	0.836	0.846
	Em \uparrow	0.763	0.762	0.648	0.847	0.855	0.883	0.897
	IoU \uparrow	0.449	0.413	0.351	0.645	0.678	0.678	0.707
CVC-CholecDB [5]	PA \uparrow	0.982	0.979	0.960	0.991	0.989	0.993	0.992
	F $_{\beta}^{max}$ \uparrow	0.880	0.858	0.776	0.927	0.924	0.940	0.926
	F $_{\beta}^{mean}$ \uparrow	0.804	0.784	0.655	0.885	0.883	0.894	0.919
	F $_{\beta}^{w}$ \uparrow	0.811	0.785	0.647	0.896	0.909	0.913	0.917
	Em \uparrow	0.889	0.872	0.793	0.935	0.935	0.942	0.938
	IoU \uparrow	0.917	0.898	0.816	0.958	0.963	0.971	0.968
ETIS [157]	PA \uparrow	0.394	0.465	0.255	0.602	0.656	0.653	0.668
	F $_{\beta}^{max}$ \uparrow	0.396	0.390	0.231	0.600	0.685	0.677	0.650
	F $_{\beta}^{mean}$ \uparrow	0.368	0.681	0.357	0.791	0.843	0.840	0.812
	F $_{\beta}^{w}$ \uparrow	0.645	0.704	0.515	0.792	0.835	0.828	0.851
	Em \uparrow	0.343	0.342	0.219	0.576	0.670	0.666	0.618
	IoU \uparrow	0.406	0.413	0.297	0.630	0.751	0.719	0.696
Kvasir [28]	PA \uparrow	0.947	0.954	0.926	0.971	0.972	0.974	0.976
	F $_{\beta}^{max}$ \uparrow	0.876	0.880	0.801	0.929	0.931	0.938	0.922
	F $_{\beta}^{mean}$ \uparrow	0.832	0.853	0.715	0.897	0.903	0.902	0.914
	F $_{\beta}^{w}$ \uparrow	0.794	0.808	0.670	0.885	0.892	0.892	0.897
	Em \uparrow	0.858	0.862	0.782	0.915	0.914	0.923	0.914
	IoU \uparrow	0.901	0.907	0.828	0.943	0.950	0.944	0.951
Top 3	0.50	0.50	0.50	0.50	31/50	34/50	39/50	49/50
	0.50	0.50	0.50	0.50	4/50	3/50	13/50	49/50

single stream GateNets still have obvious advantages against most state-of-the-art methods with different backbones.

4.5 Ablation Studies

To reflect the general contribution of each component to the overall performance, we conduct ablation studies on the largest dataset for each sub-task individually. Tab. 13 and Tab. 14 are the results for single-input tasks and the two-input task (RGB-D SOD), respectively. Tab. 15 verifies the effect of folded atrous convolution thoroughly.

• **Dual Branch Decoder.** The baseline (M1) is a FPN structure with a progressive decoder. We add the residual parallel branch to construct the dual branch decoder. We can see that M2 consistently outperforms M1 across all datasets in terms of all ten metrics. Meanwhile, M2 has been able to surpass SINet [41], PFNet [130], IS2CNet [256] and BDRAR [289]. Based on this strong dual branch network, the subsequent performance gain of gate units and fold atrous convolution is more convincing.

• **Gate Units.** We embed multi-level gate units in both the FPN and parallel branches. In Tab. 13,

Table 6 Quantitative comparison of different RGB-D SOD methods. Top 3 and Top 1 scores are highlighted in **blue** and **red**, respectively.

Metric	DCF	RD3D	UTA	DSNet	SPNet	Tri/Trans	GateNet	GateNet
	[74] CVPR 2021 Res-50	[15] AAAI 2021 Res-50	[272] TIP 2021 Res-50	[204] ICCV 2021 Res-50	[280] ICCV 2021 Res-50	[12] ACMMM 2021 Res-50	- - Res-50	- - Res2-50
DUTLE-D [46]	PA \uparrow	-	0.973	-	-	-	0.975	0.977
	F $_{\beta}^{max}$ \uparrow	-	0.946	-	-	-	0.951	0.958
	F $_{\beta}^{mean}$ \uparrow	-	0.924	-	-	-	0.938	0.946
	F $_{\beta}^{w}$ \uparrow	-	0.900	-	-	-	0.926	0.931
	Em \uparrow	-	0.931	-	-	-	0.932	0.943
	IoU \uparrow	-	0.957	-	-	-	0.966	0.969
NUID [80]	PA \uparrow	0.963	0.966	0.963	0.969	0.973	0.980	0.978
	F $_{\beta}^{max}$ \uparrow	0.917	0.923	0.915	0.930	0.935	0.934	0.943
	F $_{\beta}^{mean}$ \uparrow	0.897	0.901	0.903	0.907	0.917	0.920	0.928
	F $_{\beta}^{w}$ \uparrow	0.878	0.886	0.883	0.893	0.906	0.906	0.913
	Em \uparrow	0.903	0.916	0.902	0.921	0.924	0.920	0.931
	IoU \uparrow	0.941	0.942	0.946	0.947	0.953	0.954	0.956
NUPR [144]	PA \uparrow	0.978	0.980	0.980	0.978	0.980	0.980	0.978
	F $_{\beta}^{max}$ \uparrow	0.917	0.927	0.932	0.928	0.926	0.929	0.936
	F $_{\beta}^{mean}$ \uparrow	0.892	0.892	0.918	0.886	0.904	0.910	0.911
	F $_{\beta}^{w}$ \uparrow	0.860	0.889	0.905	0.881	0.896	0.902	0.902
	Em \uparrow	0.921	0.929	0.928	0.926	0.927	0.928	0.933
	IoU \uparrow	0.956	0.959	0.965	0.957	0.959	0.964	0.962
STERE [130]	PA \uparrow	0.965	0.965	0.968	0.967	0.965	0.967	0.970
	F $_{\beta}^{max}$ \uparrow	0.915	0.917	0.921	0.924	0.915	0.919	0.929
	F $_{\beta}^{mean}$ \uparrow	0.890	0.886	0.905	0.894	0.888	0.893	0.907
	F $_{\beta}^{w}$ \uparrow	0.873	0.871	0.887	0.876	0.873	0.882	0.889
	Em \uparrow	0.905	0.911	0.910	0.915	0.907	0.908	0.921
	IoU \uparrow	0.943	0.944	0.949	0.947	0.942	0.950	0.952
SIP [48]	PA \uparrow	0.950	0.954	0.952	0.951	0.958	0.957	0.963
	F $_{\beta}^{max}$ \uparrow	0.900	0.906	0.896	0.902	0.916	0.916	0.927
	F $_{\beta}^{mean}$ \uparrow	0.877	0.874	0.872	0.865	0.893	0.892	0.902
	F $_{\beta}^{w}$ \uparrow	0.841	0.845	0.843	0.832	0.868	0.864	0.877
	Em \uparrow	0.873	0.885	0.873	0.876	0.894	0.886	0.903
	IoU \uparrow	0.921	0.924	0.927	0.920	0.931	0.929	0.939
RGBD15 [25]	PA \uparrow	0.978	0.982	0.975	0.980	0.986	0.986	0.985
	F $_{\beta}^{max}$ \uparrow	0.926	0.941	0.921	0.939	0.950	0.946	0.951
	F $_{\beta}^{mean}$ \uparrow	0.901	0.917	0.891	0.910	0.935	0.936	0.931
	F $_{\beta}^{w}$ \uparrow	0.876	0.904	0.864	0.893	0.931	0.929	0.922
	Em \uparrow	0.916	0.935	0.901	0.928	0.945	0.943	0.941
	IoU \uparrow	0.958	0.975	0.935	0.970	0.983	0.981	0.978
SSD [287]	PA \uparrow	0.823	0.860	0.808	0.846	0.888	0.884	0.878
	F $_{\beta}^{max}$ \uparrow	0.887	0.912	0.874	0.902	0.938	0.935	0.928
	F $_{\beta}^{mean}$ \uparrow	0.065	0.050	0.071	0.058	0.033	0.035	0.041
	F $_{\beta}^{w}$ \uparrow	0.023	0.019	0.026	0.021	0.014	0.014	0.016
	Em \uparrow	0.948	0.924	0.952	0.959	0.957	0.960	0.957
	IoU \uparrow	0.857	0.805	0.860	0.895	0.883	0.889	0.876
LPSD [100]	PA \uparrow	0.931	0.929	0.911	0.935	0.931	0.935	0.945
	F $_{\beta}^{max}$ \uparrow	0.878	0.879	0.856	0.884	0.881	0.890	0.891
	F $_{\beta}^{mean}$ \uparrow	0.857	0.855	0.832	0.864	0.860	0.869	0.878
	F $_{\beta}^{w}$ \uparrow	0.824	0.816	0.797	0.823	0.823	0.840	0.841
	Em \uparrow	0.856	0.858	0.830	0.868	0.854	0.866	0.879
	IoU \uparrow	0.903	0.898	0.878	0.905	0.897	0.908	0.917
Top 3	1/70	7/80	16/70	17/70	39/70	61/80	71/80	77/80
	0/80	0/80	2/70	2/70	10/70	11/80	43/80	32/80

the M3 achieves a significant improvement compared to the M4 indicates the necessity of designing gate units-v2 with a global information perspective. Further, the performance gap between

Table 7 Quantitative comparison of different camouflaged object methods. The best scores are highlighted in **red**.

Dataset	Method	Pub.	Backbone	$PA \uparrow$	$F_{\beta}^{max} \uparrow$	$F_{\beta}^{mean} \uparrow$	$F_{\beta}^{\omega} \uparrow$	$S_m \uparrow$	$E_m \uparrow$	$IOU \uparrow$	$Dice \uparrow$	$BER \downarrow$	$M \downarrow$
CAMO [88]	SINet [41]	CVPR 2020	ResNet-50	0.907	0.762	0.709	0.606	0.751	0.835	0.546	0.639	0.201	0.100
	PFNet [130]	CVPR 2021	ResNet-50	0.917	0.795	0.751	0.695	0.782	0.855	0.624	0.725	0.150	0.085
	RankNet [125]	CVPR 2021	ResNet-50	0.922	0.791	0.756	0.696	0.787	0.859	0.626	0.722	0.154	0.080
	MGL [233]	CVPR 2021	ResNet-50	0.914	0.792	0.738	0.673	0.775	0.848	0.605	0.699	0.172	0.088
	UGTR [225]	ICCV 2021	ResNet-50	0.918	0.800	0.748	0.684	0.784	0.858	0.618	0.712	0.161	0.086
	GateNet	-	ResNet-50	0.934	0.835	0.804	0.756	0.829	0.888	0.694	0.781	0.122	0.069
CHAMELEON [160]	SINet [41]	CVPR 2020	ResNet-50	0.965	0.846	0.776	0.740	0.869	0.899	0.726	0.776	0.107	0.044
	PFNet [130]	CVPR 2021	ResNet-50	0.970	0.860	0.820	0.810	0.882	0.942	0.769	0.835	0.077	0.033
	RankNet [125]	CVPR 2021	ResNet-50	0.972	0.866	0.835	0.822	0.890	0.936	0.776	0.844	0.077	0.031
	MGL [233]	CVPR 2021	ResNet-50	0.973	0.868	0.826	0.813	0.893	0.923	0.781	0.832	0.082	0.030
	UGTR [225]	ICCV 2021	ResNet-50	0.974	0.863	0.805	0.794	0.887	0.921	0.761	0.816	0.093	0.031
	GateNet	-	ResNet-50	0.977	0.902	0.858	0.855	0.910	0.951	0.821	0.872	0.060	0.026
COD10K [41]	SINet [41]	CVPR 2020	ResNet-50	0.957	0.708	0.593	0.551	0.770	0.797	0.532	0.602	0.191	0.051
	PFNet [130]	CVPR 2021	ResNet-50	0.962	0.748	0.676	0.660	0.798	0.868	0.602	0.700	0.136	0.040
	RankNet [125]	CVPR 2021	ResNet-50	0.965	0.756	0.699	0.673	0.802	0.883	0.609	0.705	0.144	0.037
	MGL [233]	CVPR 2021	ResNet-50	0.968	0.770	0.681	0.666	0.811	0.865	0.617	0.695	0.154	0.035
	UGTR [225]	ICCV 2021	ResNet-50	0.968	0.772	0.671	0.666	0.815	0.850	0.620	0.697	0.150	0.036
	GateNet	-	ResNet-50	0.974	0.823	0.752	0.742	0.846	0.901	0.689	0.768	0.114	0.028
NC4K [125]	SINet [41]	CVPR 2020	ResNet-50	0.943	0.805	0.768	0.723	0.807	0.883	0.646	0.745	0.141	0.058
	PFNet [130]	CVPR 2021	ResNet-50	0.949	0.821	0.779	0.745	0.828	0.894	0.683	0.773	0.117	0.053
	RankNet [125]	CVPR 2021	ResNet-50	0.954	0.836	0.802	0.766	0.839	0.904	0.700	0.785	0.118	0.048
	MGL [233]	CVPR 2021	ResNet-50	0.951	0.830	0.778	0.740	0.832	0.890	0.682	0.761	0.129	0.053
	UGTR [225]	ICCV 2021	ResNet-50	0.952	0.833	0.778	0.747	0.839	0.888	0.694	0.770	0.120	0.052
	GateNet	-	ResNet-50	0.963	0.872	0.832	0.806	0.869	0.918	0.751	0.824	0.094	0.040

Table 8 Quantitative comparison of different defocus blur detection methods. The best scores are highlighted in **red**.

Dataset	Method	Pub.	Backbone	$PA \uparrow$	$F_{\beta}^{max} \uparrow$	$F_{\beta}^{mean} \uparrow$	$F_{\beta}^{\omega} \uparrow$	$S_m \uparrow$	$E_m \uparrow$	$IOU \uparrow$	$Dice \uparrow$	$BER \downarrow$	$M \downarrow$
CUHK [156]	CENet [268]	CVPR 2019	VGG-16	0.942	0.914	0.873	0.867	0.873	0.894	0.804	0.877	0.081	0.060
	Depth-Distill [31]	ECCV 2020	VGG-16	0.955	0.924	0.848	0.881	0.891	0.898	0.845	0.904	0.052	0.049
	SG [264]	CVPR 2021	VGG-16	0.881	0.820	0.641	0.737	0.762	0.749	0.673	0.788	0.123	0.123
	IS2CNet [256]	TCSVT 2021	VGG-16	0.939	0.917	0.899	0.862	0.863	0.909	0.799	0.872	0.085	0.063
	DE Nets [263]	TIP 2021	VGG-16	0.953	0.931	0.881	0.882	0.887	0.909	0.837	0.890	0.068	0.055
	GateNet	-	VGG-16	0.963	0.935	0.920	0.903	0.906	0.941	0.869	0.919	0.046	0.040
DUT [267]	CENet [268]	CVPR 2019	VGG-16	0.867	0.826	0.767	0.697	0.742	0.775	0.609	0.703	0.185	0.136
	Depth-Distill [31]	ECCV 2020	VGG-16	0.890	0.860	0.813	0.766	0.787	0.828	0.677	0.780	0.143	0.113
	SG [264]	CVPR 2021	VGG-16	0.827	0.749	0.629	0.612	0.663	0.718	0.522	0.650	0.210	0.175
	IS2CNet [256]	TCSVT 2021	VGG-16	0.865	0.827	0.784	0.699	0.731	0.788	0.601	0.710	0.188	0.136
	DE Nets [263]	TIP 2021	VGG-16	0.910	0.876	0.807	0.799	0.814	0.837	0.735	0.814	0.115	0.096
	GateNet	-	VGG-16	0.939	0.905	0.887	0.861	0.862	0.908	0.816	0.882	0.072	0.064

Table 9 Quantitative comparison of different shadow detection methods. The best scores are highlighted in **red**.

Dataset	Method	Pub.	Backbone	$PA \uparrow$	$F_{\beta}^{max} \uparrow$	$F_{\beta}^{mean} \uparrow$	$F_{\beta}^{\omega} \uparrow$	$S_m \uparrow$	$E_m \uparrow$	$IOU \uparrow$	$Dice \uparrow$	$BER \downarrow$	$M \downarrow$
SBU [182]	DSC [67]	CVPR 2018	VGG-16	0.969	0.914	0.892	0.861	0.856	0.939	0.801	0.871	0.081	0.032
	ADNet [87]	ECCV 2018	-	0.951	0.877	0.696	0.424	0.700	0.811	0.747	0.539	0.074	0.201
	BDRAR [289]	ECCV 2018	ResNeXt-101	0.961	0.884	0.830	0.827	0.844	0.930	0.784	0.863	0.052	0.039
	DSD [275]	CVPR 2019	ResNeXt-101	0.965	0.896	0.841	0.835	0.851	0.933	0.797	0.873	0.046	0.036
	GateNet	-	ResNeXt-101	0.978	0.937	0.903	0.889	0.886	0.957	0.848	0.899	0.059	0.025
	UCF [288]	DSC [67]	CVPR 2018	VGG-16	0.947	0.806	0.772	0.737	0.788	0.897	0.675	0.770	0.121
ADNet [87]		ECCV 2018	-	0.916	0.783	0.575	0.371	0.647	0.748	0.611	0.483	0.110	0.229
BDRAR [289]		ECCV 2018	ResNeXt-101	0.927	0.819	0.613	0.644	0.763	0.765	0.630	0.723	0.079	0.080
DSD [275]		CVPR 2019	ResNeXt-101	0.938	0.791	0.726	0.710	0.779	0.862	0.667	0.775	0.079	0.063
GateNet		-	ResNeXt-101	0.954	0.865	0.800	0.777	0.821	0.907	0.723	0.812	0.093	0.048
ISTD [186]		BDRAR [289]	ECCV 2018	ResNeXt-101	0.973	0.910	0.880	0.878	0.901	0.946	0.856	0.906	0.026
	DSD [275]	CVPR 2019	ResNeXt-101	0.980	0.933	0.919	0.897	0.930	0.961	0.883	0.912	0.040	0.023
	GateNet	-	ResNeXt-101	0.989	0.965	0.932	0.938	0.956	0.972	0.931	0.951	0.012	0.012

Table 10 Quantitative comparison of different transparent, glass and mirror detection methods. The best scores are highlighted in **red**.

Dataset	Method	Pub.	Backbone	$PA \uparrow$	$F_{\beta}^{max} \uparrow$	$F_{\beta}^{mean} \uparrow$	$F_{\beta}^{\omega} \uparrow$	$S_m \uparrow$	$E_m \uparrow$	$IOU \uparrow$	$Dice \uparrow$	$BER \downarrow$	$M \downarrow$
Transparent Object Detection													
Transparent-Easy [217]	Translab [217]	ECCV 2020	ResNet-50	0.978	0.955	0.953	0.941	0.935	0.974	0.921	0.957	0.027	0.022
	GateNet	-	ResNet-50	0.989	0.980	0.979	0.974	0.963	0.988	0.962	0.980	0.014	0.011
Transparent-Hard [217]	Translab [217]	ECCV 2020	ResNet-50	0.913	0.843	0.827	0.783	0.798	0.871	0.733	0.827	0.110	0.087
	GateNet	-	ResNet-50	0.947	0.913	0.904	0.874	0.871	0.923	0.838	0.899	0.069	0.053
Transparent-All [217]	Translab [217]	ECCV 2020	ResNet-50	0.964	0.931	0.927	0.907	0.906	0.952	0.881	0.929	0.044	0.036
	GateNet	-	ResNet-50	0.980	0.966	0.963	0.953	0.944	0.974	0.936	0.963	0.025	0.020
Glass Detection													
GDD [131]	GDNet [131]	CVPR 2020	ResNeXt-101	0.939	0.927	0.920	0.901	0.864	0.919	0.876	0.924	0.056	0.061
	EBLNet [58]	ICCV 2021	ResNeXt-101	0.944	0.937	0.929	0.908	0.875	0.925	0.882	0.928	0.054	0.056
	GateNet	-	ResNeXt-101	0.951	0.944	0.937	0.921	0.892	0.933	0.898	0.935	0.049	0.049
Mirror Detection													
MSD [229]	MirrorNet [?]	ICCV 2019	ResNeXt-101	0.934	0.857	0.777	0.744	0.846	0.861	0.785	0.806	0.065	0.085
	GateNet	-	ResNeXt-101	0.949	0.865	0.839	0.829	0.872	0.907	0.811	0.849	0.077	0.053

Table 11 Quantitative comparison of different ORSI SOD methods. The best scores are highlighted in **red**.

Dataset	Method	Pub.	Backbone	PA \uparrow	$F_{\beta}^{max} \uparrow$	$F_{\beta}^{mean} \uparrow$	$F_{\beta}^w \uparrow$	$S_m \uparrow$	$E_m \uparrow$	$IOU \uparrow$	$Dice \uparrow$	$BER \downarrow$	$\mathcal{M} \downarrow$
ORSSD [93]	DAFNet [249]	TIP 2020	VGG-16	0.990	0.903	0.788	0.844	0.912	0.920	0.823	0.874	0.059	0.011
	MJRBM [178]	TGRS 2021	VGG-16	0.986	0.893	0.802	0.844	0.910	0.934	0.817	0.853	0.066	0.016
	GateNet	-	VGG-16	0.990	0.914	0.847	0.875	0.925	0.959	0.839	0.885	0.048	0.011
EORSSD [249]	DAFNet [249]	TIP 2020	VGG-16	0.996	0.867	0.642	0.783	0.883	0.815	0.800	0.830	0.051	0.006
	MJRBM [178]	TGRS 2021	VGG-16	0.992	0.877	0.707	0.813	0.879	0.890	0.793	0.822	0.070	0.010
	RRNet [29]	TGRS 2021	Res2Net-50	0.994	0.887	0.725	0.827	0.885	0.873	0.834	0.862	0.067	0.008
	GateNet	-	VGG-16	0.993	0.896	0.799	0.859	0.894	0.915	0.850	0.892	0.057	0.008
ORSI-4199 [178]	MJRBM [178]	TGRS 2021	VGG-16	0.965	0.867	0.800	0.806	0.853	0.909	0.747	0.813	0.103	0.037
	GateNet	-	VGG-16	0.969	0.883	0.853	0.840	0.864	0.935	0.767	0.839	0.095	0.032

Table 12 Efficiency comparisons of the top-performing methods in Tab. 4 - Tab. 11. The best and worst results are shown in **red** and **blue**, respectively.

Model Name	TriTrans [†]	SPNet [†]	GateNet [†]	EBLNet [†]	GDNet [†]	MirrorNet [†]	DSDNet [†]	GateNet [†]	UACANet	GateNet	UGTR	MGL	Translab	CTDNet	GateNet	MJRBM	GateNet
Backbone	Res-50	Res-50	Res-50	ResX-101	ResX-101	ResX-101	ResX-101	ResX-101	Res-50	Res-50	Res-50	Res-50	Res-50	Res-50	Res-50	VGG-16	VGG-16
Model Size (MB) ↓	559	702	254	845	770	465	414	373	278	211	296	435	162	94	119	175	78
Parameters (MB) ↓	139.55	175.29	81.55	111.45	201.72	121.77	58.16	92.89	69.16	52.51	48.87	63.60	42.20	21.93	29.68	43.78	20.43
FLOPs (G) ↓	680.07	135.86	63.30	674.41	244.21	111.92	54.34	94.18	119.60	74.16	358.53	475.40	284.68	21.43	64.24	191.46	131.01
Speed (FPS) ↑	16	22	35	16	21	25	49	38	34	35	24	18	22	133	55	35	36

Table 13 Ablation experiments for seven binary segmentation tasks. M1: FPN Baseline. M2: + Residual Parallel Branch. M3: + Gate Units v1. M4: + Gate Units v2. M5: + Fold-ASPP.

Dataset	Method	PA \uparrow	$F_{\beta}^{max} \uparrow$	$F_{\beta}^{mean} \uparrow$	$F_{\beta}^w \uparrow$	$S_m \uparrow$	$E_m \uparrow$	$IOU \uparrow$	$Dice \uparrow$	$BER \downarrow$	$\mathcal{M} \downarrow$	Δ gains
DUTS [188]	M1	0.958	0.870	0.801	0.800	0.870	0.888	0.763	0.820	0.102	0.045	
	M2	0.962	0.875	0.810	0.808	0.875	0.894	0.775	0.830	0.095	0.043	11.85%
	M3	0.967	0.888	0.835	0.830	0.890	0.906	0.790	0.882	0.088	0.038	15.70%
	M4	0.970	0.895	0.842	0.836	0.892	0.914	0.807	0.856	0.071	0.035	18.20%
	M5	0.972	0.911	0.857	0.864	0.906	0.931	0.828	0.878	0.052	0.030	112.91%
Kvasir [72]	M1	0.965	0.910	0.854	0.820	0.860	0.900	0.770	0.820	0.107	0.053	
	M2	0.968	0.914	0.865	0.850	0.872	0.915	0.791	0.845	0.101	0.045	13.52%
	M3	0.969	0.925	0.887	0.874	0.890	0.932	0.820	0.875	0.089	0.034	18.54%
	M4	0.968	0.929	0.897	0.889	0.902	0.940	0.832	0.894	0.078	0.031	111.09%
	M5	0.976	0.957	0.916	0.903	0.921	0.958	0.864	0.912	0.052	0.024	116.37%
COD10K [41]	M1	0.965	0.781	0.685	0.668	0.807	0.840	0.665	0.685	0.167	0.042	
	M2	0.970	0.790	0.699	0.685	0.812	0.855	0.623	0.710	0.160	0.039	12.66%
	M3	0.972	0.805	0.722	0.708	0.823	0.874	0.648	0.736	0.141	0.037	16.32%
	M4	0.972	0.810	0.730	0.717	0.830	0.881	0.660	0.751	0.130	0.033	18.84%
	M5	0.974	0.823	0.752	0.742	0.846	0.901	0.689	0.768	0.114	0.028	112.99%
DUT [267]	M1	0.905	0.860	0.800	0.792	0.784	0.808	0.686	0.776	0.157	0.116	
	M2	0.911	0.868	0.818	0.808	0.801	0.824	0.714	0.794	0.143	0.100	13.91%
	M3	0.925	0.882	0.848	0.829	0.828	0.856	0.750	0.830	0.119	0.087	19.25%
	M4	0.930	0.890	0.860	0.838	0.838	0.871	0.775	0.848	0.102	0.079	112.34%
	M5	0.939	0.905	0.887	0.861	0.862	0.908	0.816	0.882	0.072	0.064	118.29%
SBU [182]	M1	0.961	0.880	0.836	0.820	0.840	0.900	0.774	0.857	0.068	0.041	
	M2	0.964	0.892	0.852	0.841	0.857	0.928	0.791	0.865	0.092	0.038	12.56%
	M3	0.969	0.908	0.870	0.861	0.868	0.938	0.810	0.879	0.078	0.033	16.55%
	M4	0.972	0.917	0.881	0.870	0.872	0.944	0.822	0.885	0.072	0.030	18.61%
	M5	0.978	0.937	0.903	0.889	0.886	0.957	0.848	0.899	0.059	0.025	112.86%
GDD [191]	M1	0.930	0.915	0.900	0.887	0.845	0.900	0.852	0.905	0.061	0.068	
	M2	0.933	0.920	0.909	0.891	0.855	0.906	0.861	0.910	0.060	0.065	11.18%
	M3	0.939	0.930	0.919	0.904	0.870	0.915	0.874	0.921	0.055	0.058	14.02%
	M4	0.943	0.934	0.924	0.910	0.878	0.920	0.881	0.924	0.052	0.055	15.42%
	M5	0.951	0.944	0.937	0.921	0.892	0.933	0.898	0.935	0.049	0.049	17.89%
ORSI-4199 [178]	M1	0.960	0.820	0.792	0.800	0.831	0.878	0.727	0.780	0.122	0.145	
	M2	0.961	0.832	0.812	0.808	0.836	0.890	0.730	0.785	0.120	0.143	14.22%
	M3	0.965	0.855	0.827	0.826	0.847	0.912	0.746	0.808	0.112	0.038	14.82%
	M4	0.967	0.865	0.835	0.830	0.852	0.921	0.752	0.814	0.106	0.036	16.37%
	M5	0.969	0.883	0.853	0.840	0.864	0.935	0.767	0.839	0.095	0.032	19.78%

M2 and M4 shows that the dual branch gated network obtains a considerable performance gain. In Tab. 14, M3 vs. M2 and M4 vs. M3 demonstrate the effectiveness of gate units in cross-modal fusion and encoder-decoder feature transition, respectively. In addition, the curves of gate value on each dataset in ten tasks as shown in Fig. 8. From these gated patterns, we reveal some insightful findings: **I)** For the distribution of gate values at all levels in the FPN branch, Fig. 8(a), (b), (e), (f), (g) present G1 and G2 are smaller than G3, G4, G5, while G1 in Fig. 8(c), (d), (h) has the opposite trend. Analyzed from the visual perception, camouflaged objects, orsi object and polyps are easy to be confused with the background. The

Table 14 Ablation experiments for RGB-D salient object detection. M1: FPN Baseline. M2: + Residual Parallel Branch. M3: + Cross-modal Gate Units. M4: + Encoder-Decoder Gate Units. M5: + Fold-ASPP.

Dataset	Method	PA \uparrow	$F_{\beta}^{max} \uparrow$	$F_{\beta}^{mean} \uparrow$	$F_{\beta}^w \uparrow$	$S_m \uparrow$	$E_m \uparrow$	$IOU \uparrow$	$Dice \uparrow$	$BER \downarrow$	$\mathcal{M} \downarrow$	Δ gains
STERE [143]	M1	0.944	0.882	0.853	0.802	0.860	0.874	0.817	0.833	0.057	0.048	
	M2	0.949	0.888	0.871	0.825	0.870	0.890	0.825	0.845	0.054	0.045	12.31%
	M3	0.958	0.905	0.885	0.847	0.892	0.914	0.838	0.867	0.050	0.041	15.35%
	M4	0.968	0.920	0.897	0.869	0.910	0.934	0.850	0.888	0.046	0.036	18.80%
	M5	0.970	0.929	0.907	0.889	0.921	0.952	0.862	0.909	0.043	0.03	111.42%
SIP [43]	M1	0.932	0.877	0.850	0.801	0.850	0.860	0.774	0.816	0.110	0.078	
	M2	0.935	0.885	0.861	0.817	0.862	0.874	0.795	0.830	0.097	0.070	13.41%
	M3	0.937	0.898	0.874	0.840	0.877	0.896	0.812	0.855	0.084	0.056	17.95%
	M4	0.960	0.915	0.890	0.862	0.894	0.922	0.827	0.879	0.070	0.04	112.18%
	M5	0.963	0.927	0.902	0.877	0.903	0.939	0.840	0.894	0.058	0.03	115.39%
NJUD [80]	M1	0.953	0.874	0.830	0.825	0.861	0.870	0.802	0.840	0.072	0.059	
	M2	0.957	0.886	0.845	0.840	0.876	0.886	0.820	0.860	0.067	0.055	12.73%
	M3	0.964	0.905	0.874	0.870	0.898	0.914	0.846	0.882	0.057	0.046	17.82%
	M4	0.970	0.926	0.906	0.897	0.919	0.936	0.871	0.913	0.048	0.036	112.96%
	M5	0.975	0.943	0.928	0.913	0.931	0.956	0.888	0.924	0.041	0.028	116.80%
NLPD [141]	M1	0.952	0.882	0.826	0.810	0.867	0.875	0.800	0.862	0.068	0.042	
	M2	0.956	0.893	0.840	0.826	0.880	0.890	0.818	0.870	0.062	0.038	13.01%
	M3	0.966	0.903	0.868	0.847	0.896	0.921	0.840	0.885	0.055	0.032	17.27%
	M4	0.972	0.922	0.898	0.879	0.917	0.948	0.861	0.905	0.046	0.026	112.10%
	M5	0.978	0.936	0.911	0.902	0.933	0.962	0.873	0.915	0.040	0.020	114.96%

boundary information is very important to distinguish the fore/background, which drives the network to pay more attention on low-level features. **II)** For the distribution of gate values at all levels in the parallel branch, the greater contribution of G1 and G2 in Fig. 8(d), (h) compared to the other tasks further illustrates the importance of details information in camouflaged and polyp segmentation tasks. **III)** As shown in Fig. 8(e), G4 and G5 have high values in both FPN branch and parallel branch, indicating that the accurate localization of focused regions is extremely crucial for defocus blur detection and motivate the network to consistently maintain a high pass-through pattern for high-level features. **IV)** Compared to other gate values in the FPN branch, G4 is the largest one and even exceeds 0.9 for almost all tasks. This phenomenon is also in line with our general understanding for deep networks, i.e., level-4 features effectively can construct the main

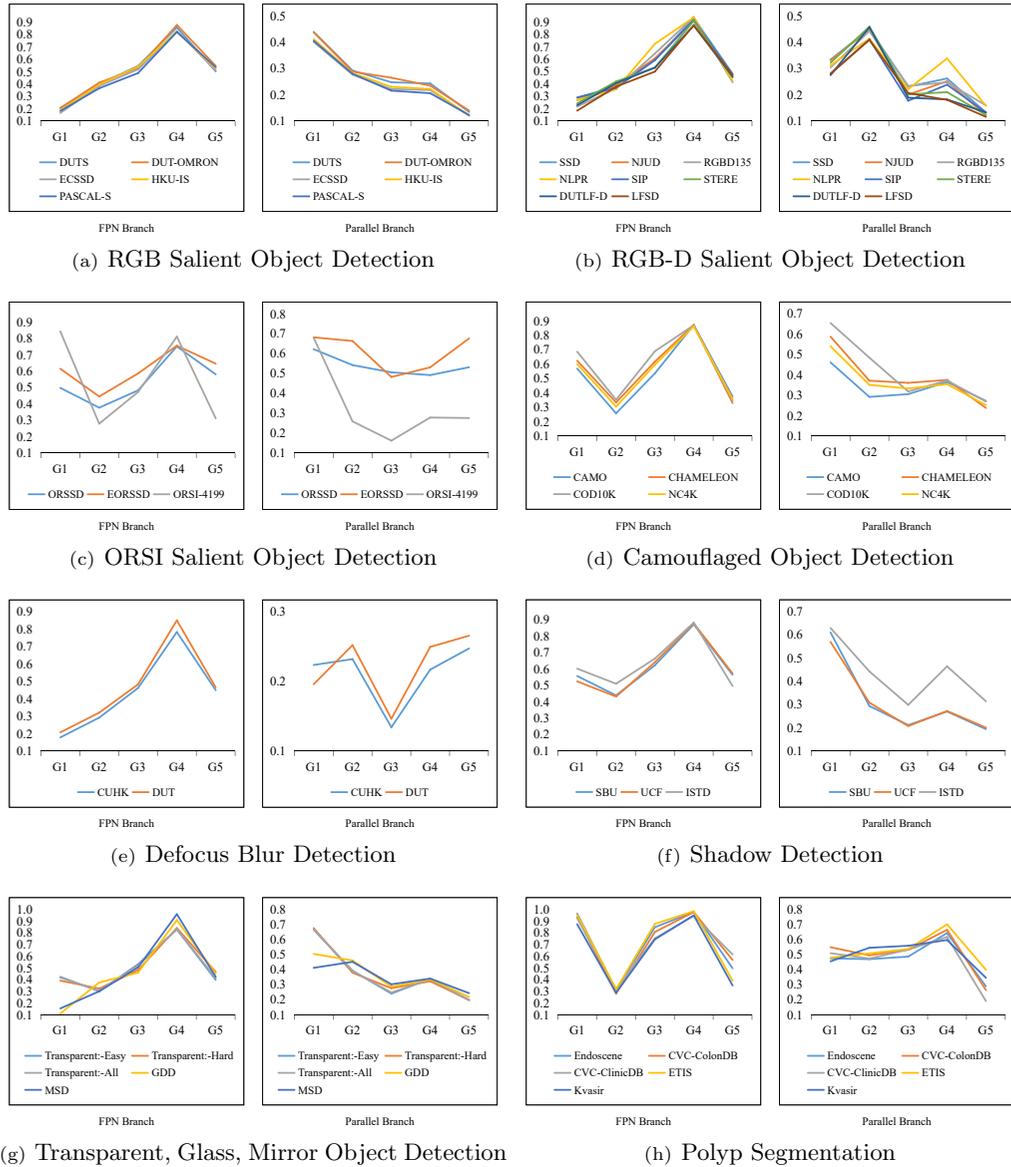


Fig. 8 Distributions of gate weights separately presented in the FPN and parallel branch on 35 datasets of 10 tasks.

body of foreground because they not only contain stable semantic information but also have larger spatial resolution than level-5 features. **V**) Distributions of gate weights can well depict the similarities and differences among diverse binary segmentation sub-tasks.

To show the effect of the gate units more intuitively, we visualize the features of different levels in Fig. 9. It can be observed that even if the dog

has a very low contrast with the chair or the billboard (see the 1st ~ 4th rows), through using multi-level gate units, the high contrast between the object region and the background is always maintained at each layer while the detailed information is continually regained, thereby making salient objects be effectively distinguished. And, the gate units can avoid excessive suppression of the slender parts of objects (see the 5th ~ 8th rows). The corners of the poster, the limbs and

Table 15 Evaluation of the folded atrous convolution. (x) stands for different sampling rates of atrous convolution. D-ASPP is DenseASPP [228].

Metric	Atrous r=2	Atrous r=4	Atrous r=6	Fold r=2	Fold r=4	Fold r=6	ASPP	Fold-ASPP	D-ASPP	Fold-D-ASPP
<i>DUTS [188]</i>	PA ↑	0.970	0.970	0.971	0.971	0.971	0.972	0.972	0.971	0.971
	F _{max} ↑	0.894	0.895	0.898	0.898	0.902	0.906	0.903	0.911	0.902
	F _{mean} ↑	0.843	0.845	0.848	0.847	0.851	0.853	0.852	0.857	0.854
	F ₅₀ ↑	0.837	0.841	0.843	0.841	0.845	0.852	0.850	0.864	0.844
	S _m ↑	0.891	0.894	0.896	0.896	0.899	0.901	0.901	0.906	0.898
	E _m ↑	0.914	0.916	0.918	0.918	0.921	0.924	0.924	0.931	0.923
	IOU ↑	0.805	0.808	0.811	0.811	0.815	0.820	0.816	0.828	0.815
	Dice ↑	0.856	0.859	0.861	0.860	0.865	0.870	0.866	0.878	0.864
	BER ↓	0.073	0.069	0.064	0.067	0.062	0.056	0.057	0.052	0.060
	M ↓	0.035	0.035	0.034	0.034	0.034	0.033	0.033	0.030	0.034
Δ gains	10.76%	11.94%	11.48%	12.48%	13.91%	13.62%	16.03%	12.78%	14.73%	
<i>Kwaf [79]</i>	PA ↑	0.968	0.968	0.970	0.971	0.973	0.975	0.974	0.976	0.976
	F _{max} ↑	0.929	0.930	0.932	0.932	0.933	0.935	0.935	0.937	0.941
	F _{mean} ↑	0.899	0.902	0.904	0.905	0.908	0.912	0.909	0.916	0.913
	F ₅₀ ↑	0.888	0.889	0.892	0.893	0.896	0.899	0.897	0.903	0.897
	S _m ↑	0.902	0.905	0.912	0.907	0.912	0.917	0.915	0.921	0.925
	E _m ↑	0.941	0.943	0.945	0.945	0.949	0.953	0.952	0.958	0.949
	IOU ↑	0.827	0.831	0.835	0.842	0.844	0.847	0.853	0.864	0.850
	Dice ↑	0.892	0.898	0.900	0.898	0.901	0.908	0.908	0.912	0.905
	BER ↓	0.076	0.074	0.070	0.071	0.068	0.064	0.064	0.052	0.065
	M ↓	0.031	0.030	0.029	0.029	0.027	0.026	0.027	0.024	0.025
Δ gains	10.81%	11.93%	11.84%	13.13%	13.82%	13.96%	16.86%	13.80%	16.30%	
<i>COD10K [41]</i>	PA ↑	0.972	0.972	0.972	0.972	0.974	0.974	0.973	0.974	0.972
	F _{max} ↑	0.808	0.811	0.813	0.814	0.817	0.819	0.819	0.823	0.810
	F _{mean} ↑	0.730	0.734	0.738	0.737	0.741	0.747	0.746	0.752	0.740
	F ₅₀ ↑	0.717	0.720	0.722	0.724	0.729	0.734	0.730	0.742	0.717
	S _m ↑	0.828	0.831	0.834	0.833	0.837	0.840	0.836	0.846	0.833
	E _m ↑	0.878	0.882	0.886	0.884	0.890	0.893	0.893	0.901	0.890
	IOU ↑	0.663	0.667	0.671	0.670	0.677	0.680	0.679	0.689	0.665
	Dice ↑	0.753	0.755	0.756	0.758	0.761	0.764	0.761	0.768	0.747
	BER ↓	0.135	0.132	0.127	0.130	0.123	0.119	0.121	0.114	0.123
	M ↓	0.033	0.032	0.032	0.031	0.030	0.030	0.031	0.028	0.032
Δ gains	10.83%	11.46%	11.54%	12.81%	13.44%	12.81%	14.94%	12.76%	12.45%	
<i>DUT [90]</i>	PA ↑	0.931	0.932	0.934	0.934	0.935	0.937	0.937	0.939	0.937
	F _{max} ↑	0.892	0.895	0.896	0.896	0.899	0.901	0.899	0.905	0.901
	F _{mean} ↑	0.863	0.867	0.871	0.872	0.875	0.881	0.879	0.887	0.887
	F ₅₀ ↑	0.840	0.844	0.847	0.847	0.851	0.854	0.852	0.861	0.854
	S _m ↑	0.837	0.840	0.845	0.844	0.850	0.854	0.852	0.862	0.853
	E _m ↑	0.872	0.877	0.883	0.882	0.887	0.892	0.892	0.908	0.886
	IOU ↑	0.779	0.784	0.790	0.788	0.796	0.804	0.800	0.816	0.805
	Dice ↑	0.855	0.859	0.863	0.865	0.870	0.874	0.872	0.882	0.874
	BER ↓	0.107	0.099	0.092	0.089	0.084	0.800	0.084	0.072	0.080
	M ↓	0.079	0.076	0.074	0.071	0.069	0.069	0.070	0.064	0.070
Δ gains	11.47%	12.74%	13.39%	14.40%	15.31%	14.64%	17.50%	15.08%	18.03%	
<i>SRU [188]</i>	PA ↑	0.972	0.974	0.975	0.975	0.976	0.977	0.977	0.978	0.976
	F _{max} ↑	0.917	0.921	0.924	0.923	0.927	0.931	0.930	0.937	0.927
	F _{mean} ↑	0.881	0.886	0.891	0.890	0.893	0.897	0.896	0.903	0.894
	F ₅₀ ↑	0.873	0.876	0.877	0.876	0.880	0.883	0.882	0.889	0.877
	S _m ↑	0.870	0.873	0.875	0.876	0.878	0.881	0.880	0.886	0.875
	E _m ↑	0.944	0.946	0.949	0.948	0.951	0.952	0.951	0.957	0.950
	IOU ↑	0.825	0.831	0.836	0.833	0.839	0.843	0.842	0.848	0.836
	Dice ↑	0.882	0.885	0.888	0.888	0.891	0.893	0.894	0.899	0.885
	BER ↓	0.072	0.071	0.065	0.067	0.065	0.063	0.063	0.059	0.067
	M ↓	0.031	0.030	0.029	0.029	0.027	0.027	0.028	0.025	0.028
Δ gains	10.78%	12.29%	11.85%	13.07%	13.59%	13.22%	15.39%	12.29%	13.08%	
<i>GID [131]</i>	PA ↑	0.943	0.939	0.943	0.944	0.947	0.947	0.947	0.951	0.946
	F _{max} ↑	0.934	0.925	0.928	0.929	0.934	0.937	0.939	0.944	0.940
	F _{mean} ↑	0.923	0.925	0.929	0.927	0.931	0.933	0.933	0.937	0.931
	F ₅₀ ↑	0.912	0.913	0.914	0.913	0.916	0.917	0.917	0.921	0.912
	S _m ↑	0.881	0.883	0.885	0.884	0.886	0.888	0.888	0.892	0.870
	E _m ↑	0.917	0.917	0.923	0.922	0.925	0.927	0.923	0.933	0.908
	IOU ↑	0.878	0.882	0.886	0.885	0.891	0.893	0.890	0.898	0.890
	Dice ↑	0.922	0.925	0.925	0.927	0.929	0.930	0.929	0.935	0.903
	BER ↓	0.054	0.052	0.052	0.052	0.052	0.050	0.049	0.049	0.051
	M ↓	0.055	0.055	0.054	0.054	0.053	0.051	0.052	0.049	0.054
Δ gains	10.37%	10.93%	10.79%	12.27%	12.15%	12.09%	13.13%	13.10%	11.54%	
<i>ONS-1190 [78]</i>	PA ↑	0.966	0.967	0.967	0.968	0.967	0.968	0.967	0.969	0.968
	F _{max} ↑	0.864	0.867	0.869	0.870	0.873	0.877	0.876	0.883	0.876
	F _{mean} ↑	0.834	0.837	0.840	0.839	0.845	0.847	0.846	0.853	0.845
	F ₅₀ ↑	0.830	0.831	0.833	0.833	0.836	0.838	0.836	0.840	0.838
	S _m ↑	0.850	0.854	0.856	0.855	0.858	0.860	0.860	0.864	0.862
	E _m ↑	0.919	0.923	0.926	0.925	0.929	0.930	0.929	0.935	0.932
	IOU ↑	0.744	0.755	0.758	0.758	0.760	0.763	0.763	0.767	0.766
	Dice ↑	0.816	0.820	0.824	0.823	0.829	0.832	0.830	0.839	0.835
	BER ↓	0.111	0.105	0.103	0.103	0.101	0.100	0.101	0.095	0.098
	M ↓	0.037	0.037	0.036	0.036	0.034	0.034	0.035	0.032	0.035
Δ gains	10.79%	11.47%	11.47%	12.50%	12.78%	12.32%	14.06%	12.77%	15.59%	

even tentacles of the mantis are retained well. Besides, we show the visual results of the gate units in the two-stream network for RGB-D SOD, as shown in Fig. 10. Intuitively, the depth branch has more significant and pure position and edge information about the foreground (cloth) than the RGB branch on E4, E2 and E1, thus distributes larger gate weights correspondingly in cross-modal fusion.

• **Folded Atrous Convolution.** Based on the gated dual branch network, we design a series of experimental options to verify the effectiveness of the folded atrous convolution. Tab. 15

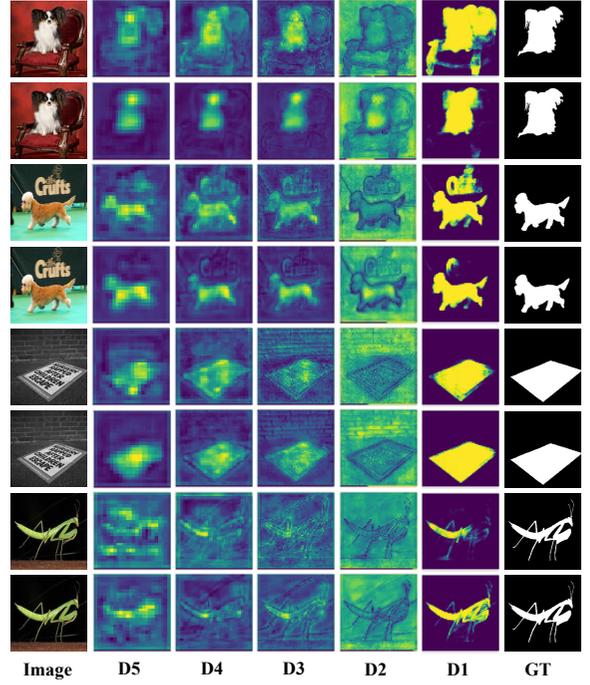


Fig. 9 Visual comparison of feature maps for showing the effect of the multi-level gate units. D5 ~ D1 represent the feature maps of each decoder block from high level to low level. Odd rows and even rows are the results of the FPN baseline without or with multi-level gate units, respectively.

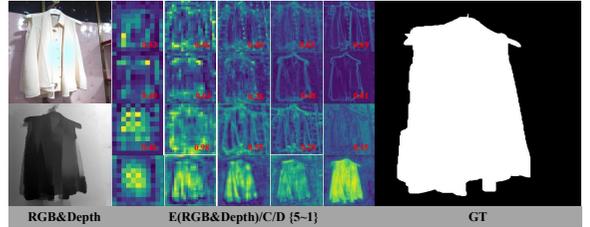


Fig. 10 Visual results of feature maps. Each RGB-D input image corresponds to four rows of feature maps. The first two rows are RGB and Depth encoder feature maps (E5 - E1), respectively. The third row is the cross-modal fusion feature maps (C5 - C1). The last row is the decoder feature maps (D5 - D1). The naming of these feature maps is consistent with those in Fig. 7.

illustrates the results in detail. We adopt the atrous convolution with dilation rates of [2, 4, 6] and the same dilation rates are also applied to the folded atrous convolution. It can be observed that the folded atrous convolution consistently yields significant performance improvement at

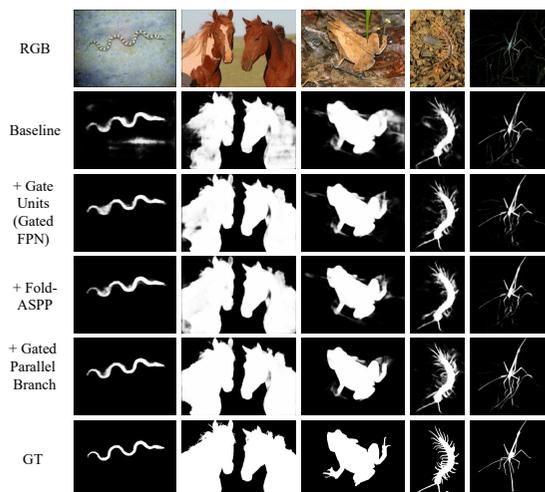


Fig. 11 Illustration of the benefit of each component.

each dilation rate than the corresponding atrous convolution in terms of all ten metrics. And the single-layer Fold(6) already performs better than the ASPP and DenseASPP of aggregating three atrous convolution layers. The Fold-ASPP and Fold-DenseASPP naturally outperforms the ASPP and DenseASPP, respectively. Our fold operation can naturally increase the receptive field. For a fair comparison, we can also see that compared with Atrous(4) with the same receptive field, Fold(2) still has an advantage under all metrics.

Fig.11 shows visual results of the above ablation studies on some examples. It can be seen that the gated FPN model accurately determines where is the foreground object. With the help of Fold-ASPP, the overall integrity of the object is further captured. It should also be noted that the gated parallel branch can improve perceptual results greatly by highlighting the fore/background difference and preserving the intra-class consistency, thereby yielding the sharpened boundary.

4.6 Gate Unit Meets Transformer

With the development of vision transformer [179], recent binary works achieve good performance on many important benchmarks. In this section, we first analyse the advantages of GateNet compared to transformer-based methods in terms of accuracy and efficiency. Next, we quantitatively and qualitatively show the limitations of transformer-based methods in cross-branch prediction. Finally,

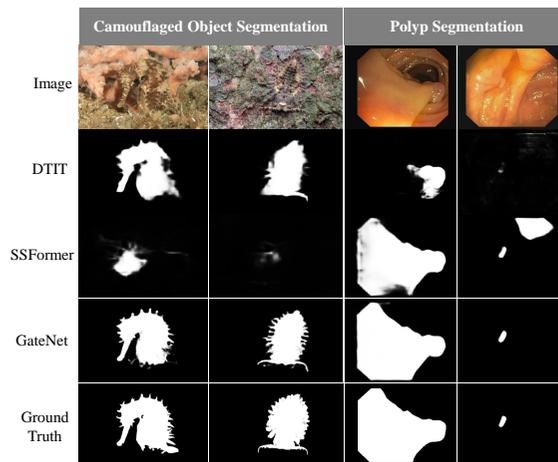


Fig. 12 Qualitative evaluation of DTIT [122], SSFormer [187] and GateNet. For DTIT and SSFormer, Polyp segmentation and camouflaged object segmentation are their cross-branch validations, respectively.

we explore the positive impact of the gate unit on transformer.

• **Advantages in Accuracy and Efficiency.** In Tab. 16, we can see that the GateNet has obvious advantages in accuracy, model size, training time, inference speed and memory requirements. Compared to transformer-based architectures [64, 69, 122, 139], GateNet achieves a good balance between accuracy and efficiency.

• **Advantages in Cross-branch Prediction.** To investigate the performance of transformer-based methods on cross-branch prediction, we separately select two representative transformer-based methods [122, 187] from camouflaged object segmentation and polyp segmentation field for cross-branch training and then conduct quantitative and qualitative evaluation. As shown in Tab. 17, both two transformer-based methods perform poorly in cross-branch comparison. We summarize some instructive reasons as follows: **I) Motivation of Designs.** The motivation of GateNet is to solve the generalized binary segmentation challenge. We propose the gate unit, fold-aspp and residual parallel branch for suppressing background inference, perceiving multi-scale objects and restoring edge details, respectively. As a result, GateNet can be well generalized to diverse binary segmentation tasks. However, SSFormer [187] and DTIT [122] focus more on specific characteristics within the sub-branch and propose expert designs for polyp segmentation

Table 16 Accuracy and efficiency comparison with different transformer-based methods on the COD10K [41] test set. The best scores are highlighted in red.

Method	Publication	Backbone	Parameters ↓	Training Time ↓	Inference Speed ↑	Inference Memory ↓	F_{β}^{ω} ↑	S_m ↑	E_m ↑
OSformer [139]	ECCV 2022	ResNet-50	46.6 MB	10 Hours	15 Fps	2.5 GB	0.685	0.813	0.893
DTIT [122]	ICPR 2022	MiT-B5	253.7 MB	23 Hours	8 Fps	4.5 GB	0.695	0.824	0.896
HitNet [64]	AAAI 2023	PvTv2-B2	24.4 MB	13 Hours	7 Fps	4.2 GB	0.806	0.868	0.936
FSPNet [69]	CVPR 2023	ViT-B	84.2 MB	64 Hours	19 Fps	3.2 GB	0.735	0.851	0.930
GateNet	-	ResNet-50	29.68 MB	6 Hours	55 Fps	2.1 GB	0.742	0.846	0.901
GateNet	-	PvTv2-B2	20.32 MB	5 Hours	58 Fps	1.9 GB	0.813	0.876	0.942
GateNet	-	ViT-B	43.12 MB	8 Hours	43 Fps	2.7 GB	0.828	0.888	0.947

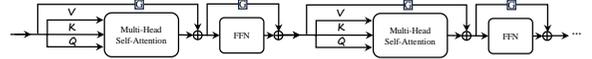
Table 17 Cross-branch validation using two transformer-based methods on camouflaged object dataset COD10K [41] and polyp dataset CVC-ClinicDB [5].

Method	COD10K			CVC-ClinicDB	
	F_{β}^{ω} ↑	S_m ↑	E_m ↑	IOU ↑	$Dice$ ↑
SSFormer [187]	0.635	0.773	0.848	0.876	0.927
DTIT [122]	0.695	0.824	0.896	0.749	0.803
GateNet	0.742	0.846	0.901	0.902	0.943

and camouflaged object segmentation, respectively. SSFormer [187] introduces the multi-stage pyramid transformer architecture and proposes the progressive locality decoder to smooth and emphasise the local features in the transformer, thereby improving the detailed information processing ability of the neural network. Authors think that the morphology of polyps is variable, but the structure of polyp images is relatively simple. Therefore, SSFormer [187] focuses on capturing the morphology and local information but ignores the background inference, which makes it perform poorly in camouflaged object segmentation where background scenes are often complex, as shown in Fig. 12. DTIT [122] is bio-inspired by the discovery of camouflaged objects, in which the boundary feature is considered as query to improve the object detection and the object feature is taken as query to improve the boundary detection. The object and boundary detection are fully interacted by multi-head self-attention. However, DTIT [122] ignores the scale varying in different objects and may produce failure prediction for tiny or large objects, as shown in Fig. 12.

II) Model Complexity. Transformer-based models usually have high complexity and require a large amount of data and computational resources for training. If they are not adequately trained or the training data is not sufficient, it may lead to performance degradation when conducting cross-branch prediction.

III) Hyperparameter Selection. Many works [36, 177, 292] show that the transformer-based methods are very sensitive for

**Fig. 13** Illustration of the simple gated transformer.**Table 18** Qualitative evaluation of applying simple gated transformer and multi-level gate units to existing transformer-based COD methods on the COD10K test set.

Method	Publication	Backbone	F_{β}^{ω} ↑	S_m ↑	E_m ↑
DTIT [122]	ICPR 2022	MiT-B5	0.695	0.824	0.896
DTIT-Gate	ICPR 2022	MiT-B5	0.721	0.847	0.928
FSPNet [69]	CVPR 2023	ViT-B	0.735	0.851	0.930
FSPNet-Gate	CVPR 2023	ViT-B	0.764	0.869	0.938

the learning rate and optimizer settings during the training phase. Improper choice of hyperparameters may degrade the performance of the cross-branch model. Different from the transformer-based approaches, GateNet consistently achieves good results with uniform training settings for all tasks, including image size, enhancement techniques, optimizer parameters, learning rate, and the numbers of epoch.

• **Gated Mechanism Powers Transformer.** We explore the potential of improving the transformer-based methods by incorporating gate design. The vanilla transformer uses all pass skip connection to fuse the original input features and the output features through multi-head self-attention (MHSA) and FFN. With the help of MHSA and FFN, query, key and value can generate task-specific strong attention features. However, all pass skip connection may introduce incompatible interference information and reduce the performance of the transformer. To this end, we naturally apply our gate unit to the vanilla transformer. We integrate the initial features and the output features through MHSA/FFN to generate gate values, which can adaptively control the information transition from skip connection. The internal structure of the simple gated transformer is shown in Fig. 13. We replace the vanilla

transformer in the transformer-based methods [69, 122] with the gated transformer and multi-level gate units to evaluate the effectiveness of our designs. In Tab. 18, we can see that the gated versions consistently surpass the corresponding vanilla transformer versions.

5 Discussion

In this section, we further provide deeper theoretical explanation of the multi-level gated mechanism and give some potential applications:

- **Prototype I:** In cognitive science, inhibitory neurons, also known as interneurons, play a crucial inhibitory role in the nervous system. Inhibitory neurons play a crucial inhibitory role by balancing excitation and inhibition, improving signal quality, participating in cognitive and emotional processes, and protecting the nervous system. Firstly, they balance excitation and inhibition by suppressing the activity of other neurons, which is important for maintaining normal nervous system function. Secondly, they improve signal quality by reducing neuronal noise and interference, increasing the signal-to-noise ratio and making the signal clearer and more reliable, thereby enhancing the brain’s information processing capabilities. In addition, they participate in various cognitive and emotional processes including working memory, long-term memory, learning, attention, and emotional regulation by regulating the excitability and inhibitory nature of neurons. Lastly, they protect the nervous system from the harm of excessive excitation or inhibition, thereby avoiding the occurrence of some neurological diseases.
- **Prototype II:** In circuit electronics analysis, a gated circuit can control the on/off state of the output signal based on the voltage of the input signal. For a combinational circuit with n outputs, we only need add $n - 1$ gates without other additional designs. In addition, gated circuits are less susceptible to external interference, which can ensure the stability and reliability of the circuit. Due to their fast state transitions, gated circuits are well suited for applications that require high-speed digital control. In terms of achieving adaptive regulation and balance of circuit output, multi-level gated unit circuits combined with feedback control mechanisms play a crucial role. For example, resistors and capacitors can be used to adjust the impedance and phase of the circuit to balance

Table 19 Quantitative comparison of different semantic segmentation methods on the Cityscapes [30] val set. GateNet-JT and GateNet-ST refer to models trained separately or jointly for each category. The best scores are highlighted in **red**.

Method	Publication	Backbone	mIoU \uparrow
FCN [123]	CVPR 2015	ResNet-101	76.6
EncNet [236]	CVPR 2018	ResNet-101	76.9
PSPNet [258]	CVPR 2017	ResNet-101	78.5
CCNet [70]	ICCV 2019	ResNet-101	80.2
DeeplabV3+ [14]	ECCV 2018	ResNet-101	80.9
SETR [276]	CVPR 2021	ViT-Large	82.2
SegFormer [216]	NeurIPS 2021	MiT-B5	84.0
Mask2Former [20]	CVPR 2022	Swin-Large	84.3
GateNetv2-JT	-	ResNet-101	78.3
GateNetv2-JT	-	Swin-Large	80.4
GateNetv2-JT	-	ConNext-Large	80.6
GateNetv2-ST	-	ResNet-101	82.8
GateNetv2-ST	-	Swin-Large	84.9
GateNetv2-ST	-	ConNext-Large	85.2

different sections. Furthermore, feedback control and adaptive control methods can be employed to dynamically adjust the work state of the circuit to achieve adaptive balance.

- **Modeling guidance:** Prototype I provides the basic principles of biological neural networks for introducing gated mechanisms into artificial neural networks. Prototype II provides our GateNet with modular functional guidance. On the one hand, our gate units suppress both channel-wise and spatial feature response. In this way, the network actually learns adaptive thresholding. The area, in which feature values are below this threshold, has a lower response in the prediction, while the feature values above this threshold correspond to the task-specific activation area. It helps the decoder to gradually filter out the region with strong feature response. Our gate unit achieves the same function as the gated circuit in controlling the on/off state of the output signal based on the voltage of the input signal. On the other hand, our GateNet only inserts several gate units between encoder blocks and decoder blocks of the FPN baseline. It has the same convenience of design as the gated circuit. Finally, the backward propagation in the neural networks has the same function as the feedback controlling mechanism in circuit electronics. Therefore, our GateNet has the same adaptive balance function as the gated circuit.

- **Limitations:** The proposed gated mechanism is unsuitable for the multi-class semantic segmentation task. Because this task needs to treat all pixels of the whole image equally importantly and

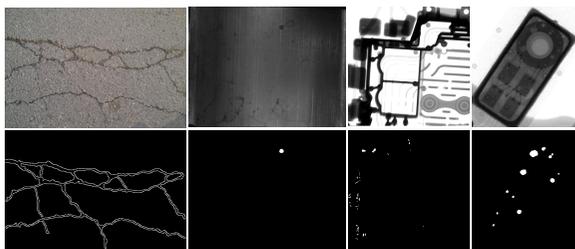


Fig. 14 Some examples of surface defect detection (*e.g.*, crack, magnetic tiles, car parts, electronic components).

all categories have the same importance, the information suppression design is out of place. We apply GateNet separately for semantic segmentation of each class on the popular Cityscapes dataset [30]. In Tab. 19, we can see that GateNet-ST outperforms other models, but GateNet-JT performs poorly. Therefore, the proposed gated mechanism has advantages in binary segmentation focusing on a single class, rather than the semantic segmentation task that require balancing multiple classes. This also means the GateNet has wider applicability to binary segmentation problems.

- **Application:** In this paper, we have given detailed experimental analyses in ten popular binary segmentation tasks. Besides, GateNet has potential application in the field of industry with complex scenes as shown in Fig 14. We hope that this study can provide deep insights into the underlying design for more binary segmentation tasks and spark novel ideas.

6 Conclusions

As far as we know, this is the first work to comprehensively review recent progress in binary segmentation, which summarizes more than 140 fully supervised models according to task settings, technique contributions, and learning strategies. To unify all the sub-branches and establish a fair model benchmark to promote the prosperous development of the binary segmentation field, we propose a novel yet general gated network architecture. We first adopt multi-level gate units to balance the contribution of each encoder block and suppress the activation of the features of non-task-aware regions, which can provide useful context information for the decoder while minimizing interference. We quantitatively reveal the role played by features at all levels of the encoder for different segmentation tasks, which provides

a new perspective on the interpretability of deep learning. Next, we use the Fold-ASPP to gather multi-scale semantic information for the decoder. By the folded operation, the atrous convolution achieves a local-in-local effect, which not only expands the receptive field but also retains the correlation among local sampling points. Finally, to further supplement the details, we combine all encoder features in parallel and construct a residual structure. Experimental results on 33 benchmark datasets towards 10 binary segmentation tasks demonstrate that the proposed model outperforms 42 state-of-the-art methods under 10 evaluation metrics.

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Appendix A Qualitative Evaluation

Fig. A1 - Fig. A10 illustrate some visual comparisons on each sub-task. We summarize the advantages of the GateNet compared to others when facing some challenges: **I) Interference produced by complex.** In camouflaged object detection and poly segmentation tasks, foreground objects usually share the similar appearance to the background, which can easily deceive predictors.

But the GateNet can accurately capture the hidden objects and separate them from the surrounding environment (see the Fig. A9 and Fig. A10). The gated mechanism also plays an important role in RGB -D salient object detection. As shown in Fig. A3, the proposed two-stream GateNet can effectively utilize the guidance information provided by the high-quality depth map while suppressing the interference information from the low-quality depth map, thereby identifying the whole object precisely.

II) Interference produced by adjacent objects. In the real world, shadows often exist on the ground or desktop, and are closely adjacent to the original object. This characteristic requires shadow detection networks to have the ability to distinguish between adjacent objects. As shown in Fig. A5, most methods are disturbed by the surface or the original object, but our method can focus on the shadow regions.

III) The foreground exists multiple or small objects. On the one hand, glass-like objects are often present in groups in the real world, which poses a serious challenge to the perception capability of the network for the multiple objects. On the other hand, small objects usually appear in remote sensing images. Benefiting from the Fold-ASPP, both multiple and small objects can be localized accurately. Fig. A4 and Fig. A7 show that our method can accurately distinguish each independent connected region without sticking to each other. GateNet is the only one can provide clean prediction maps and maintain the basic shape of the aircraft (see the 6th - 8th columns in Fig. A2).

IV) Boundary and details. Our GateNet has a mix feature aggregation decoder that a parallel branch by concatenating the output of the progressive branch and the features of the gated encoder, so that the residual information complementary to the progressive branch is supplemented to generate the final prediction. In this way, the prediction can restore more details, therefore, the limbs and even tentacles of the insects are retained well (see the 3th and 8th columns in Fig. A9).

V) Regional consistency. In defocus blur detection task, the focused area usually has incomplete semantic information because the blurred region may also belong to the semantic part of the foreground. Benefiting from the folded operation, our model can obtain more stable structural features to improve the intra-class consistency. From the results in Fig. A6, it can be

observed that our method can segment the foreground well while the other methods more or less lose similar areas inside or around focused regions.



Fig. A1 Visual comparison between our GateNet results and the state-of-the-art methods (CTDNet [273], VST [116], LDF [203], Auto-MSF [242], KRN [220], MINet [136], ITSD [278], F3Net [202]) on **RGB SOD** datasets.



Fig. A2 Visual comparison between our GateNet results and the state-of-the-art methods (RRNet [29], MJRBM [178], DAFNet [249]) on **ORSI SOD** datasets.

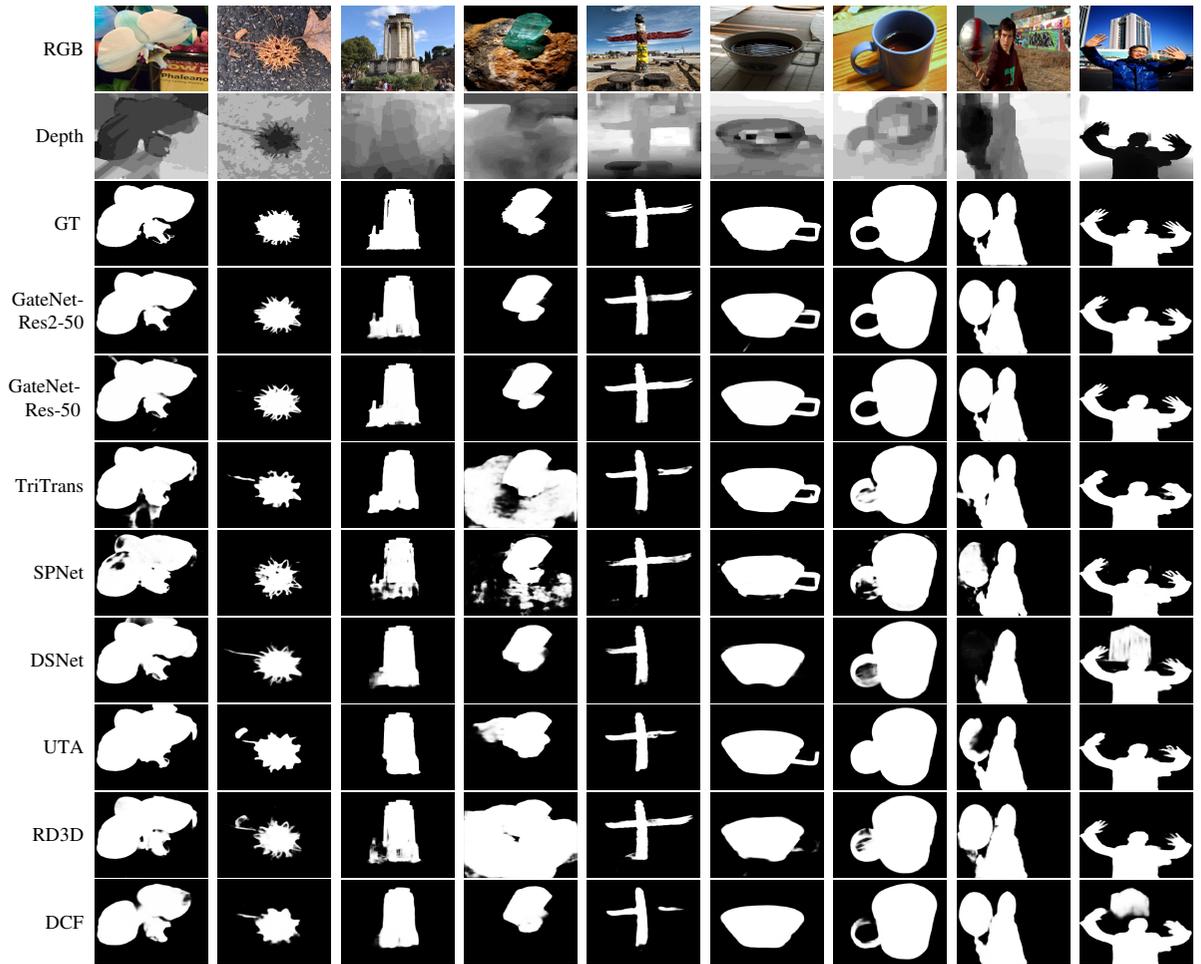


Fig. A3 Visual comparison between our GateNet results and the state-of-the-art methods (TriTransNet [121], SPNet [280], DSNet [204], UTA [272], RD3D [15], DCF [74]) on RGB-D SOD datasets.

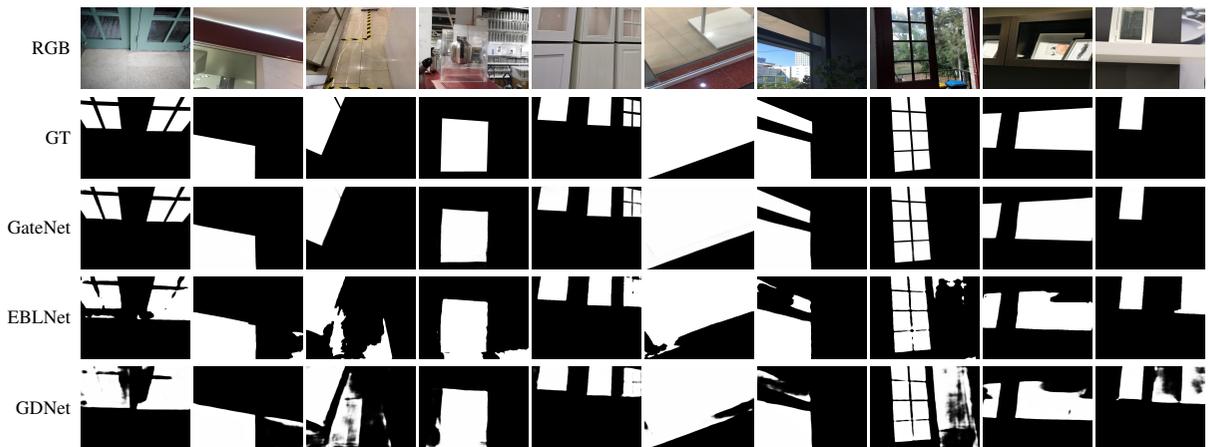


Fig. A4 Visual comparison between our GateNet results and the state-of-the-art methods (EBLNet [58], GDNet [131]) on Glass Object Detection datasets.

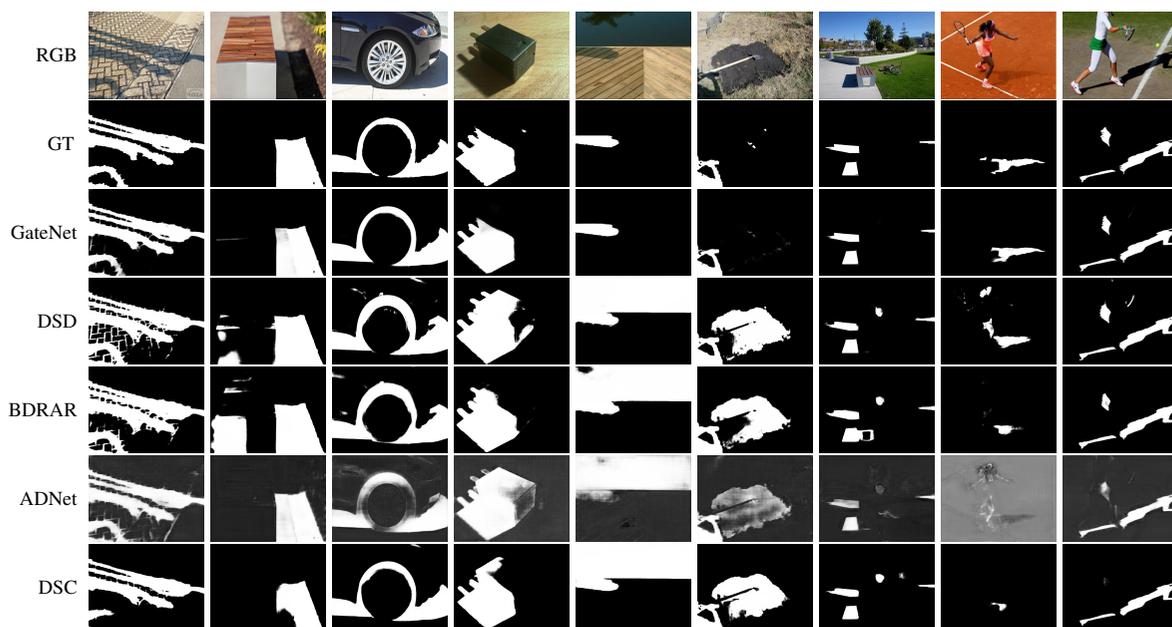


Fig. A5 Visual comparison between our GateNet results and the state-of-the-art methods (DSD [275], BDRAR [289], ADNet [87], DSC [67]) on **Shadow Detection** datasets.



Fig. A6 Visual comparison between our GateNet results and the state-of-the-art methods (DENets [263], IS2CNet [256], SG [264], Depth-Distill [31], CENet [268]) on **Defocus Blur Detection** datasets.

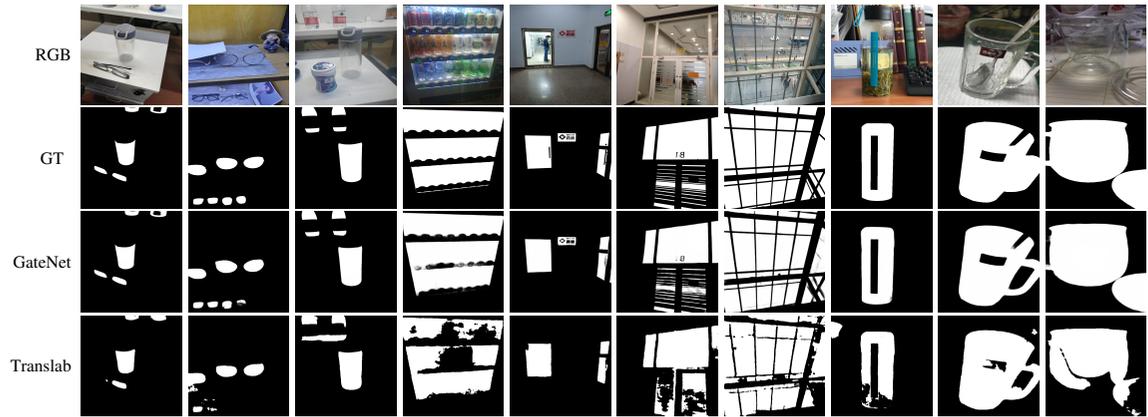


Fig. A7 Visual comparison between our GateNet results and the state-of-the-art method (Translab [217]) on **Transparent Object Detection** datasets.

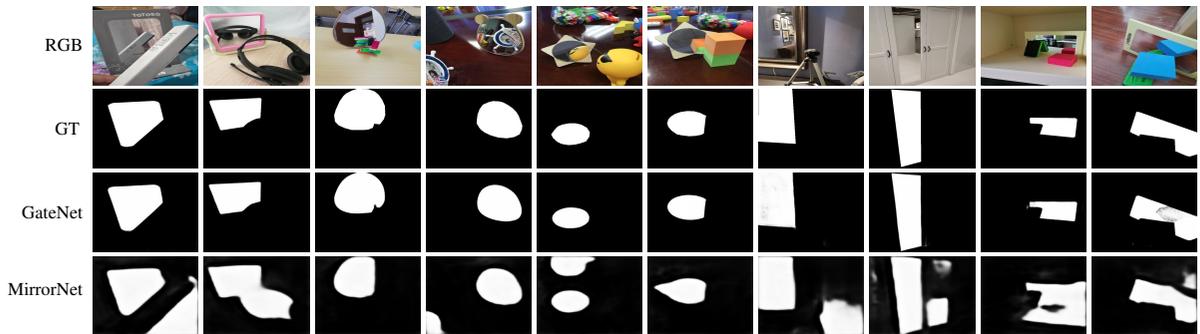


Fig. A8 Visual comparison between our GateNet results and the state-of-the-art method (MirrorNet [229]) on **Mirror Detection** datasets.

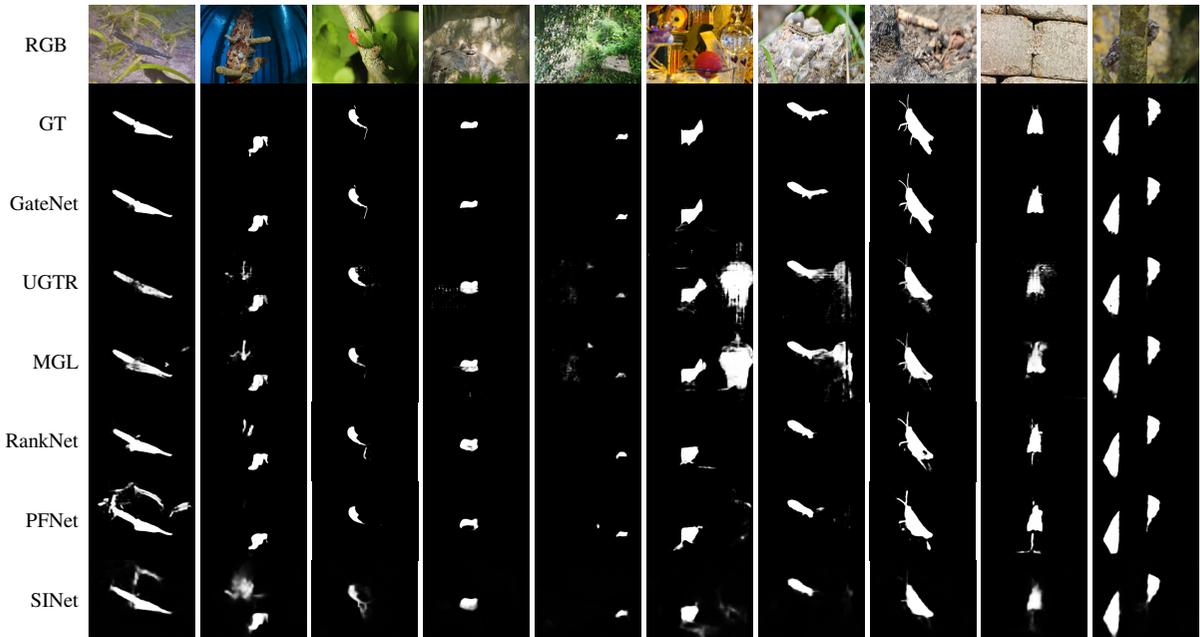


Fig. A9 Visual comparison between our GateNet results and the state-of-the-art methods (UGTR [225], IS2CNet [233], RankNet [125], PFNet [130], SINet [41]) on **Camouflaged Object Detection** datasets.

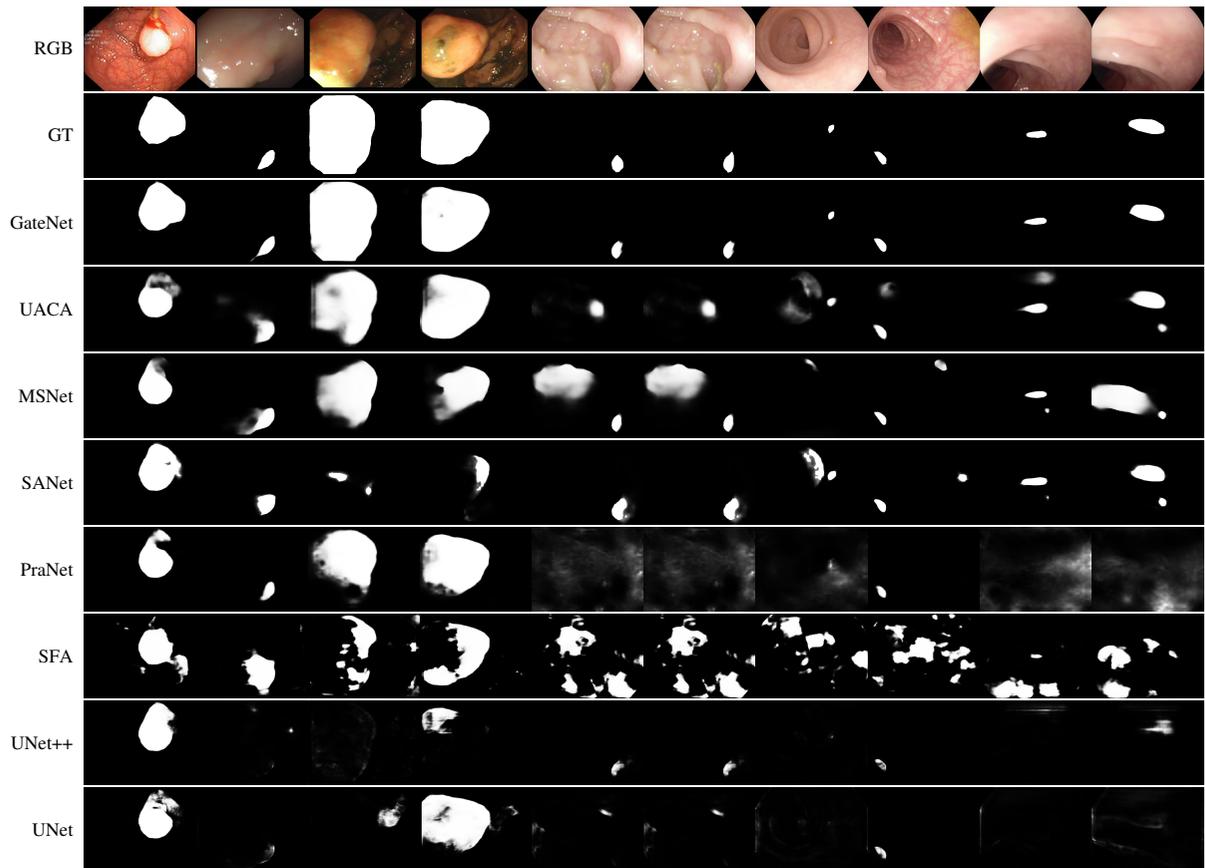


Fig. A10 Visual comparison between our GateNet results and the state-of-the-art methods (UACA [85], MSNet [270], SANet [201], PraNet [42], SFA [48], UNet++ [285], UNet [149]) on **Polyp Segmentation** datasets.