Dual-Stream Adapters for Open-Set Segmentation in Driving Scenes

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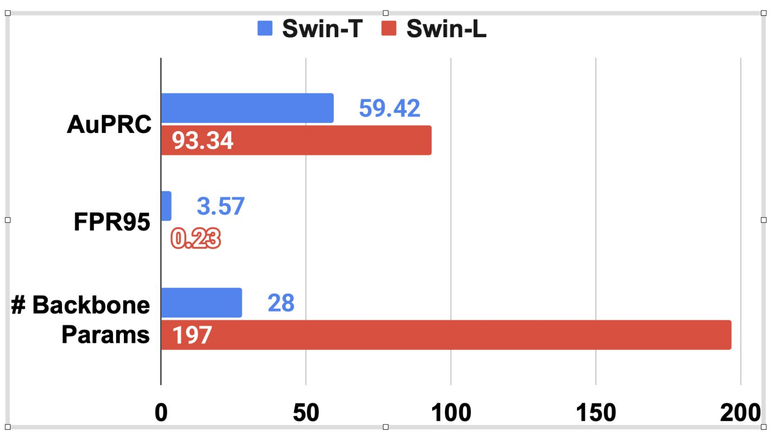
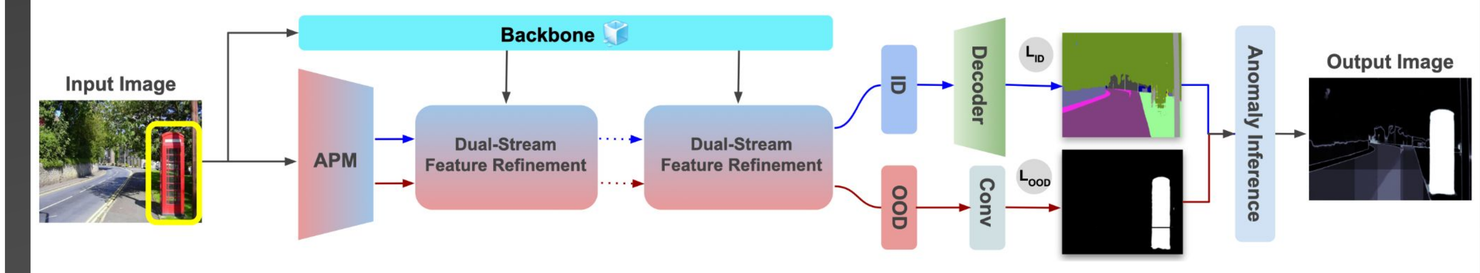
Problem Statement

- Anomaly segmentation performance depends on backbone size.
- Significant number of training parameters.
- High Training Cost.

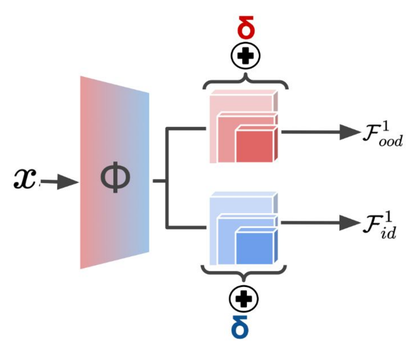


Dual Stream Adapter



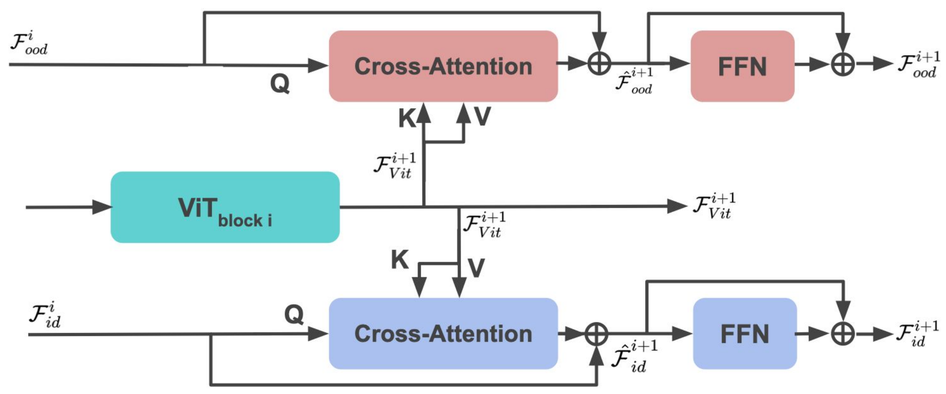
Anomaly Prior Module (APM)

- Learns to extract the initial ID and OOD features from the input image.



Dual-Stream Feature Refinement

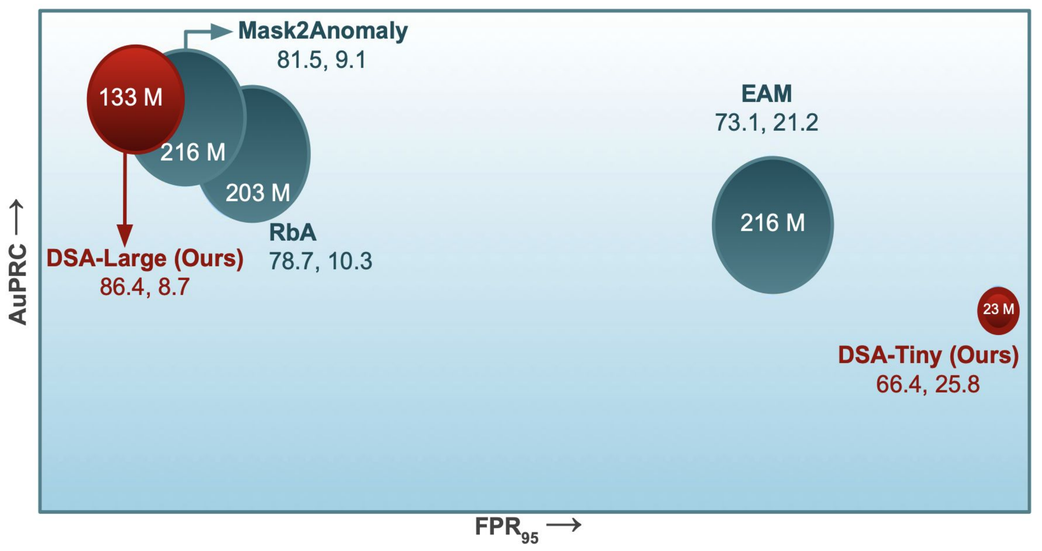
- APM feature refinement and augmentation with the ViT features.



Quantitative Results

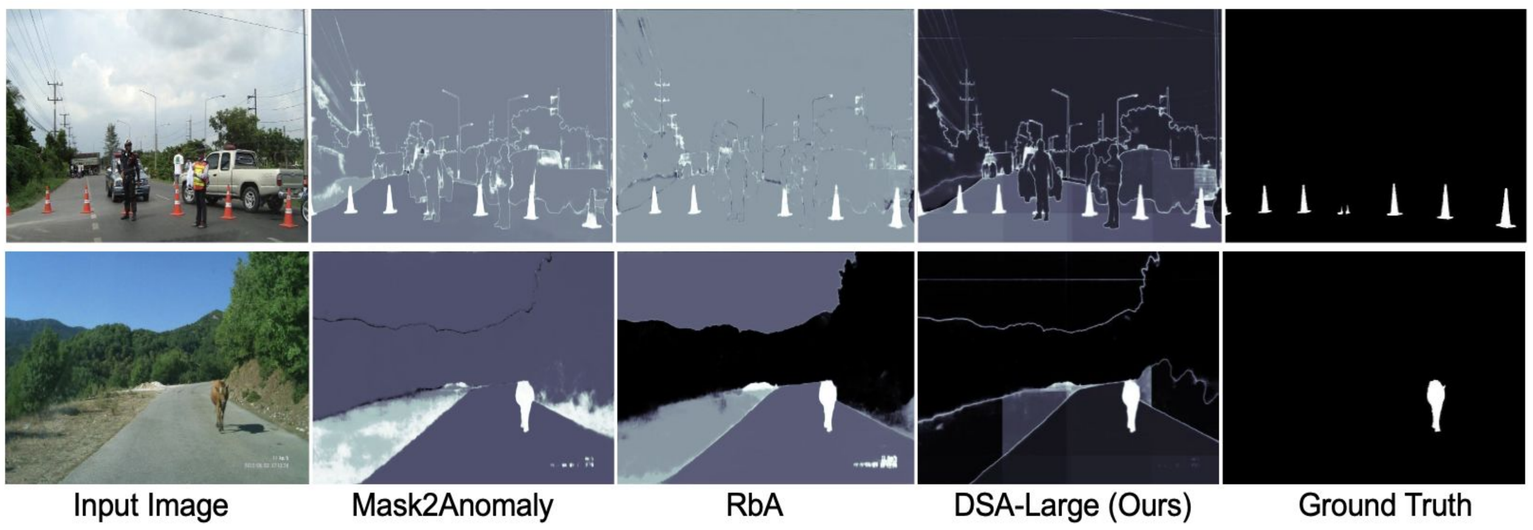
Methods	Real Negatives	SMIYC RA-21 AuPRC ↑	SMIYC RA-21 FPR_{95} ↓	SMIYC RO-21 AuPRC ↑	SMIYC RO-21 FPR_{95} ↓	FS L&F AuPRC ↑	FS L&F FPR_{95} ↓	FS Static AuPRC ↑	FS Static FPR_{95} ↓	Road Anomaly AuPRC ↑	Road Anomaly FPR_{95} ↓	Average AuPRC ↑	Average FPR_{95} ↓
Max Softmax [24]	✗	27.9	72.0	15.7	16.6	4.5	40.5	19.0	23.9	15.7	71.3	16.6	44.9
Mahanalobis [30]	✗	20.0	86.9	20.9	13.0	56.3	11.2	27.3	11.7	14.3	81.0	27.8	40.8
Image Resynthesis [34]	✗	52.2	25.9	37.7	4.7	5.7	47.7	8.0	62.7	-	-	25.9	35.3
MC Dropout [36]	✗	28.8	69.4	4.8	50.3	12.2	32.8	42.1	13.2	-	-	22.0	41.4
Learning Embedding [3]	✗	37.5	70.7	0.8	46.3	4.1	22.3	43.5	16.8	-	-	53.1	42.6
SML [27]	✗	46.8	39.5	3.4	36.8	36.5	14.5	48.6	16.7	17.5	70.7	22.0	41.4
ATTA [16]	✗	67.0	31.5	76.4	2.8	**65.5**	4.4	**93.6**	**1.1**	59.0	33.4	72.3	14.6
FlowEneDet [22]	✗	36.7	77.8	73.7	0.9	56.1	**3.8**	66.6	8.9	-	-	58.3	22.9
Maximized Entropy [5]	✗	85.4	15.0	85.0	**0.7**	40.8	37.2	72.4	12.9	48.8	31.7	66.5	19.5
SynBoost [12]	✓	56.4	61.8	81.7	4.6	40.9	34.4	48.4	47.7	38.2	64.7	21.5	39.0
JSRNet [46]	✓	33.6	43.8	28.0	18.5	0.2	69.3	1.4	60.4	**94.4**	**9.2**	31.5	40.2
Dense Hybrid [19]	✓	77.9	9.8	87.0	**0.2**	63.8	6.1	60.0	4.9	31.3	63.9	64.0	17.0
PEBEL [44]	✓	49.1	40.8	4.9	12.6	59.8	6.4	82.7	6.8	45.1	44.5	48.3	22.2
EAM [20]	✓	76.3	93.9	66.9	17.9	52.0	20.5	87.3	**2.1**	29.8	54.9	62.5	37.9
Maskomaly [1]	✓	**93.4**	**6.9**	-	-	-	-	69.5	14.4	16.3	73.1	59.7	31.5
Mask2Anomaly [40]	✓	90.5	9.8	72.6	8.0	**66.8**	**4.6**	**91.2**	6.0	75.4	**9.8**	**79.3**	**7.7**
RBA [37]	✓	**92.3**	**7.2**	**92.4**	**0.3**	50.4	10.8	69.5	6.0	**83.5**	18.7	**77.6**	**8.6**
UNO [11]	✓	91.3	8.8	**89.4**	1.3	35.0	42.8	82.3	12.2	54.1	17.0	70.5	16.4
DSA-Large (Ours)	✓	**92.0**	**4.3**	**85.5**	5.3	**73.9**	11.4	**89.9**	**2.0**	**80.1**	**11.4**	**84.2**	**6.8**

DSA-Large model obtains the best results among the baseline anomaly segmentation methods.



DSA-Large surpasses top performing methods using 38% fewer trainable parameters.

Qualitative Results



DSA-Large provide better and crisper anomaly masks w.r.t. other baselined methods. Anomalies are represented in white.

Limitation