Masked Attention ConvNeXt Unet with Multi-Synthesis Dynamic Weighting for Anomaly Detection and Localization

BMVC 2023

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ABSTRACT

Our study introduces a novel multi-synthesis weighting strategy, denoted as MSdW, aimed at harnessing the advantage of diverse data synthesis strategies. We also construct a model architecture comprising reconstructive and discriminative subnetworks built upon the U-Net architecture with a ConvNextV2 base. We conduct a comprehensive evaluation of our proposed model across various datasets for the tasks of anomaly detection and segmentation. Notably, the datasets used for evaluation include MVTecAD, BTAD, and KSDD2. Our experimental results demonstrate that our model surpasses existing state-of-the-art methods, exhibiting significant improvements in Pixel AP and PRO indices.

REFERENCE

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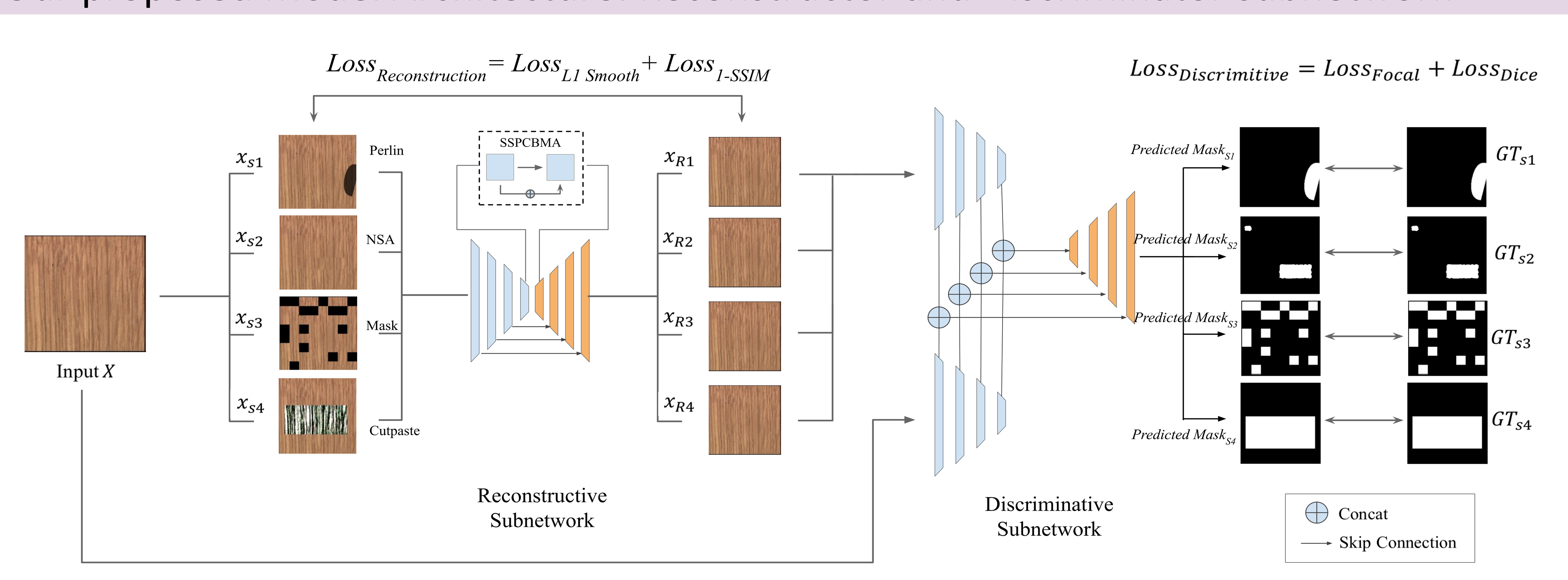
Proposed Method

Our proposed Model Architecture: Reconstructor and Discriminator subnetwork



*M*ulti-*S*ynthesis *D*ynamic *W*eighting (MSdW)

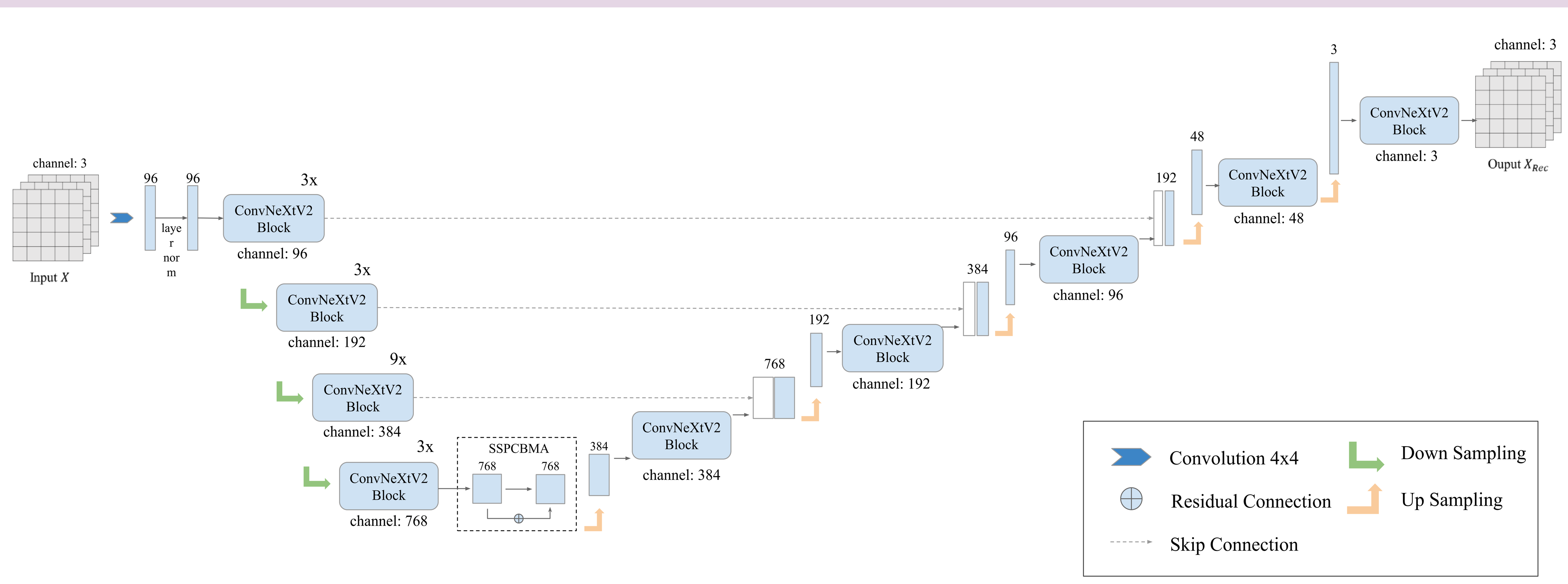
$$
\begin{aligned}
Multi\_Loss(t)_{S_i} = {} & \alpha_1(t)\cdot Loss_{L1smooth}(X_{Si}, X_{Ri}) \; + \\
& \alpha_2(t)\cdot Loss_{1-SSIM}(X_{Si}, X_{Ri}) \; + \\
& \alpha_3(t)\cdot Loss_{Focal}(PredictedMask_{S_i}, GT_{Si}) \; + \\
& \alpha_4(t)\cdot Loss_{Dice}(PredictedMask_{S_i}, GT_{Si})
\end{aligned}
$$

where $\alpha_1+\alpha_2+\alpha_3+\alpha_4 = 1.$

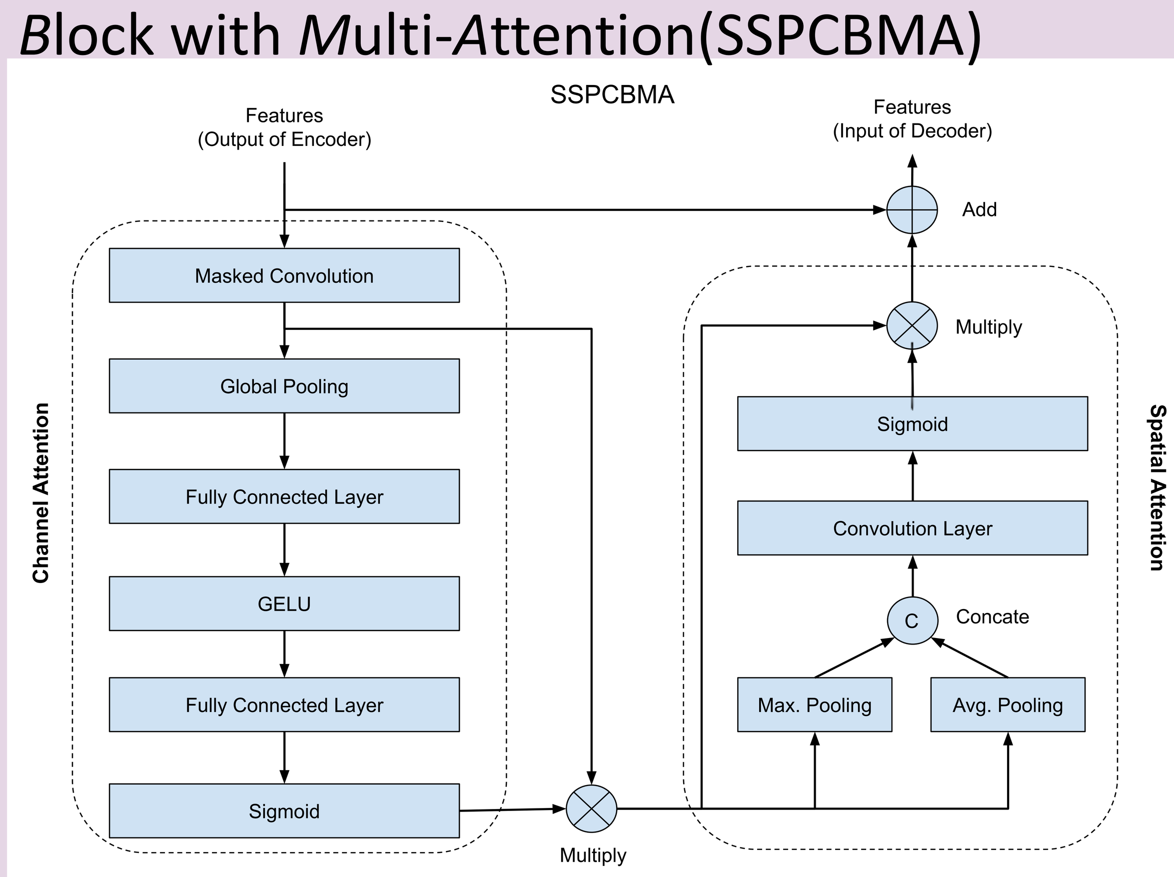
$$
\begin{aligned}
Synthesis\_Loss(t)_{Total} = {} & \beta_1(t)\cdot Multi\_Loss_{s_1} \; + \\
& \beta_2(t)\cdot Mutli\_Loss_{s_2} \; + \\
& \beta_3(t)\cdot Mutli\_Loss_{s_3} \; + \\
& \beta_4(t)\cdot Mutli\_Loss_{s_4}
\end{aligned}
$$

where $\beta_1+\beta_2+\beta_3+\beta_4 = 1.$

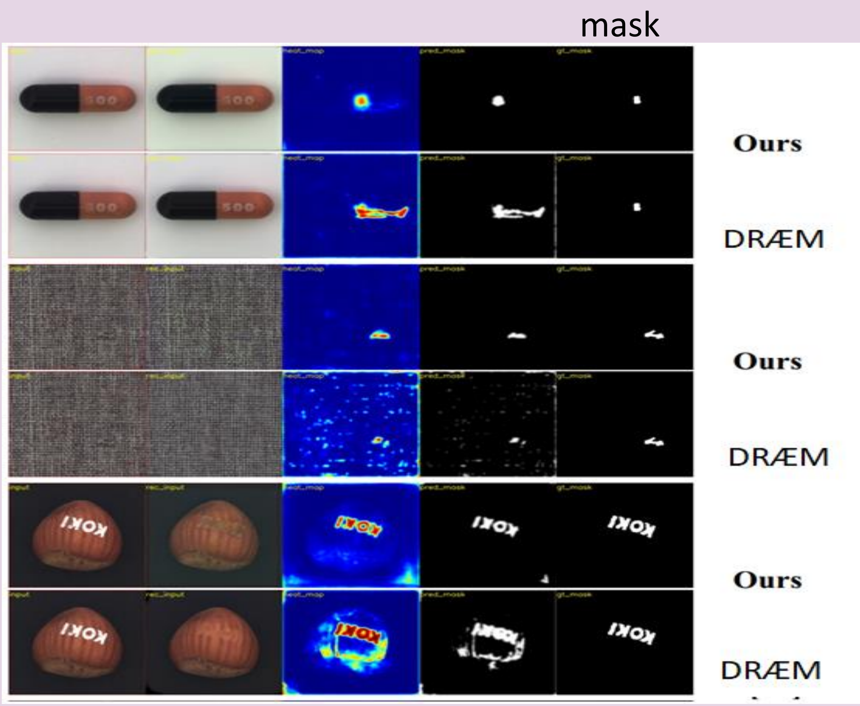
Reconstruction Unet(ConvNeXtUnetV2)



*S*elf-*S*upervised *P*redictive *C*onvolutional *B*lock with *M*ulti-*A*ttention(SSPCBMA)



Experiment Result



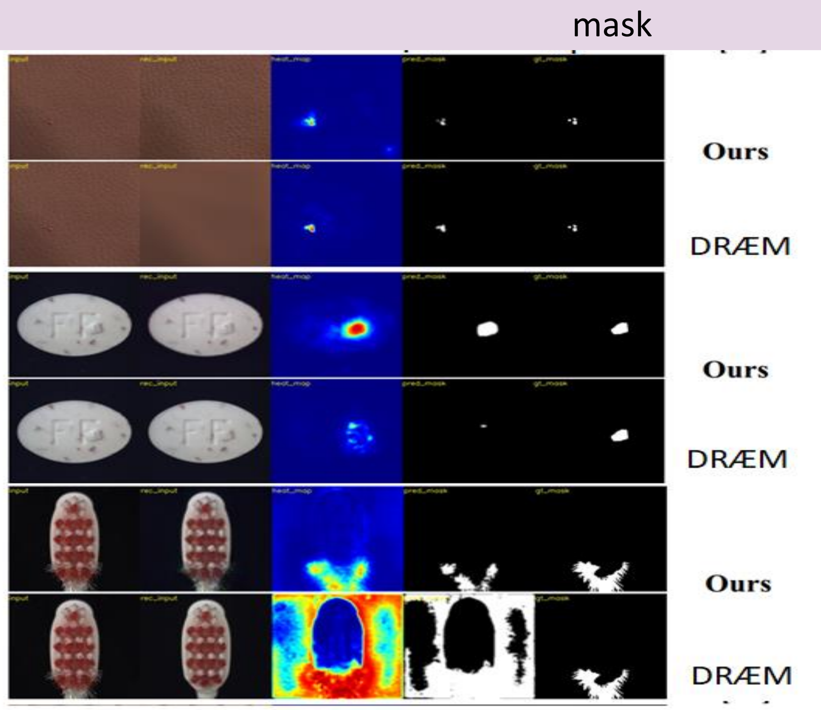


Image-level AUROC/ Pixel-level AUROC

Category	CutPaste	DRÆM	SSPCAB	RD	NSA	DSR	Patchcore	Ours
Carpet	93.9 / 98.3	96.9 / 97.5	93.1 / 92.6	98.7 / 98.9	95.6 / 95.5	**100.0** / 95.5	99.1 / 99.0	99.6 / **99.4**
Grid	**100.0** / 97.5	99.9 / 99.7	99.7 / 99.5	**100.0** / 98.3	99.9 / 99.2	**100.0** / 99.6	97.3 / 98.7	**100.0 / 99.8**
Leather	**100.0** / 99.5	**100.0** / 99.0	98.7 / 96.3	**100.0** / 99.4	99.9 / 99.5	**100.0 / 99.6**	**100.0** / 99.3	**100.0 / 99.6**
Tile	94.6 / 90.5	**100.0** / 99.2	**100.0** / 99.4	99.7 / 95.7	**100.0** / 99.3	**100.0** / 98.2	99.3 / 95.8	**100.0 / 99.5**
Wood	99.1 / 95.5	99.5 / 95.5	98.4 / **96.5**	99.5 / 95.8	97.5 / 90.7	96.3 / 92.5	**99.6** / 95.1	96.8 / 96.2
Average	97.5 / 96.3	99.3 / 98.2	98.0 / 96.9	**99.6** / 97.6	98.6 / 96.8	99.3 / 97.1	99.1 / 97.6	99.3 / **98.9**
Bottle	98.2 / 97.6	98.0 / 99.1	95.6 / **99.2**	**100.0** / 98.8	97.7 / 98.3	**100.0** / 98.9	**100.0** / 98.6	**100.0** / 98.4
Cable	81.2 / 90.0	90.9 / 95.2	92.7 / 95.1	96.1 / 97.2	94.5 / 96.0	93.8 / 96.7	**99.9 / 98.5**	95.7 / 94.4
Capsule	98.2 / 97.4	91.3 / 88.1	96.9 / 90.2	96.1 / 98.7	95.2 / 97.6	98.1 / 95.4	98.0 / 99.0	**99.0 / 99.1**
Hazelnut	98.3 / 97.3	**100.0 / 99.7**	**100.0 / 99.7**	**100.0** / 99.0	94.7 / 97.6	95.6 / 99.2	**100.0** / 98.7	98.9 / 99.5
Metal Nut	99.9 / 93.1	**100.0 / 99.6**	**100.0** / 99.4	**100.0** / 97.3	98.7 / 98.4	98.5 / 93.7	99.9 / 98.3	**100.0** / 98.9
Pill	94.9 / 95.7	97.1 / 97.3	97.4 / 97.2	98.7 / 98.1	**99.2 / 98.5**	97.5 / 93.4	97.5 / 97.6	97.2 / 97.3
Screw	88.7 / 96.7	**98.7** / 99.3	97.8 / 99.0	97.8 / **99.7**	90.2 / 96.5	96.2 / 98.5	98.2 / 99.5	97.5 / 99.3
Toothbrush	99.4 / 98.1	**100.0** / 97.3	97.9 / 97.3	**100.0** / 99.1	**100.0** / 94.9	99.7 / **99.5**	**100.0** / 98.6	99.2 / 99.3
Transistor	96.1 / 93.0	91.7 / 85.2	88.0 / 84.8	95.5 / 92.3	95.1 / 88.0	97.8 / 83.2	**99.9 / 96.5**	96.3 / 92.8
Zipper	99.9 / 99.3	**100.0** / 99.1	**100.0** / 98.4	97.9 / 98.3	99.8 / 94.2	**100.0** / 98.9	99.5 / 98.9	**100.0 / 99.4**
Average	95.5 / 95.8	96.8 / 96.0	96.6 / 96.0	98.2 / 97.9	96.5 / 96.0	97.7 / 95.7	**99.3 / 98.4**	98.4 / 97.8
TotalAverage	96.1 / 96.0	97.6 / 96.7	97.1 / 96.3	98.7 / 97.8	97.2 / 96.3	98.2 / 96.2	**99.2** / 98.1	98.7 / **98.2**

Per Region Overlap (PRO) score/ Pixel-level Average Precision (Pixel-AP)

Category	CutPaste	DRÆM	SSPCAB	RD	NSA	DSR	Patchcore	Ours
Carpet	50.4 / -	92.9 / 65.1	86.4 / 48.6	95.4 / 56.5	85.0 / -	- / 78.2	95.5 / 62.2	**99.8 / 80.6**
Grid	91.5 / -	98.3 / 62.8	98.0 / 57.9	94.2 / 15.8	96.8 / -	- / 68.0	94.0 / 24.5	**99.1 / 77.0**
Leather	83.7 / -	97.4 / 72.9	94.0 / 60.7	98.2 / 47.6	98.7 / -	- / 62.5	96.9 / 45.3	**99.2 / 68.3**
Tile	54.4 / -	98.2 / **95.2**	98.1 / 96.1	85.6 / 54.1	95.3 / -	- / 93.9	91.3 / 56.2	**98.3** / 94.3
Wood	64.0 / -	90.3 / 74.6	92.8 / **78.9**	91.4 / 48.3	85.3 / -	- / 68.4	87.1 / 49.3	**96.7** / 74.9
Average	68.8 / -	95.4 / 74.1	93.9 / 68.4	93.0 / 44.5	92.2 / -	- / 74.2	93.0 / 47.5	**98.6 / 79.0**
Bottle	91.2 / -	**96.8** / 88.9	96.3 / **89.4**	96.3 / 78.0	92.9 / -	- / 91.5	95.4 / 76.8	**96.8** / 86.5
Cable	59.8 / -	81.0 / 56.4	80.4 / 52.0	94.1 / 52.6	89.9 / -	- / **70.4**	**96.8** / 67.0	95.2 / 66.8
Capsule	83.5 / -	82.7 / 39.6	92.5 / 46.4	95.5 / 47.2	91.4 / -	- / 53.3	93.4 / 46.0	**95.9 / 57.6**
Hazelnut	81.3 / -	**98.5** / 92.6	98.2 / **93.4**	96.9 / 60.7	93.6 / -	- / 87.3	90.9 / 53.2	96.9 / 87.4
Metal Nut	54.4 / -	97.0 / **97.0**	**97.7** / 94.7	94.9 / 78.6	94.6 / -	- / 67.5	92.6 / 86.6	96.9 / 89.3
Pill	83.1 / -	88.4 / 47.6	89.6 / 48.3	**96.7 / 76.5**	96.0 / -	- / 65.7	94.5 / 75.7	93.6 / 68.8
Screw	72.6 / -	95.0 / **66.5**	95.2 / 61.7	98.5 / 52.1	90.1 / -	- / 52.5	97.5 / 34.7	**99.4** / 54.4
Toothbrush	88.1 / -	85.6 / 45.5	85.5 / 39.3	92.3 / 51.1	90.7 / -	- / **74.2**	**94.0** / 37.9	92.6 / 62.5
Transistor	68.5 / -	70.4 / 39.0	62.5 / 38.1	83.3 / 54.1	75.3 / -	- / 41.1	**92.3 / 66.9**	72.4 / 49.2
Zipper	84.9 / -	96.8 / 77.6	95.2 / 76.4	95.3 / 57.5	89.2 / -	- / 78.5	96.1 / 62.3	**98.9 / 83.0**
Average	76.7 / -	89.2 / 65.1	89.3 / 64.0	**94.4** / 60.8	90.4 / -	- / 68.2	**94.4** / 60.7	93.4 / **70.6**
TotalAverage	74.1 / -	91.3 / 68.1	90.8 / 65.5	93.9 / 55.4	91.0 / -	- / 70.2	93.9 / 56.3	**95.4 / 73.4**