



**TUE-AM-373**

# DeSTSeg: Segmentation Guided Denoising Student-Teacher for Anomaly Detection

Xuan Zhang, Shiyu Li, Xi Li, Ping Huang, Jiulong Shan, Ting Chen

Presenter: **Xuan Zhang**

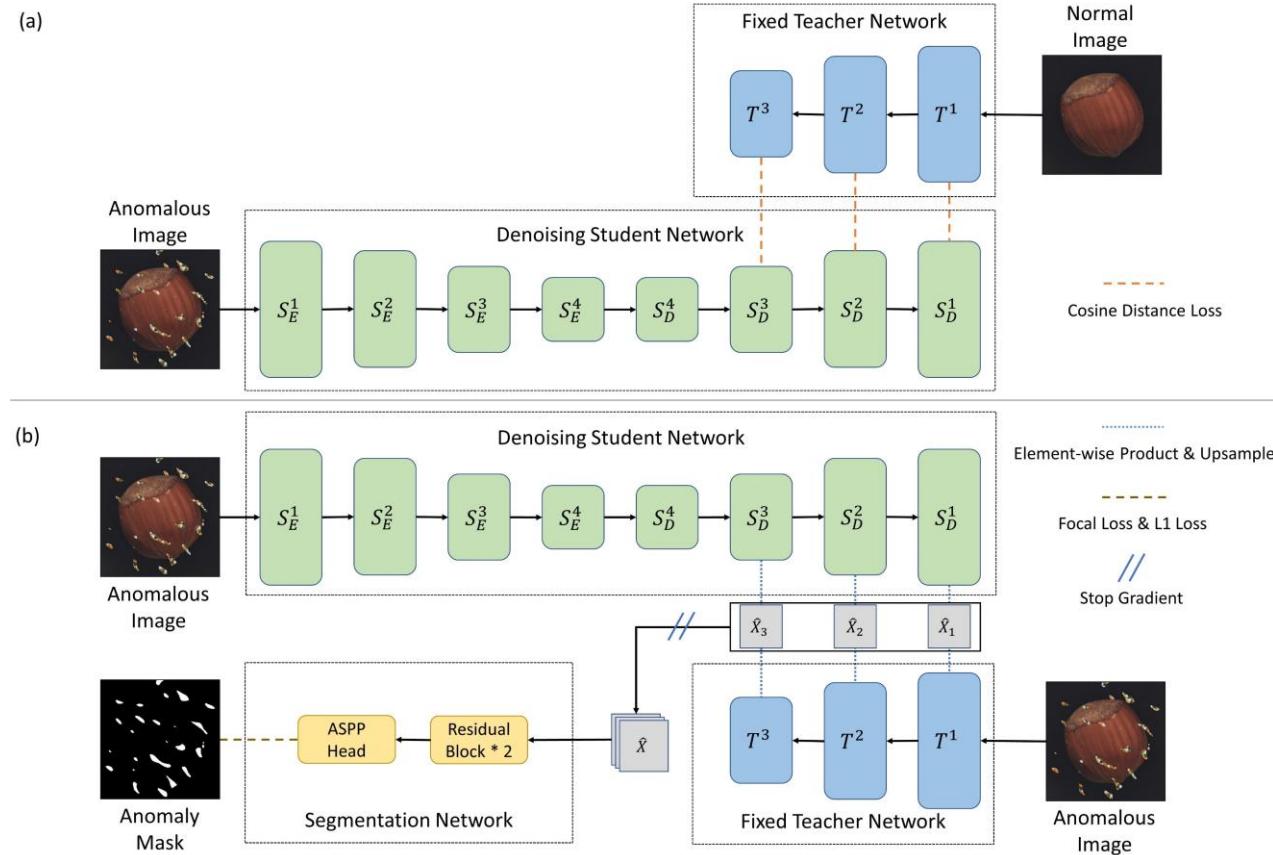
Department of Computer Science and Technology,  
Tsinghua University, Beijing, China

*x-zhang18@mails.tsinghua.edu.cn*

# Overview



- We propose a model called **DeSTSeg** for visual anomaly detection.



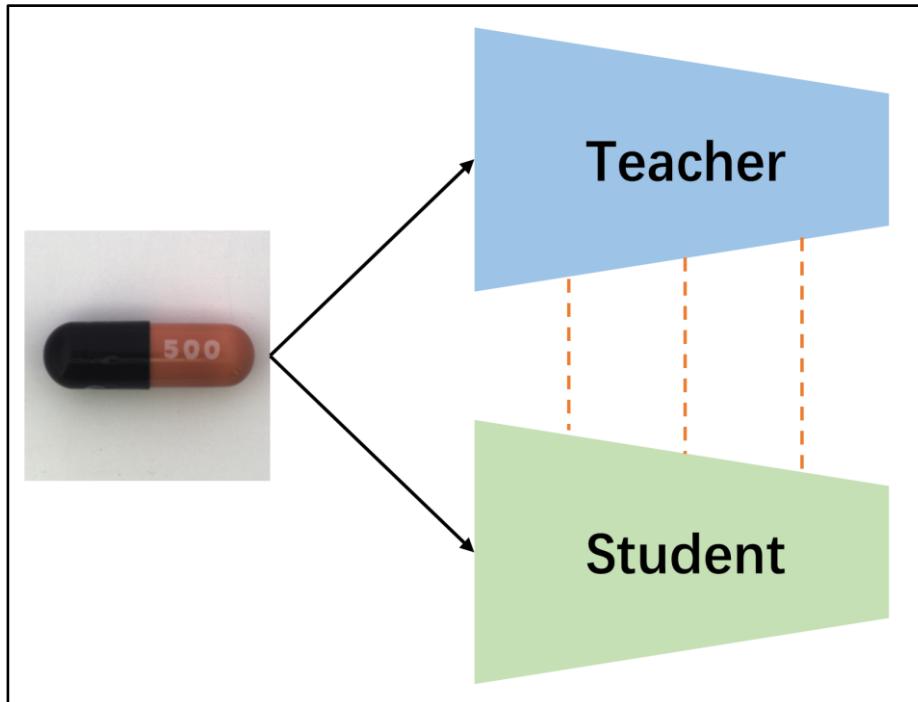
# Highlights



- Denoising student encoder-decoder
  - Explicitly generate different feature representations from the teacher with anomalous inputs
- Segmentation network
  - Adaptively fuse the multi-level feature similarities
- High performances on benchmark dataset



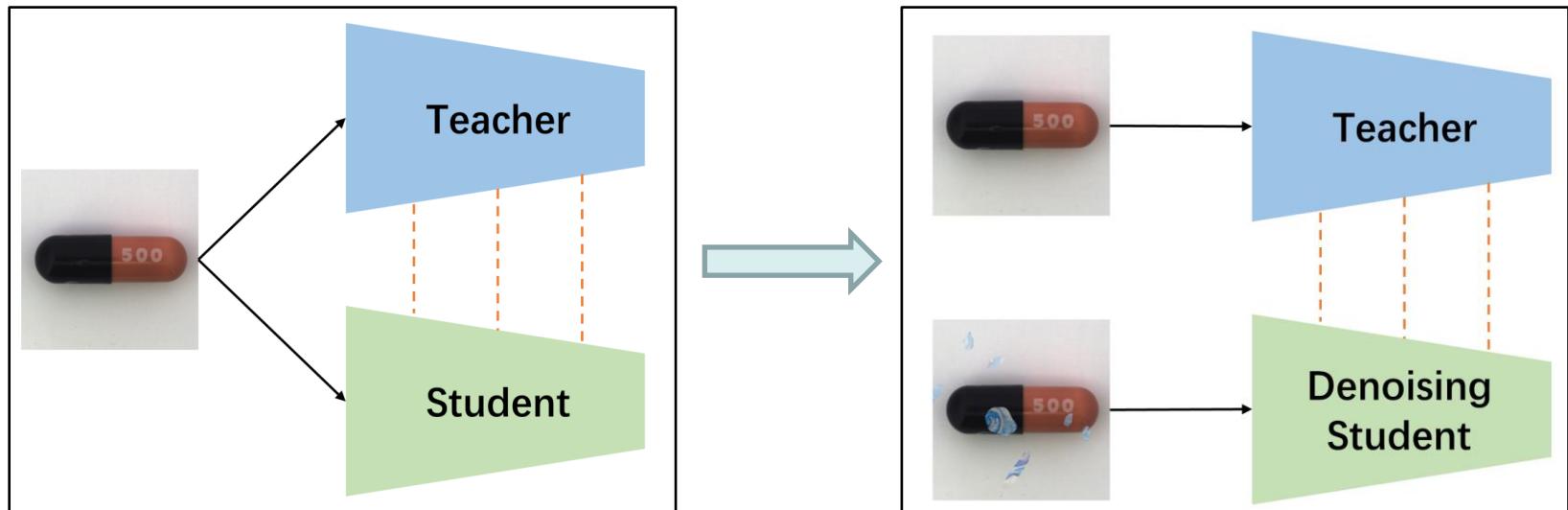
- Characteristic of anomalies
  - Limited anomaly samples
  - Long-tailed distribution
- Formulation of vision anomaly detection
  - Training: use normal data only
  - Inference: localize anomaly pixels

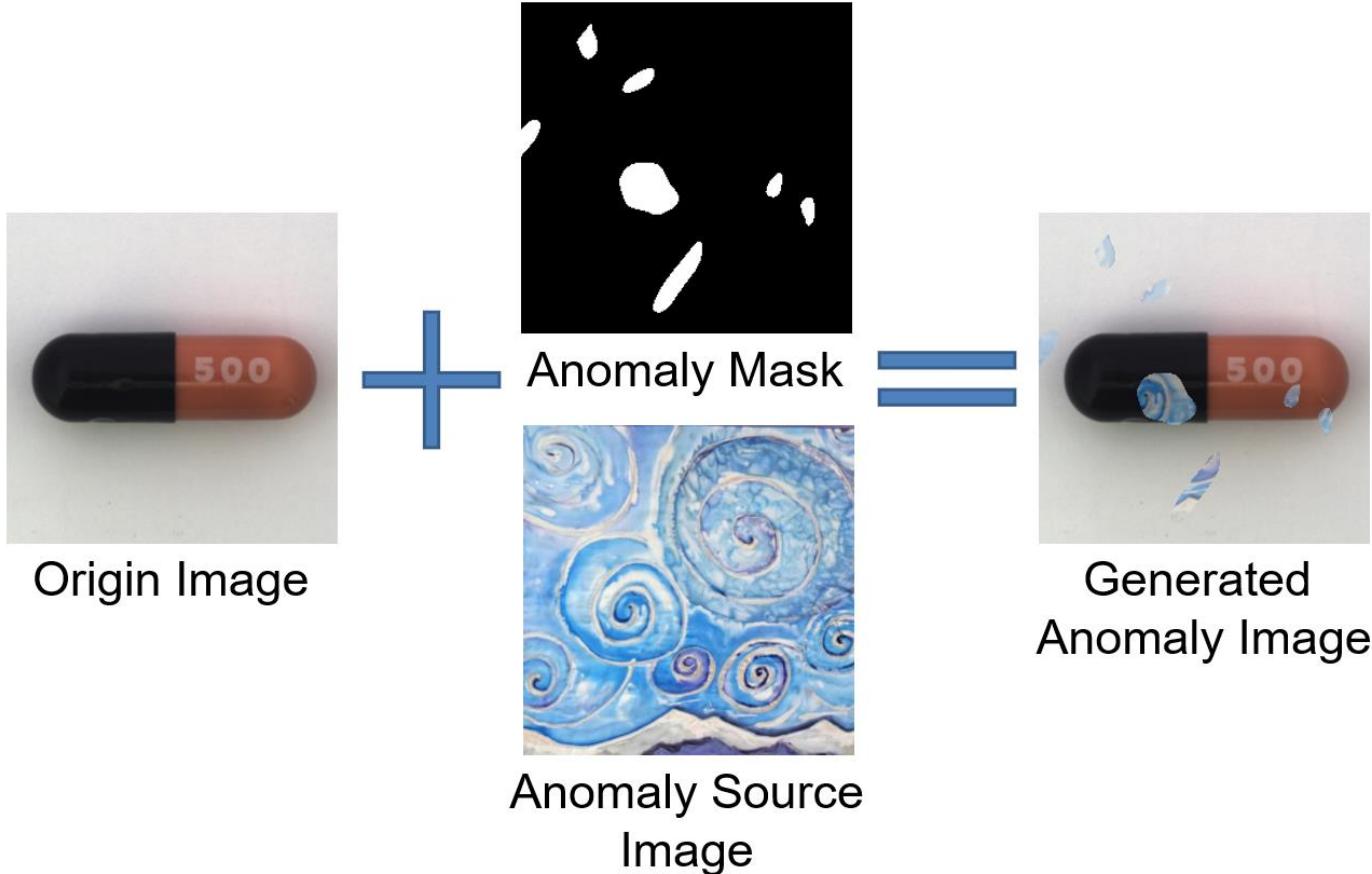


Cosine Distance Loss



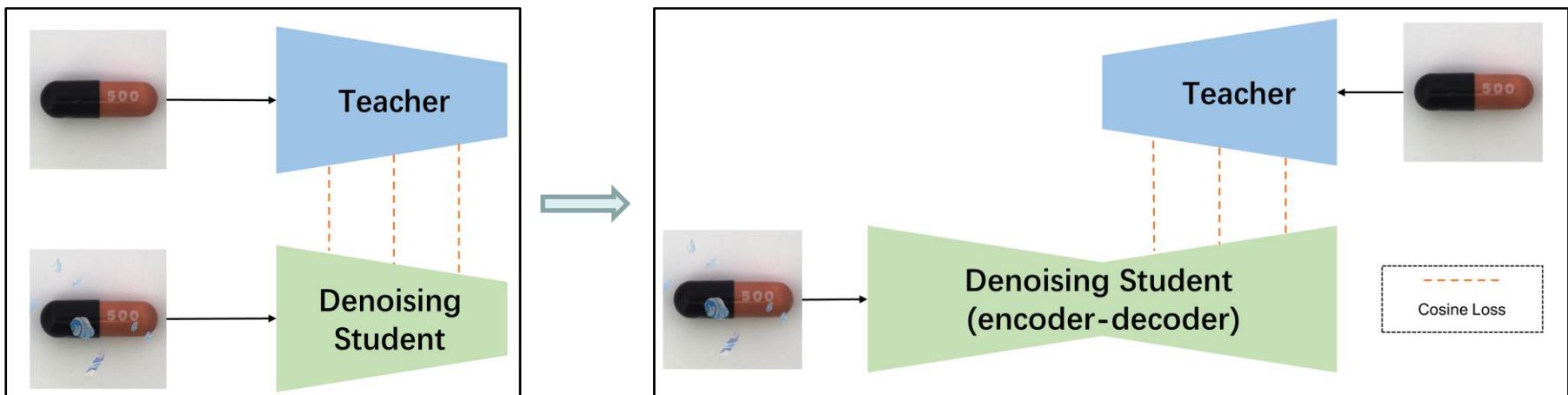
- Apply constraints on anomalous data





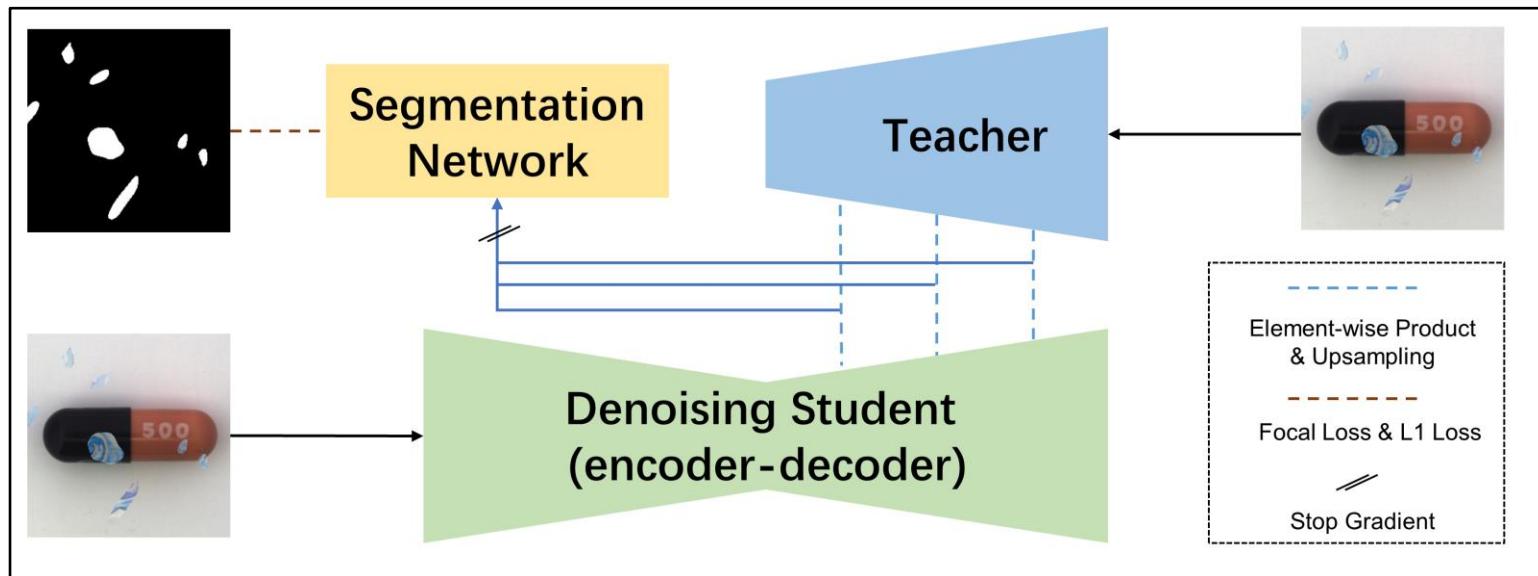


- Use encoder-decoder architecture to better support the feature denoising task





- Fuse the multi-level features adaptively





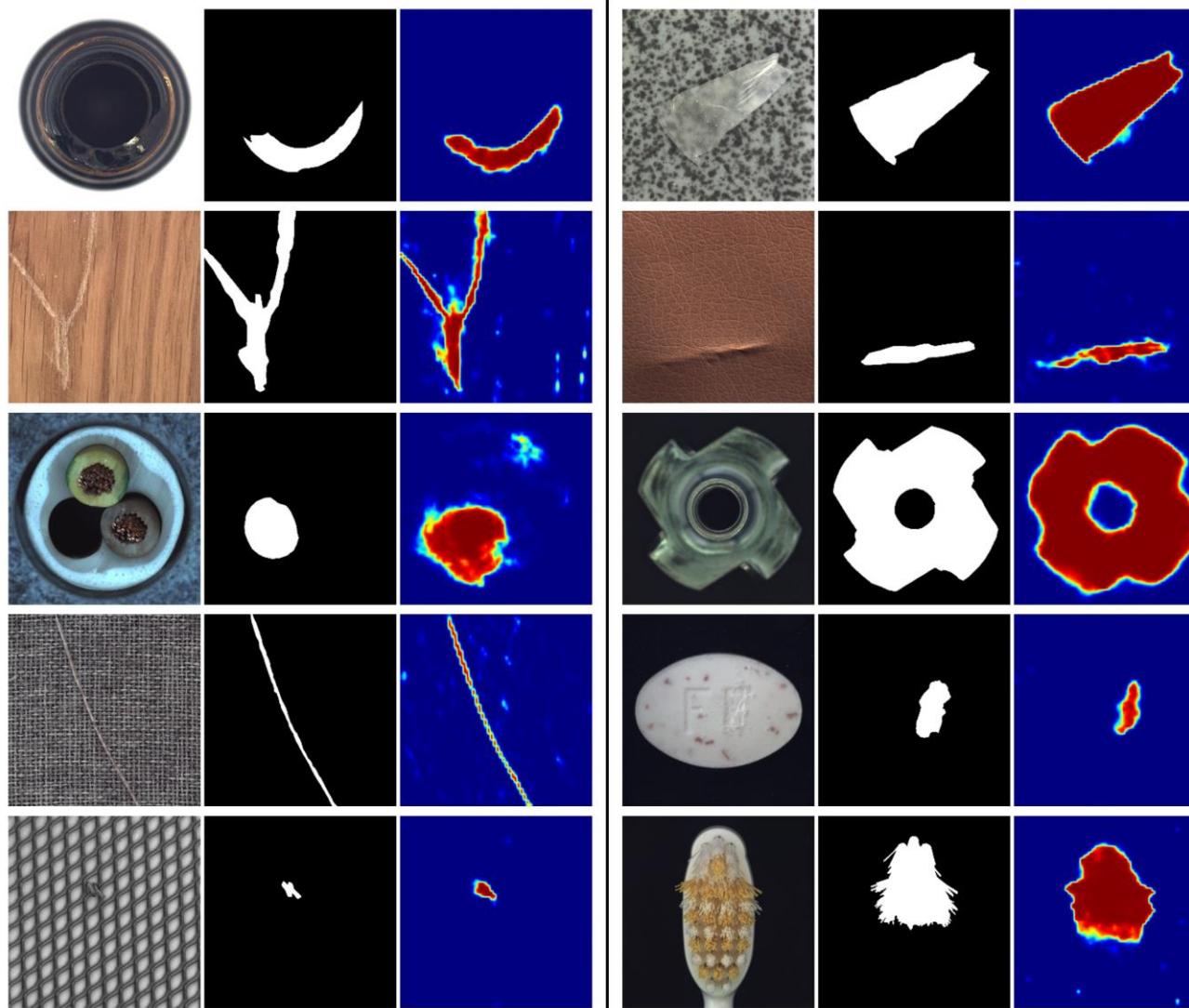
- Dataset
  - MVTec AD Dataset<sup>[3]</sup>
  - 10 object + 5 texture
- Metrics
  - Image-level AD: AUC
  - Pixel-level AD: AUC, AP
  - Instance-level AD: we propose a metric, **IAP** (instance average precision)

# Quantitative Results

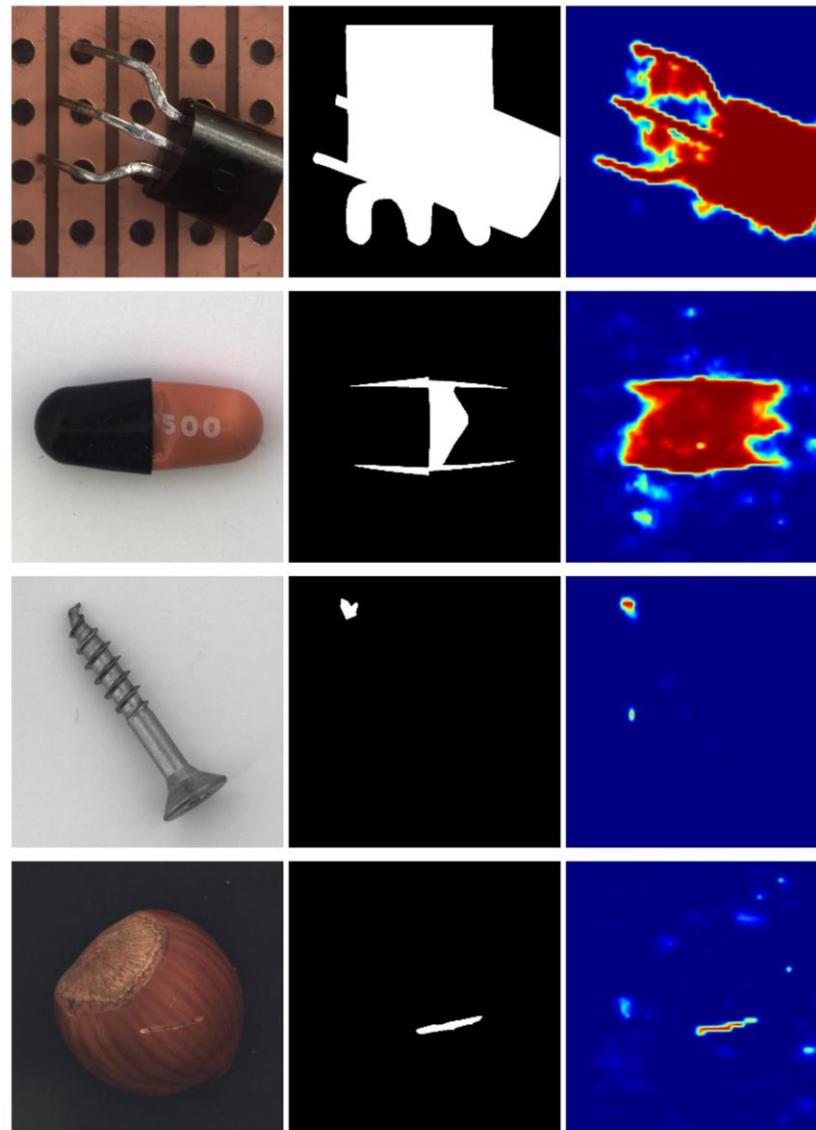


Task and metric	Ours	SOTA
Image-level AUC	<b>98.6</b> $\pm$ 0.4	98.5 (PatchCore <sup>[4]</sup> )
Pixel-level AUC	97.9 $\pm$ 0.3	<b>98.4</b> (PatchCore <sup>[4]</sup> )
Pixel-level AP	<b>75.8</b> $\pm$ 0.8	70.2 (DSR <sup>[5]</sup> )
Instance-level IAP	<b>76.4</b> $\pm$ 1.0	71.5 (DRAEM <sup>[2]</sup> )
Instance-level IAP@90	<b>57.8</b> $\pm$ 1.8	51.7 (DRAEM <sup>[2]</sup> )
Instance-level PRO	94.4 $\pm$ 0.4	<b>94.5</b> (PatchCore <sup>[4]</sup> )

# Visualization Examples



# Failure Cases





- **den**: use denoising student network (checked) or use origin student network (unchecked)
- **ed**: use encoder-decoder student (checked) or use decoder student (unchecked)
- **seg**: use segmentation network (checked) or use the product of cosine distances (unchecked) for anomaly localization

Exp.	den	ed	seg	img (AUC)	pix (AP)	ins (IAP)
1				94.8	52.9	55.8
2	✓			93.4	49.6	53.9
3		✓		95.4	53.3	57.7
4			✓	97.3	70.1	71.8
5	✓	✓		94.5	54.0	58.5
6	✓		✓	97.3	70.9	72.3
7		✓	✓	97.7	69.7	71.2
8	✓	✓	✓	<b>98.6</b>	<b>75.8</b>	<b>76.4</b>

# Summary



- We design DeSTSeg for anomaly detection and localization.
  - Denoising student-teacher network
  - Encoder-decoder student network architecture
  - Segmentation network
- We prove the effectiveness of our method.
  - DeSTSeg achieves high performance on MVTec AD dataset
  - Detailed ablations are discussed

# References



1. Wang G, Han S, Ding E, et al. Student-teacher feature pyramid matching for anomaly detection [C]//Proceedings of the British Machine Vision Conference (BMVC). 2021: 1-14.
2. Zavrtanik V, Kristan M, Skočaj D. Draem-a discriminatively trained reconstruction embedding for surface anomaly detection[C]//Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 2021: 8330-8339.
3. Bergmann P, Fauser M, Sattlegger D, et al. Mvtex ad—a comprehensive real-world dataset for unsupervised anomaly detection[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2019: 9592-9600.
4. Roth K, Pemula L, Zepeda J, et al. Towards total recall in industrial anomaly detection [C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2022: 14318-14328.
5. Zavrtanik V, Kristan M, Skočaj D. Dsr—a dual subspace re-projection network for surface anomaly detection[C]//Proceedings of the European Conference on Computer Vision (ECCV). Springer, 2022: 539-554.

JUNE 18-22, 2023



# Thanks



Paper



Code