Anomaly Detection by Effectively Leveraging Synthetic Images


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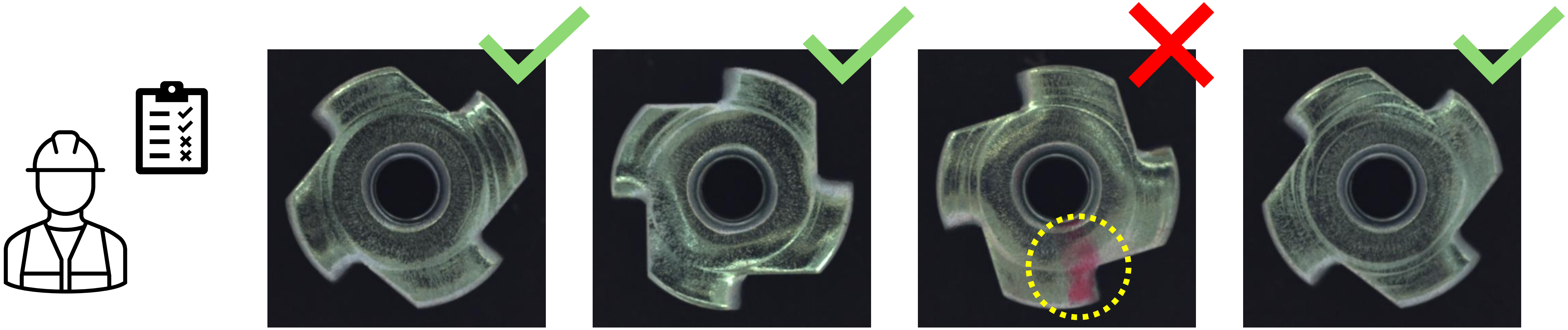
Background: what is *anomaly detection*?

- Detecting anomalous patterns



Normal Normal Defective Normal

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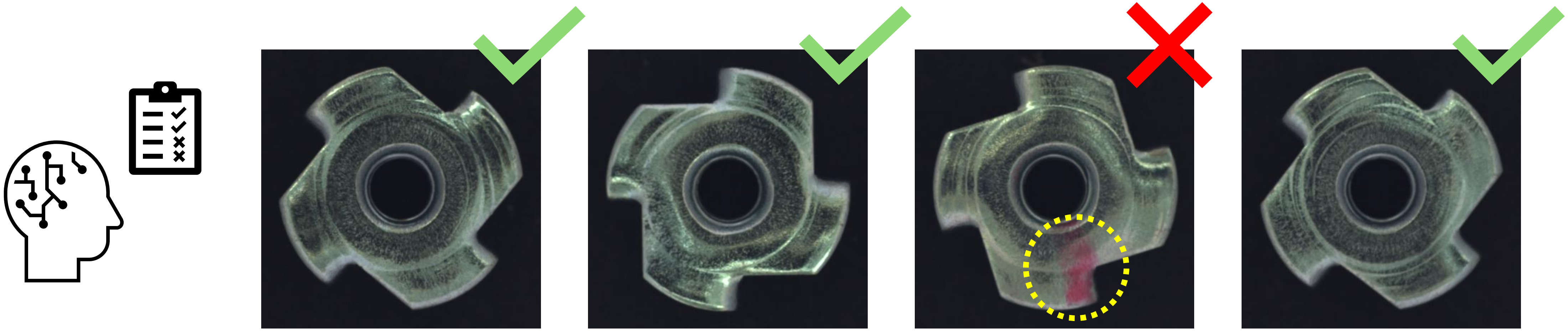

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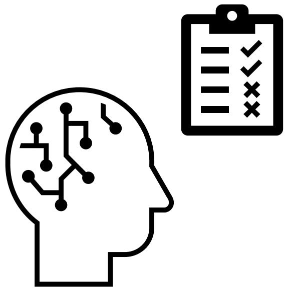

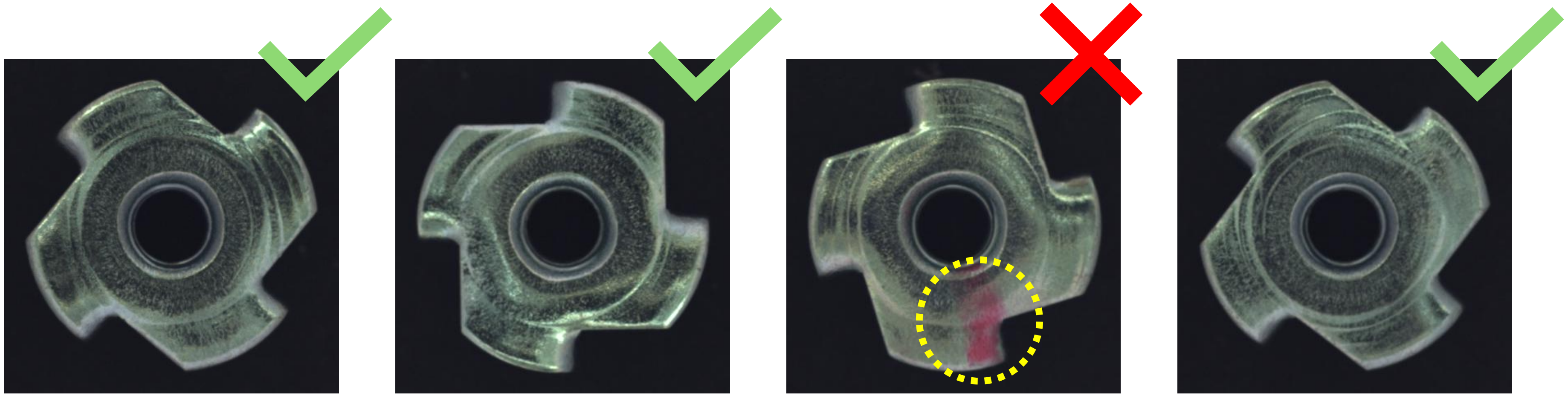

Normal Normal Defective Normal

Problem: Scarcity of defect samples for training

Our approach

Exploiting synthetic anomalous images

- Generating plausible and realistic anomalous images based on the rationale below

On the whole, anomalous images still should look similar to normal images

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Exploiting synthetic anomalous images

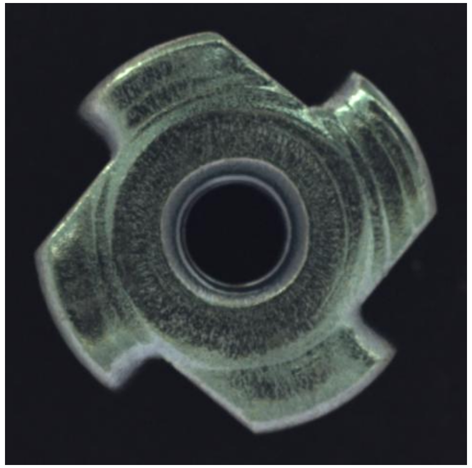
- Generating plausible and realistic anomalous images based on the rationale below

On the whole, anomalous images still should look similar to normal images

- Designing an effective training strategy when using synthetic anomalous images

Anomaly synthesis approaches

- Generating anomalies via rule-based synthesis [1,2] and generative model-based synthesis [3,4]



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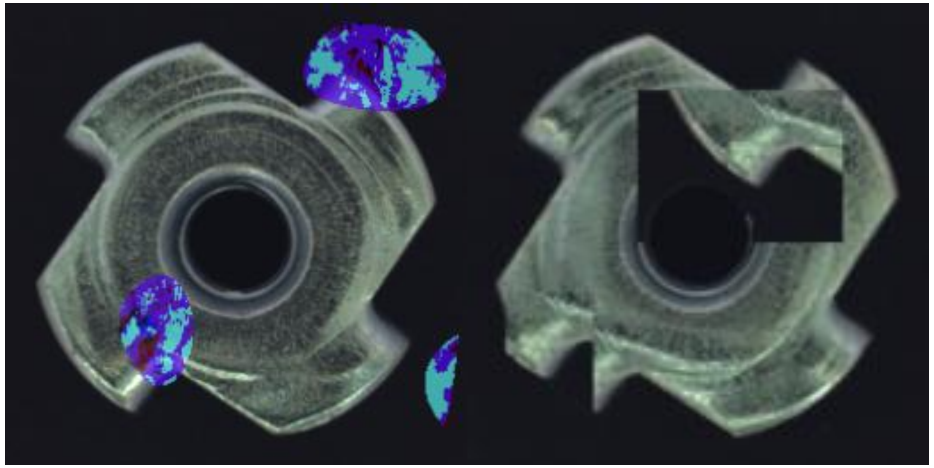
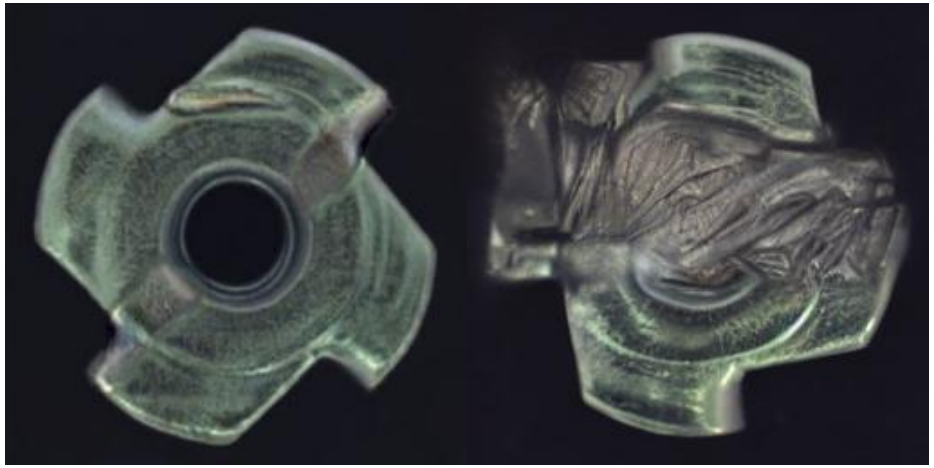


DRÆM [1] CutPaste [2]



DFMGAN [3] Anomaly Diffusion [4]

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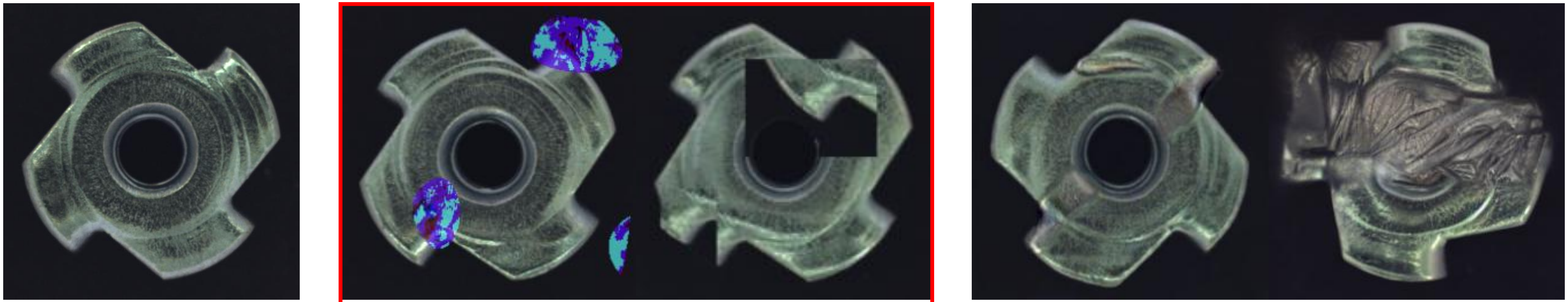
Anomaly synthesis approaches

- Rule-based synthesis: generate defective images via pasting texture dataset [1] or patch [2]



Normal | DRÆM [1] | CutPaste [2] | DFMGAN [3] | Anomaly Diffusion [4]

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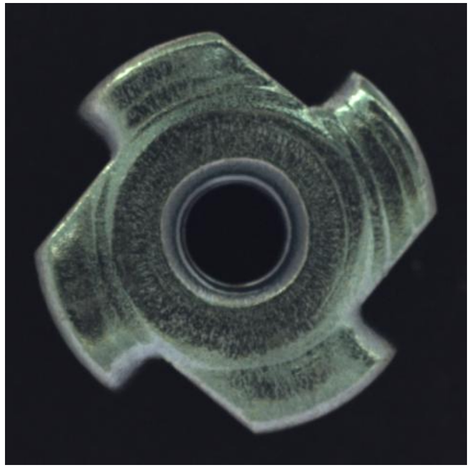
Anomaly synthesis approaches

- Rule-based synthesis: cost-effective but lack of realism



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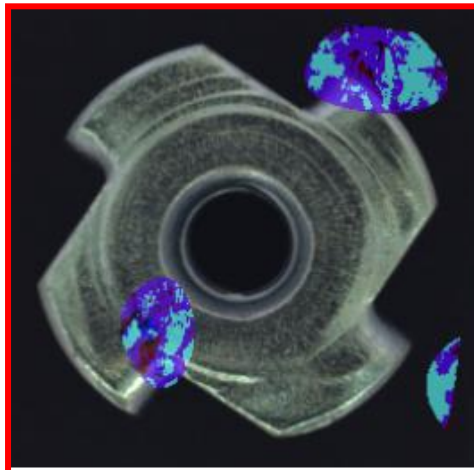
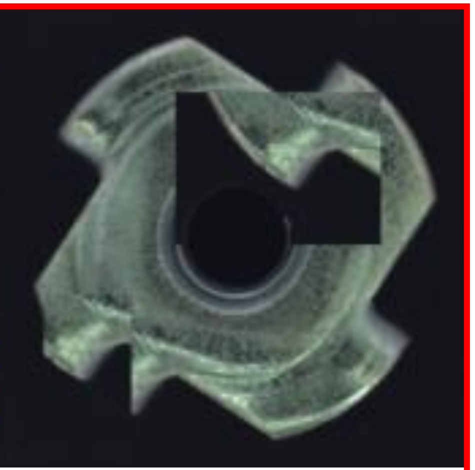
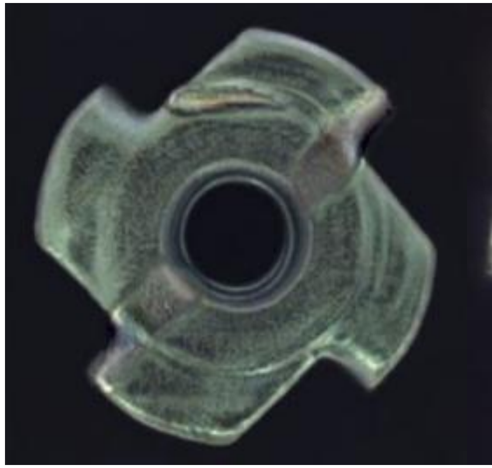


DRÆM [1]



CutPaste [2]



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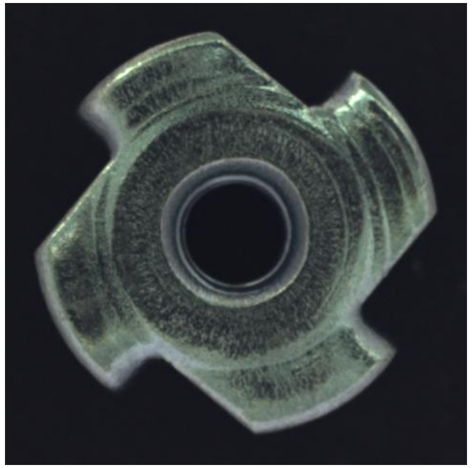
Anomaly synthesis approaches

- Generative model-based synthesis: generate defective images via GAN [3] or diffusion [4]



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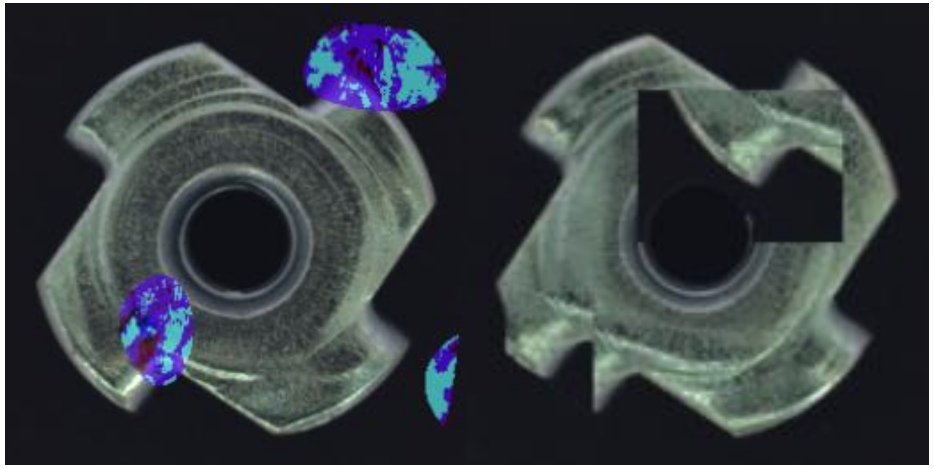

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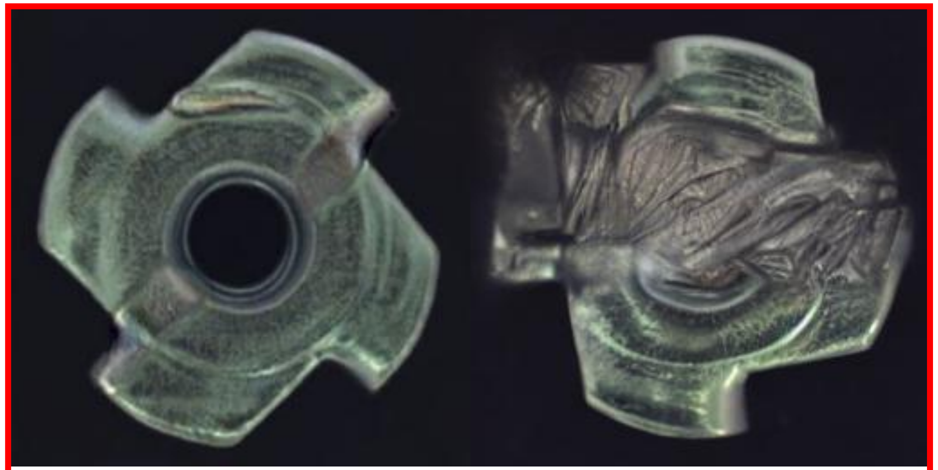

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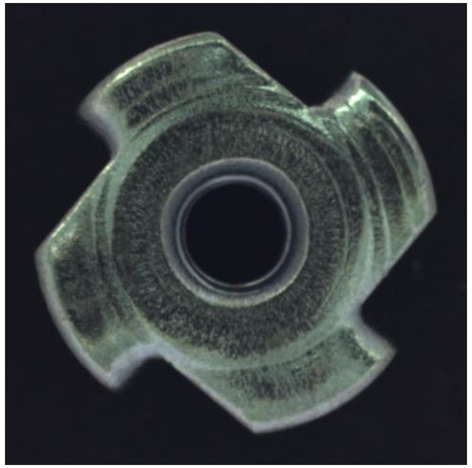
Anomaly synthesis approaches

- Generative model-based synthesis: resource-intensive but realistic



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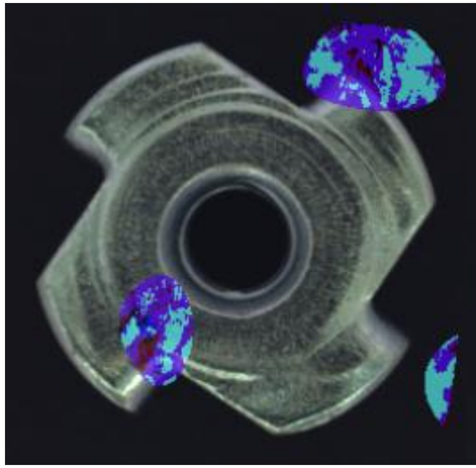

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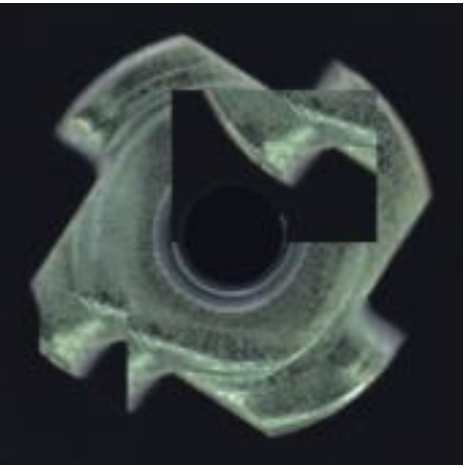
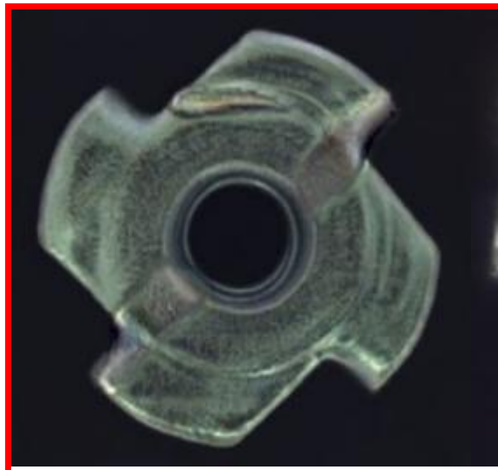


CutPaste [2]



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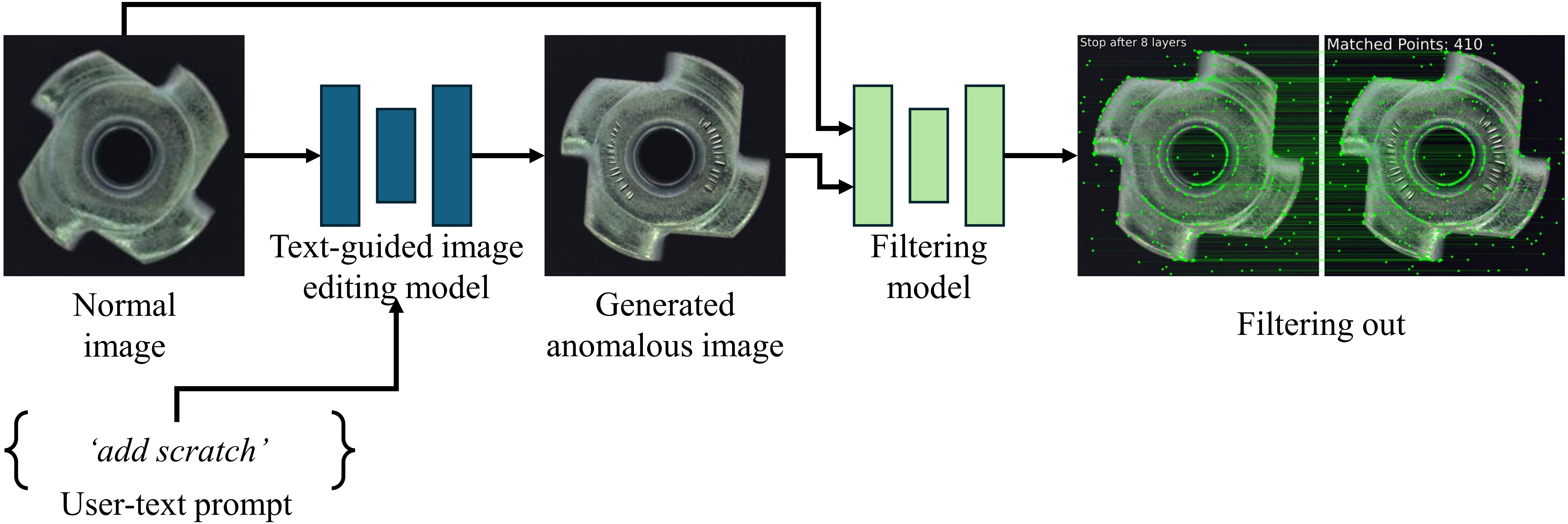
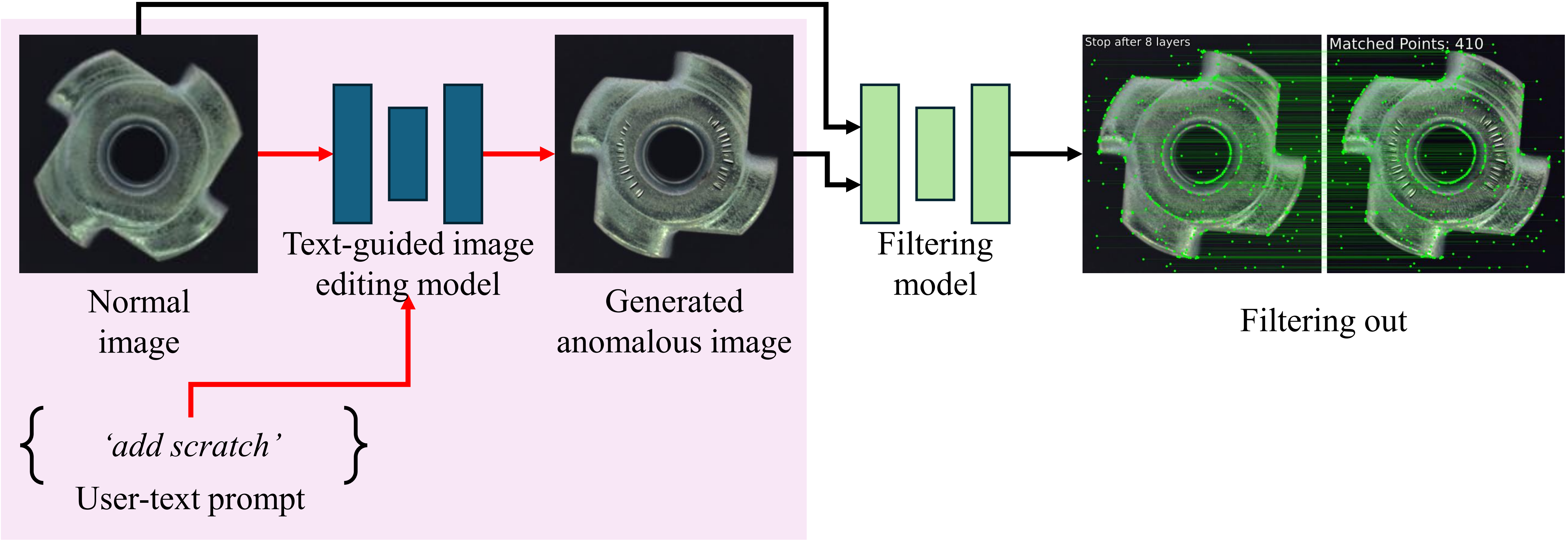
Anomaly synthesis framework

- Employing a pre-trained text-guided image editing model and filtering model



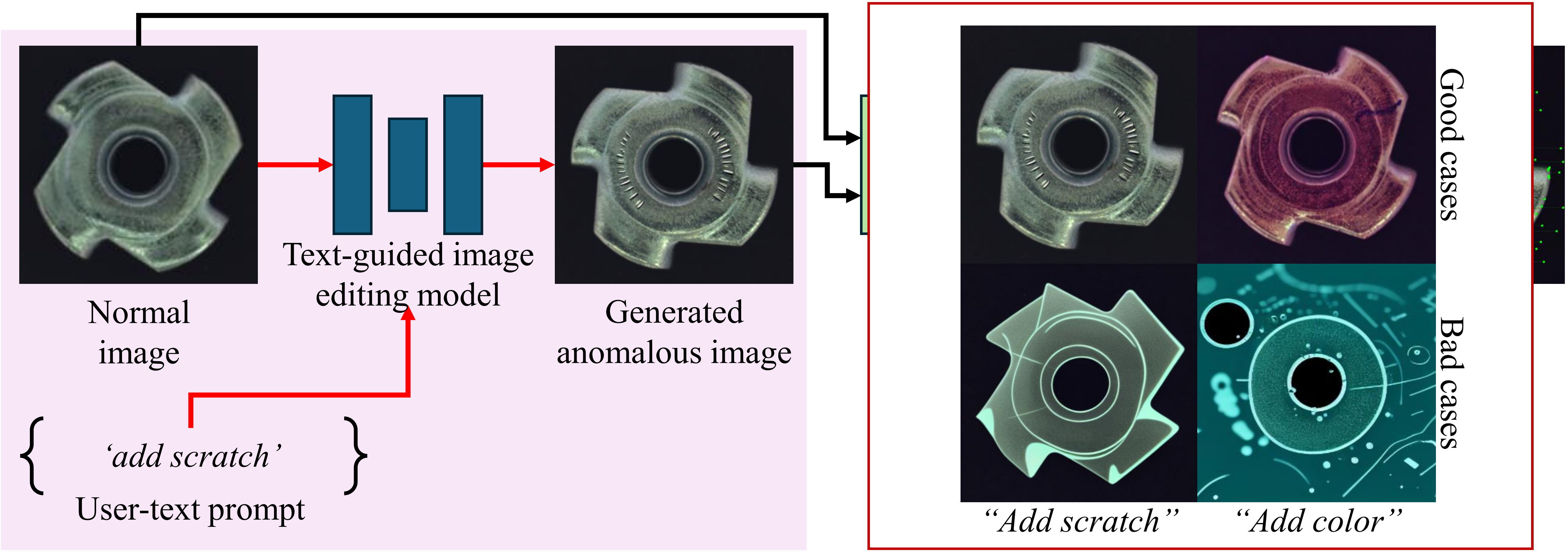
Anomaly synthesis framework

- Inputting a normal image and a prompt into the model to generate a defect image



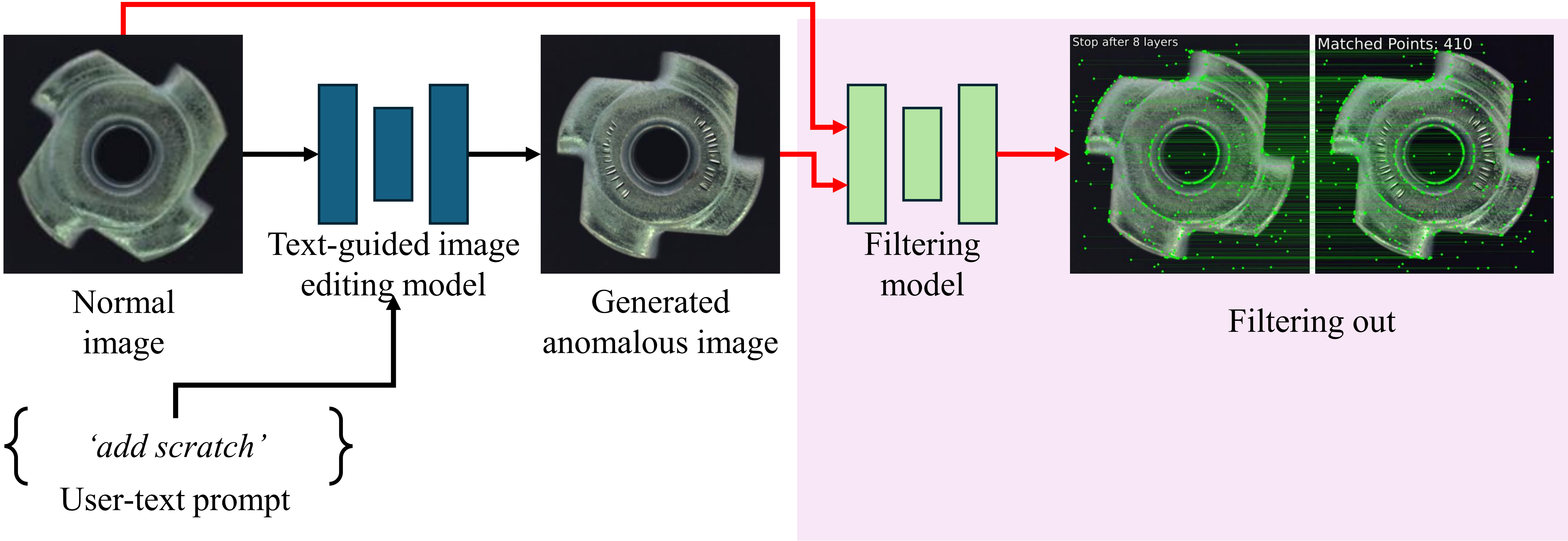
Anomaly synthesis framework

- Occasionally producing unrealistic results due to an irrelevant training dataset



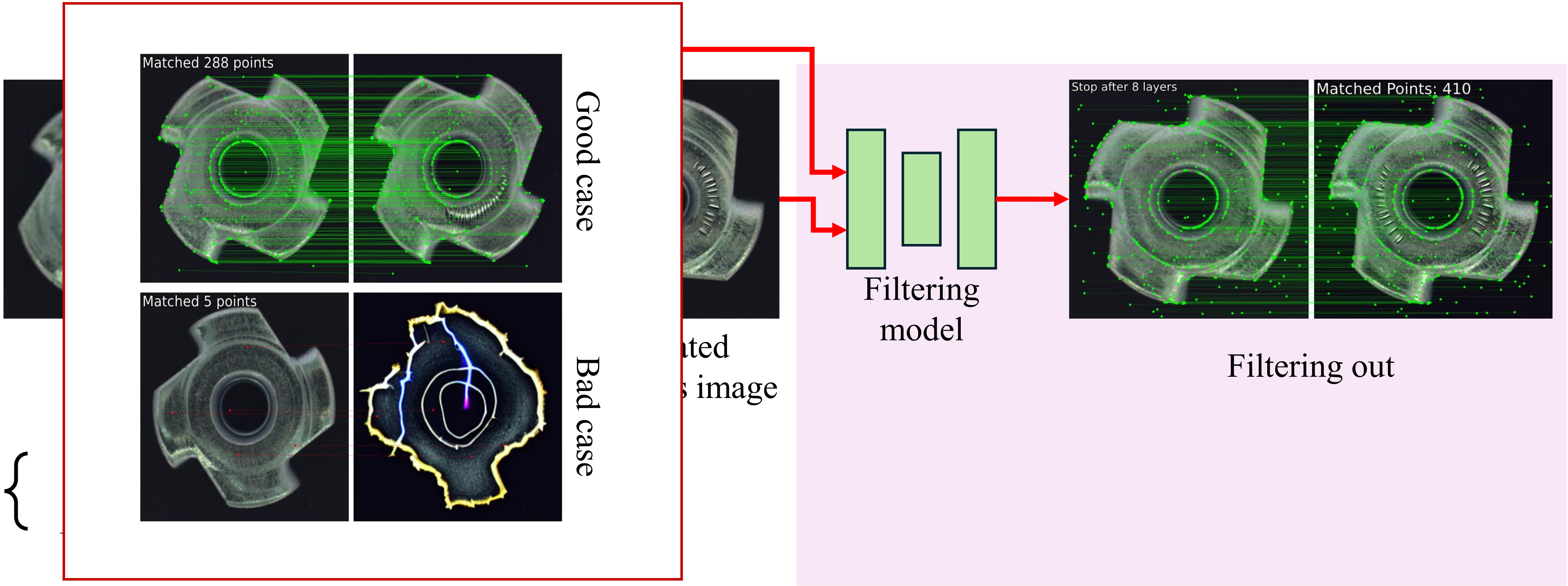
Anomaly synthesis framework

- Measuring similarity between the normal image and the generated image



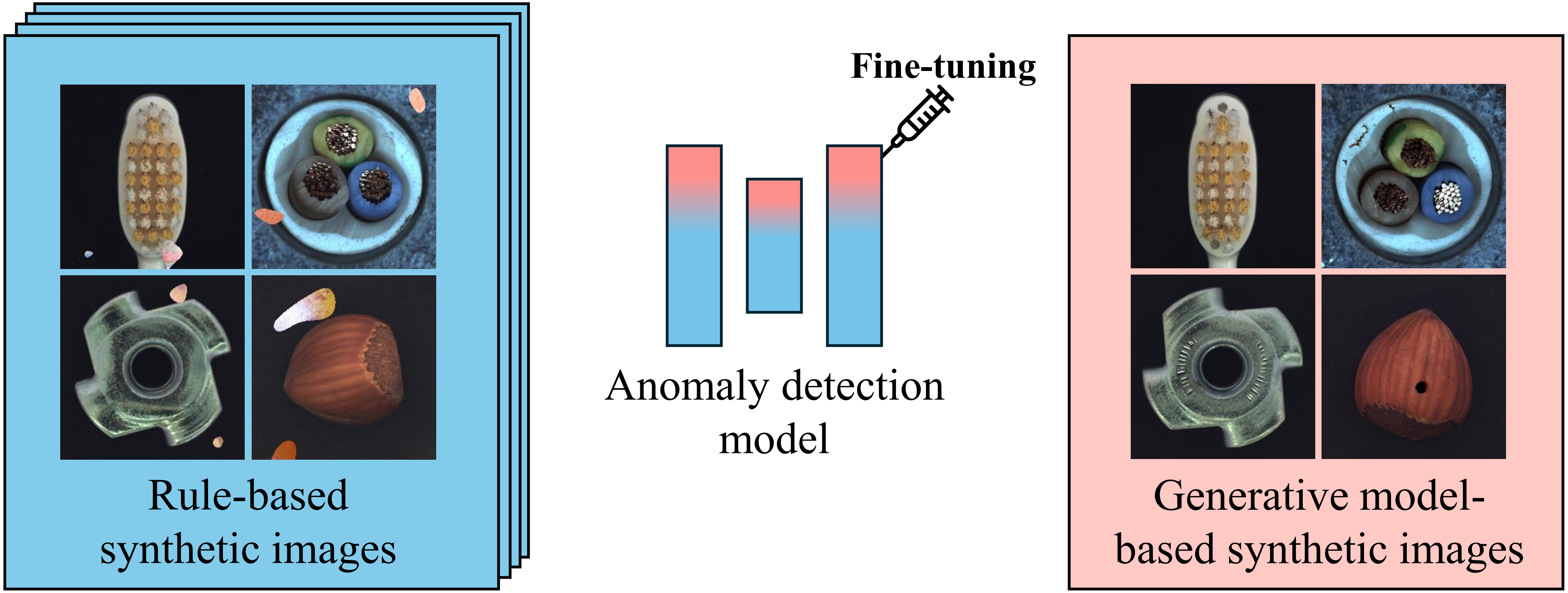
Anomaly synthesis framework

- Filtering out unrealistic defect images



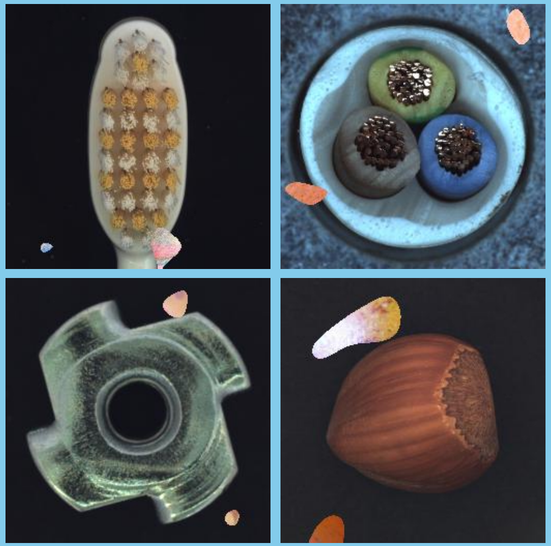
Training strategy

- Leveraging both rule-based synthesis and generative model-based synthesis

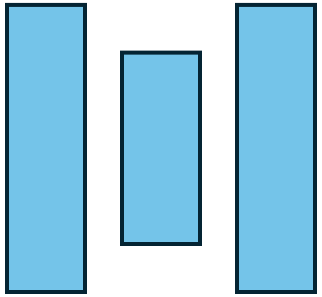


Training strategy

- Initial training with a large number of rule-based synthetic images



Rule-based synthetic images

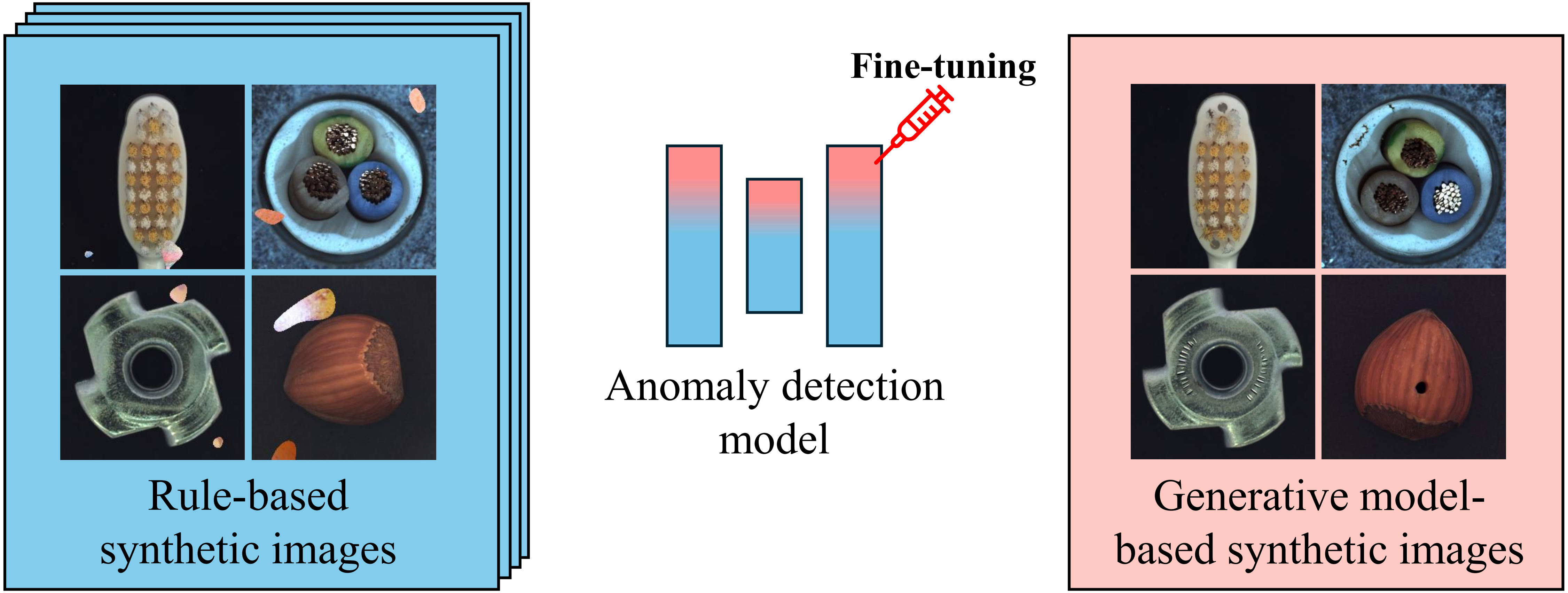


Anomaly detection model

Generative model-based synthetic images

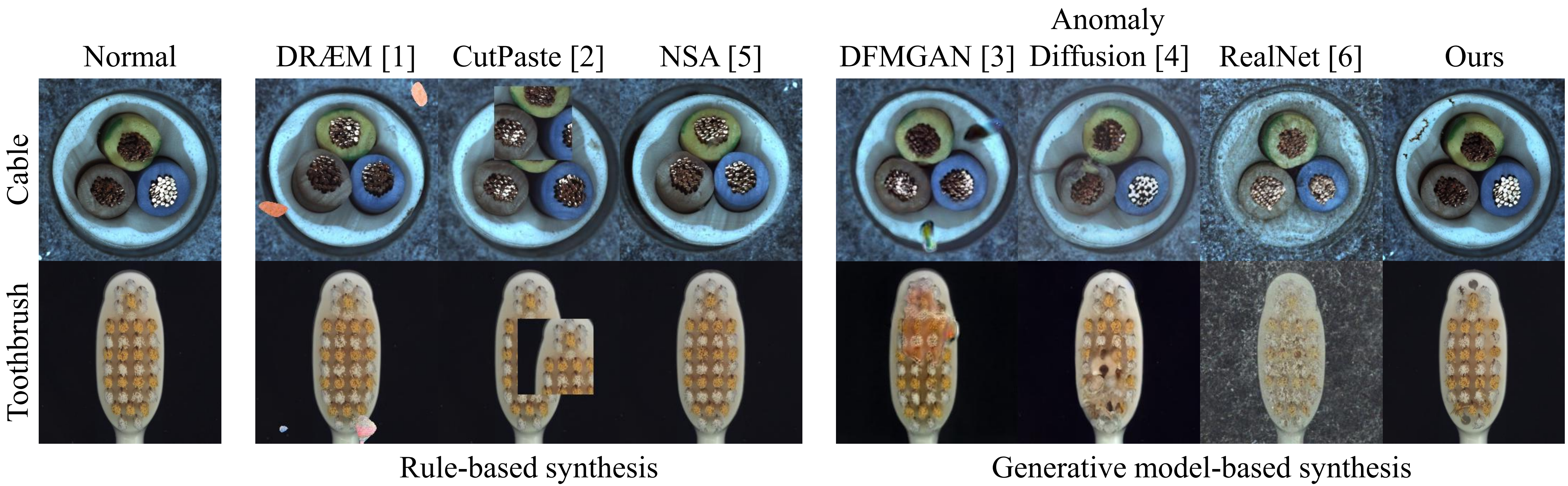
Training strategy

- Fine-tuning with generative model-based synthetic images



Experiment results

- Generating synthetic defective images for the MVTec AD dataset [7]



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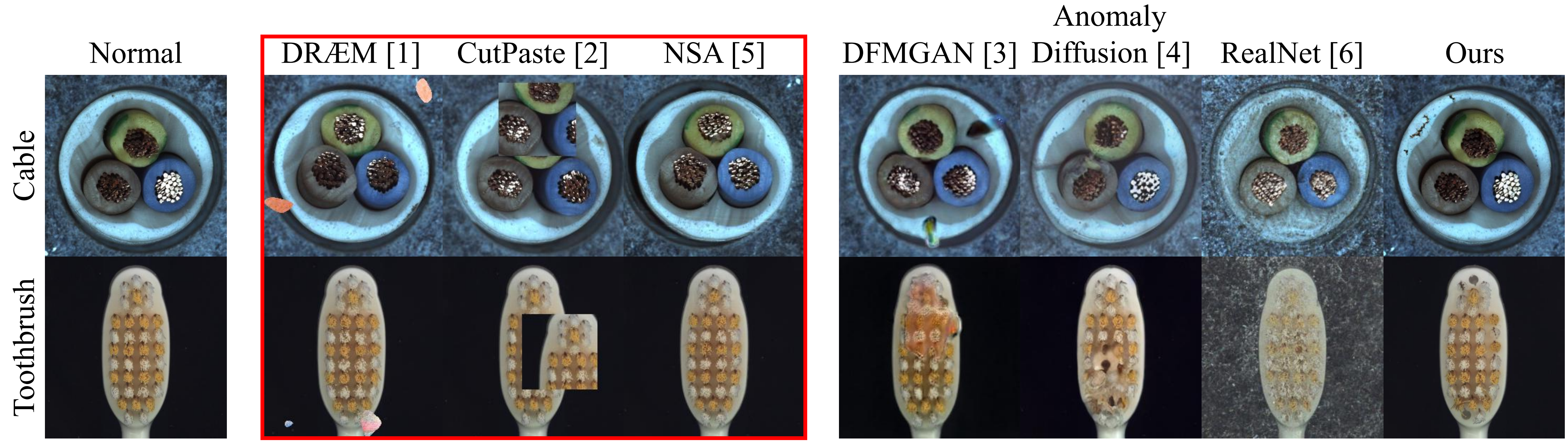

Rule-based synthesis

Generative model-based synthesis

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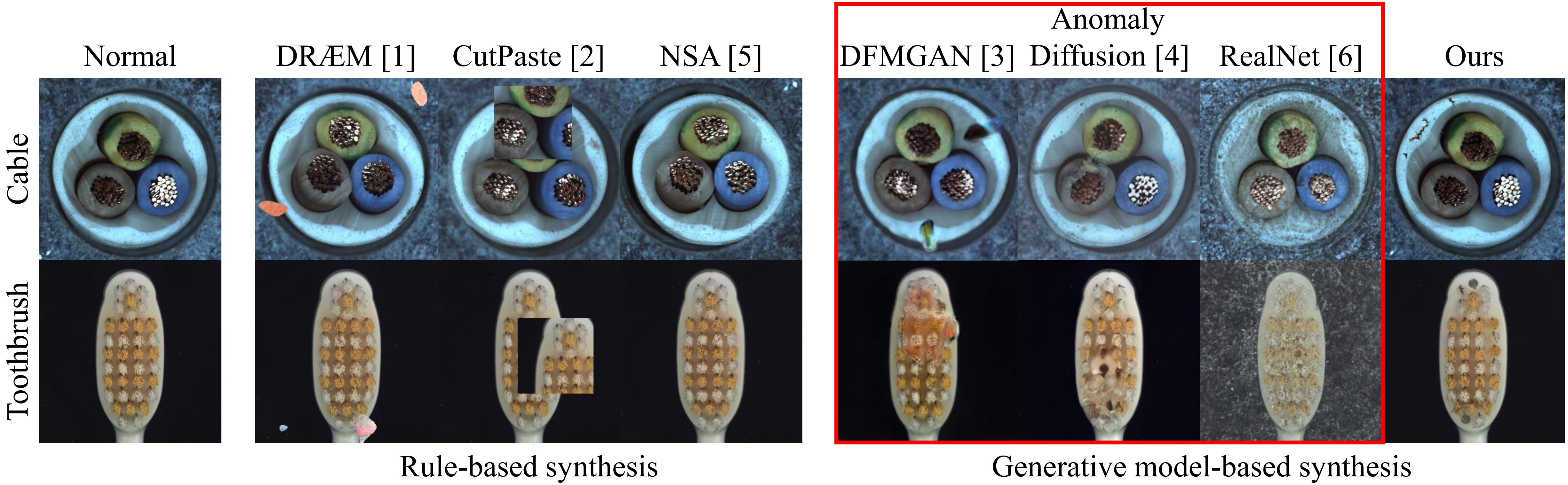

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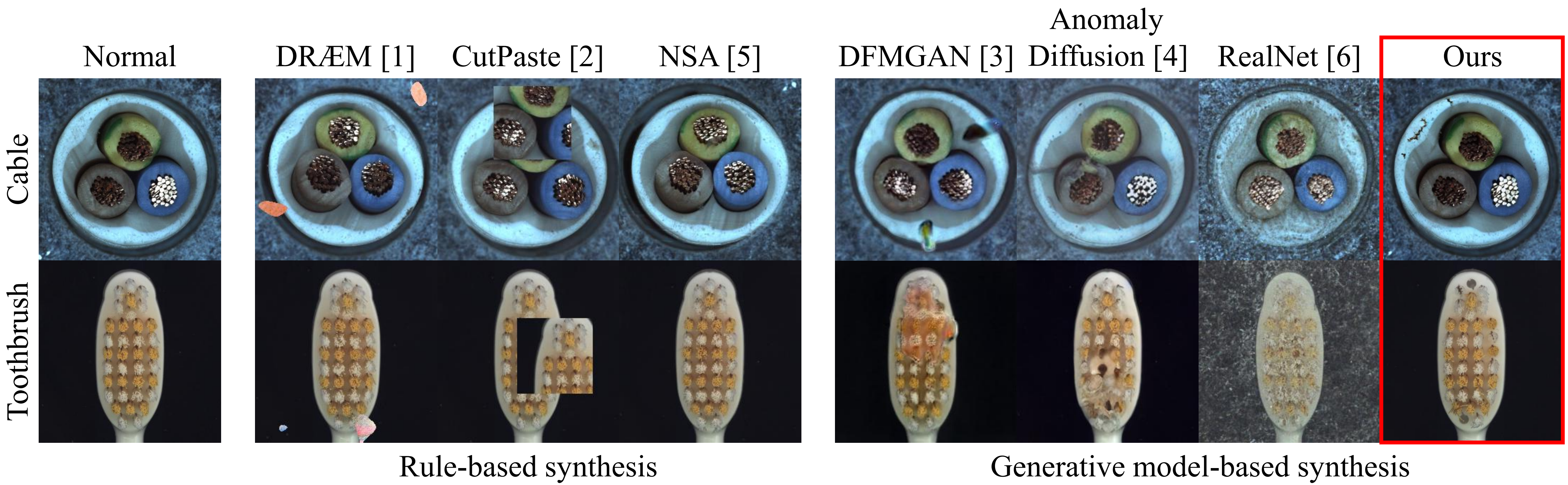

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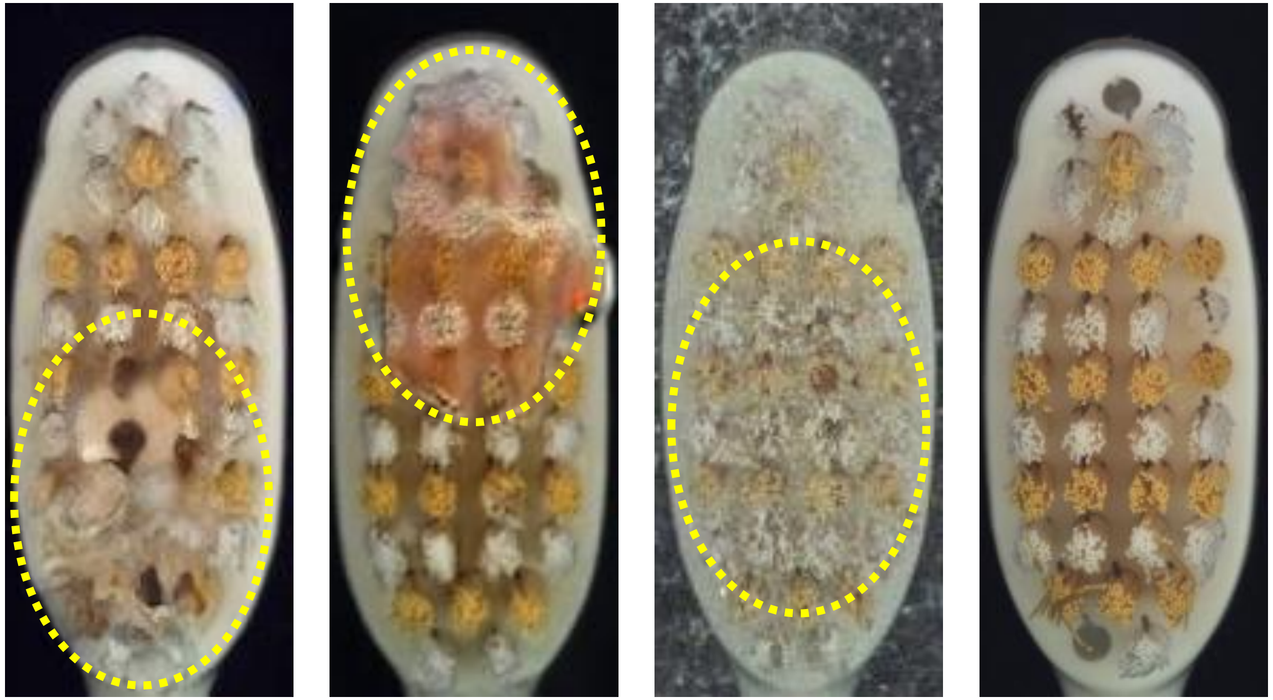

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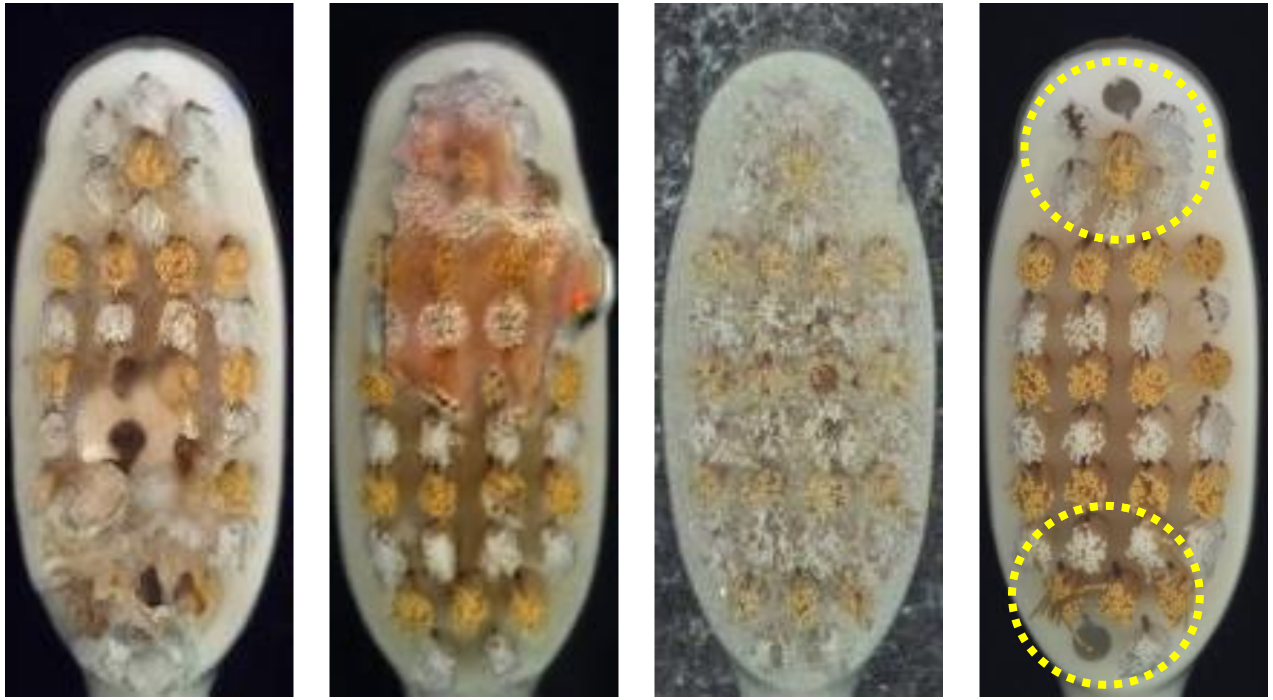

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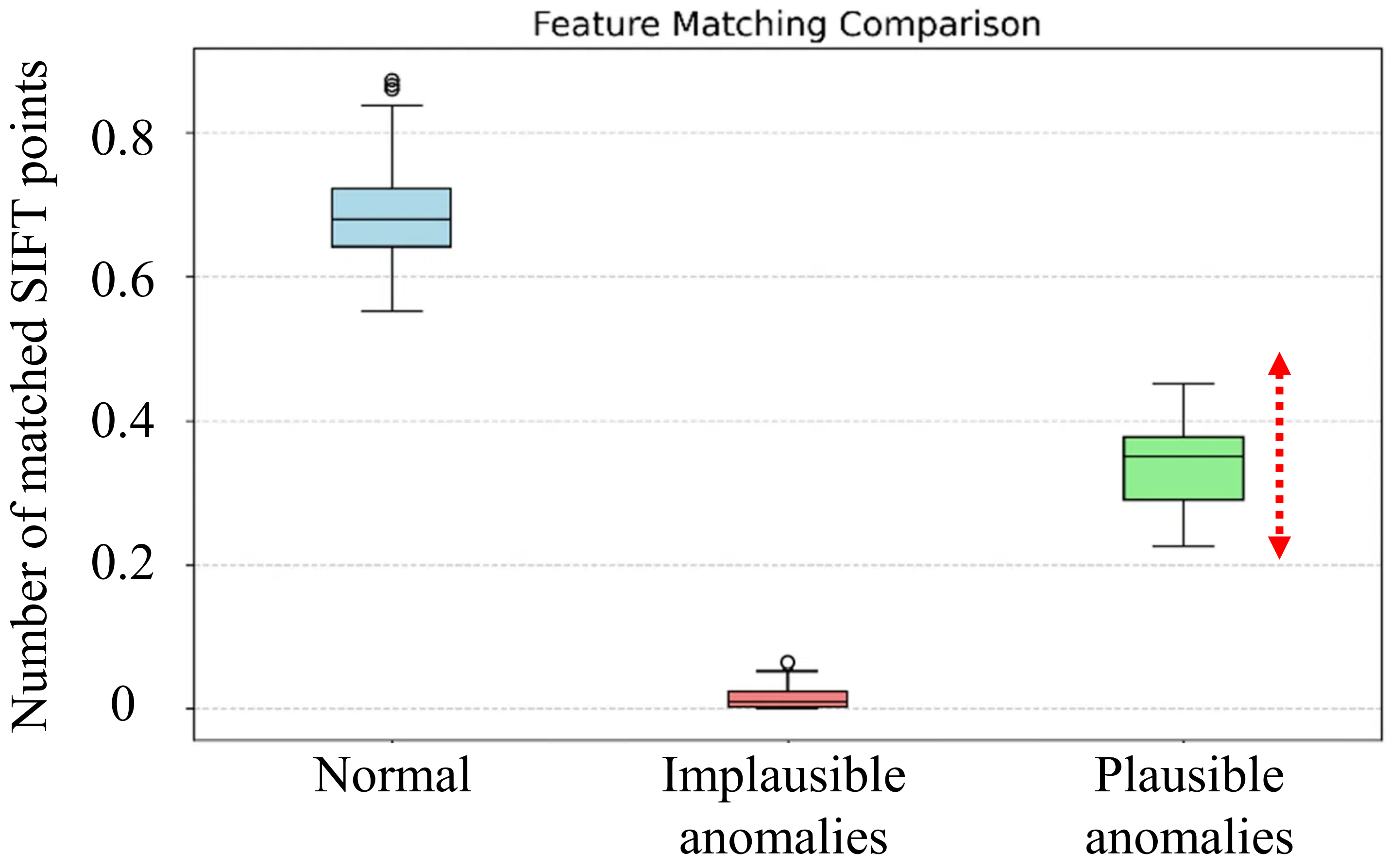
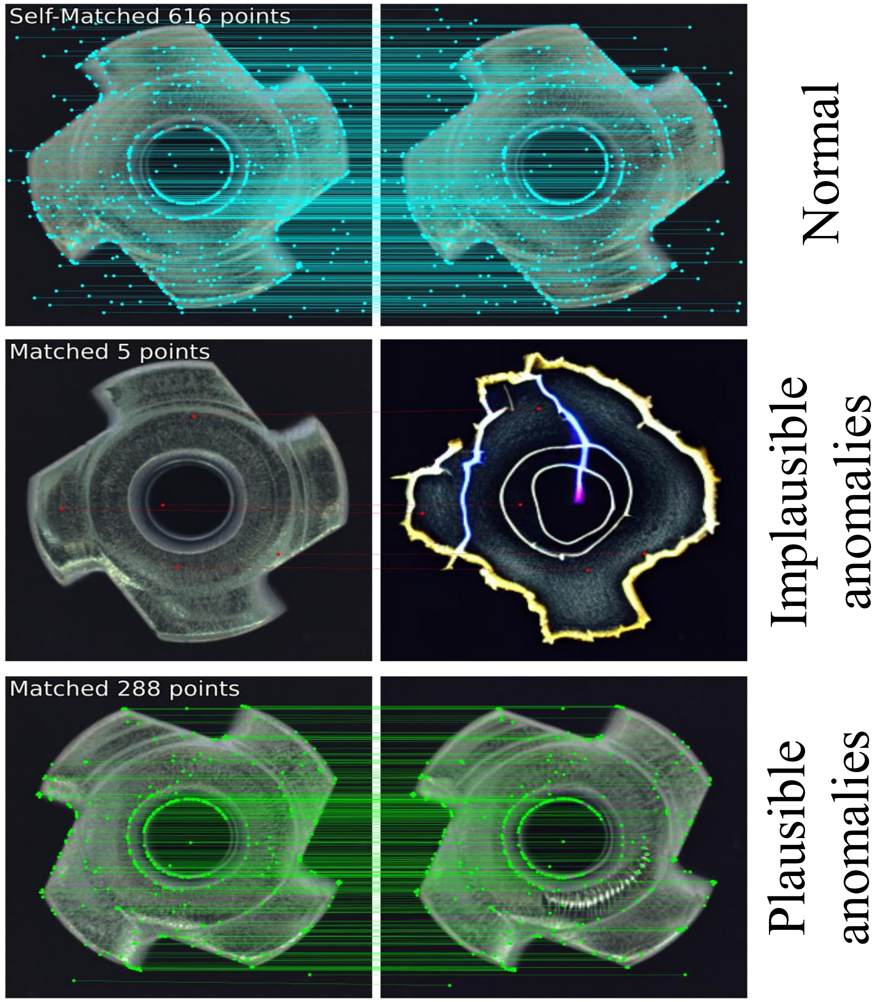
Experiment results

- Discarding implausible anomalies using SIFT points corresponding ratio





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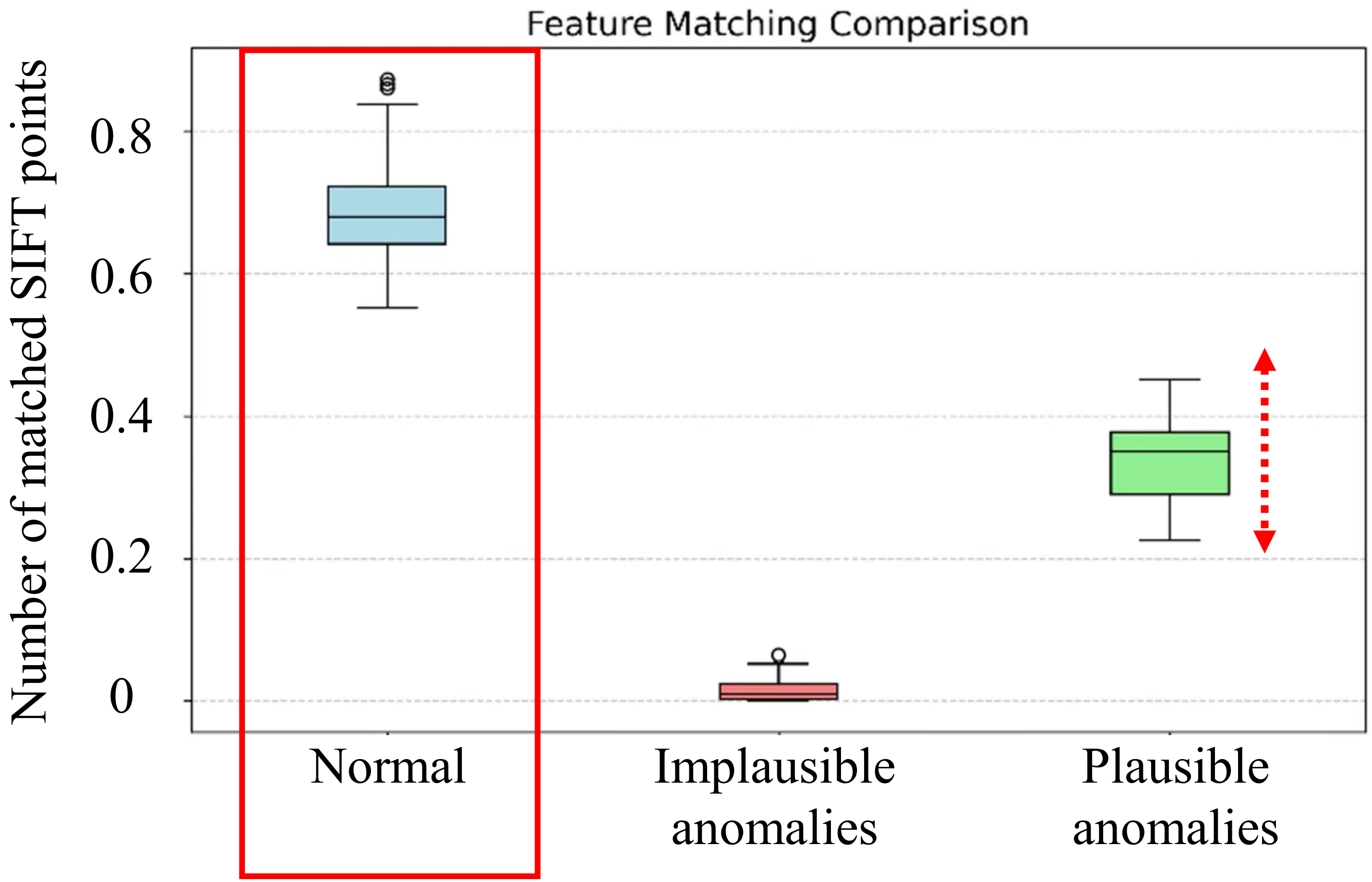

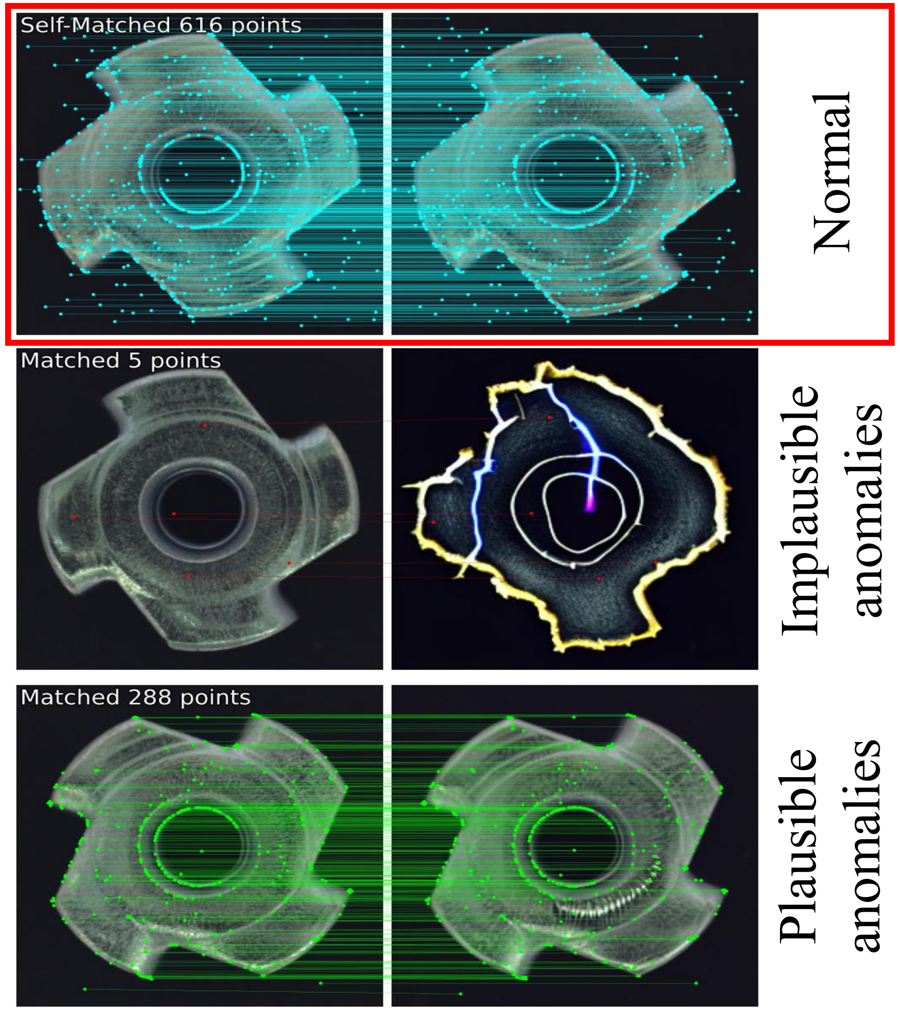

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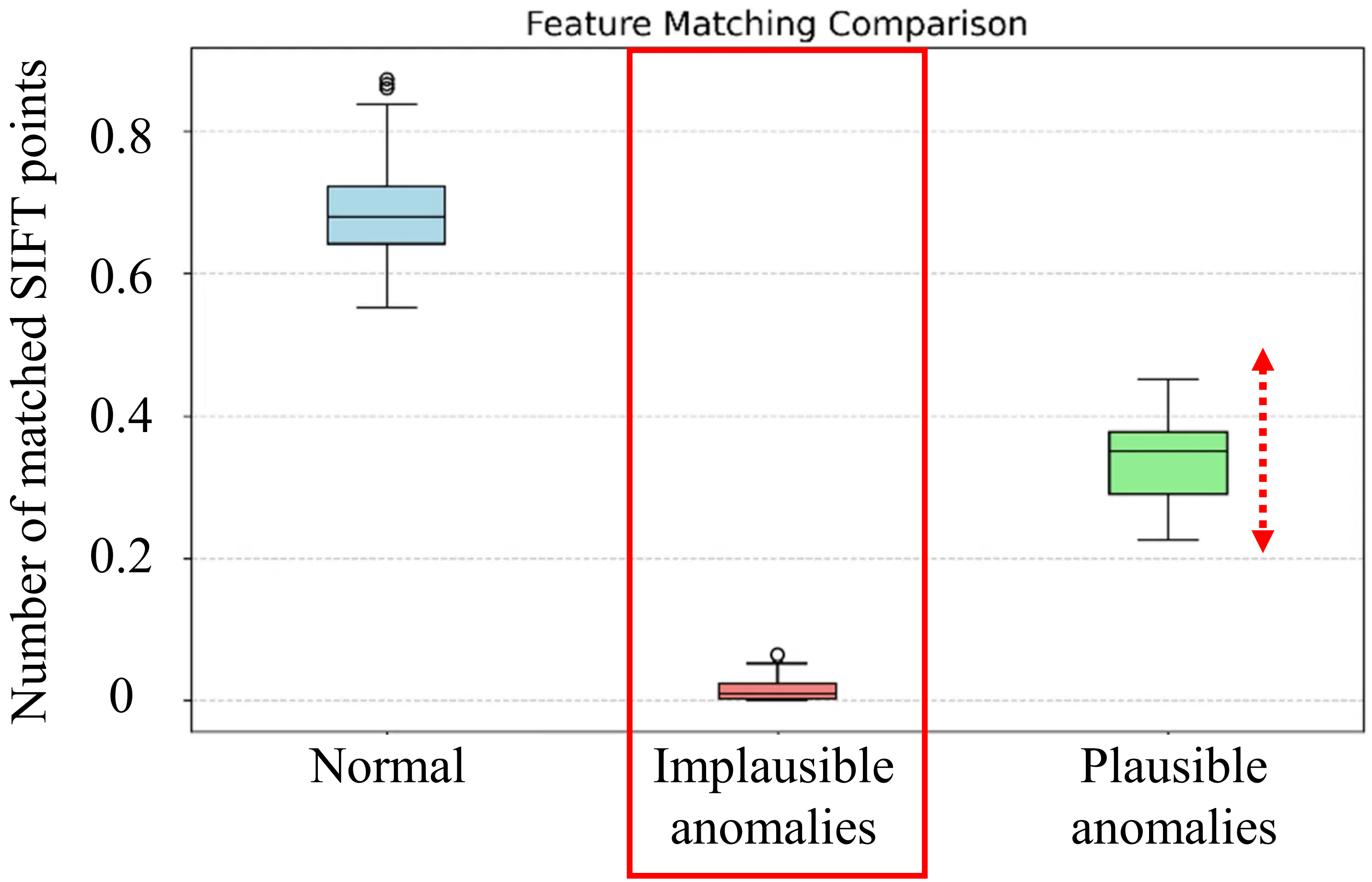

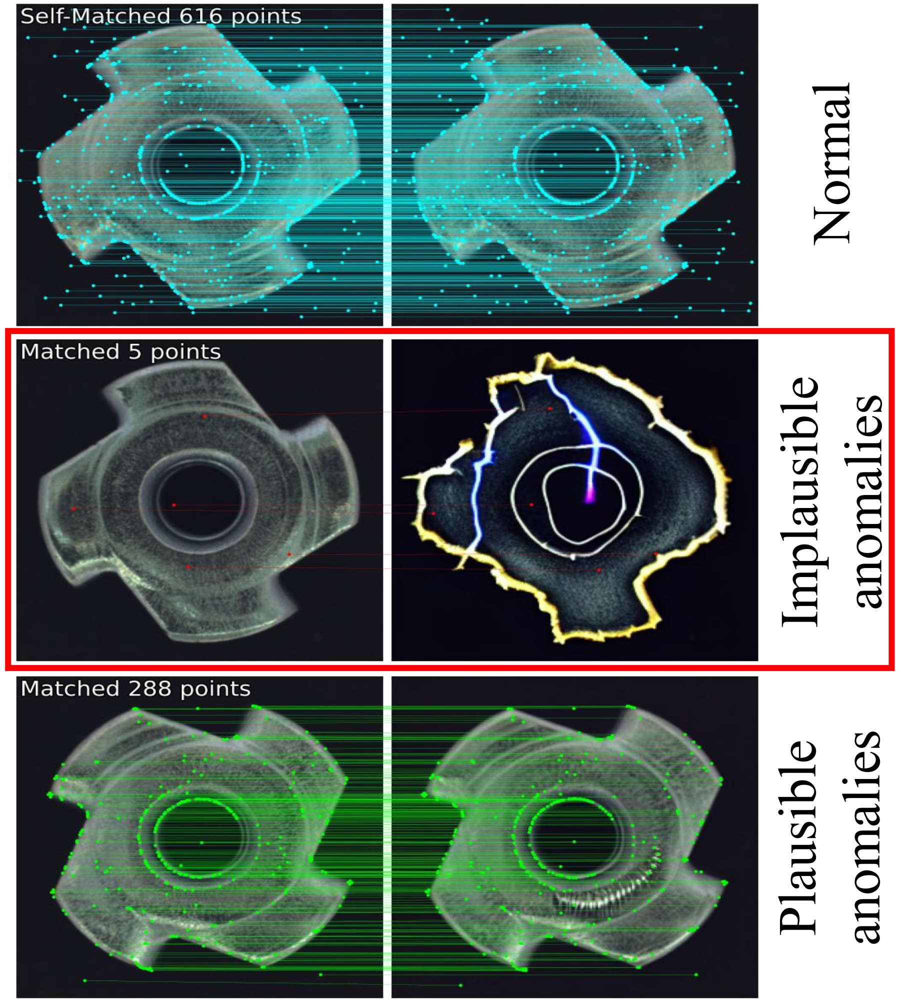

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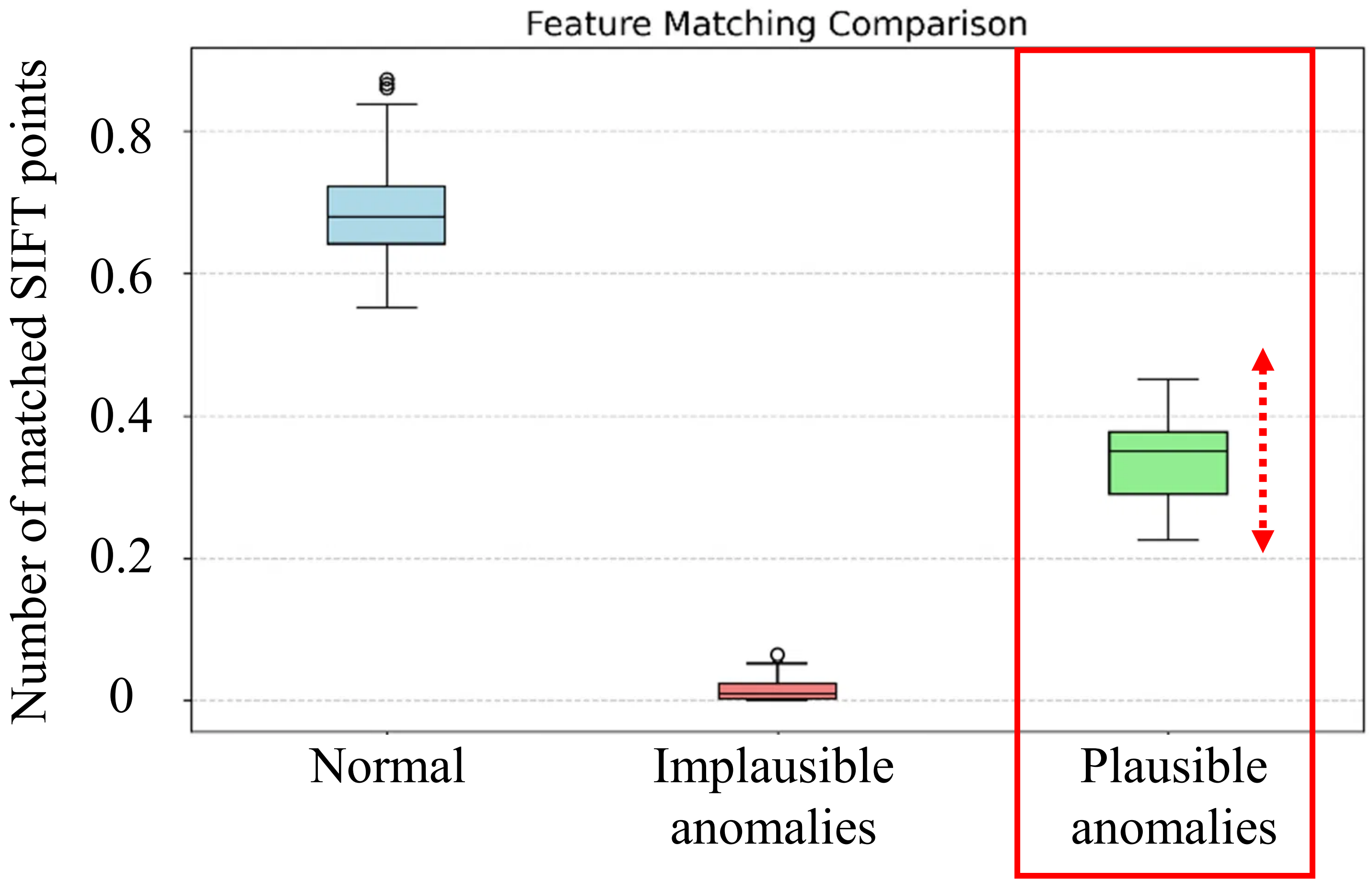
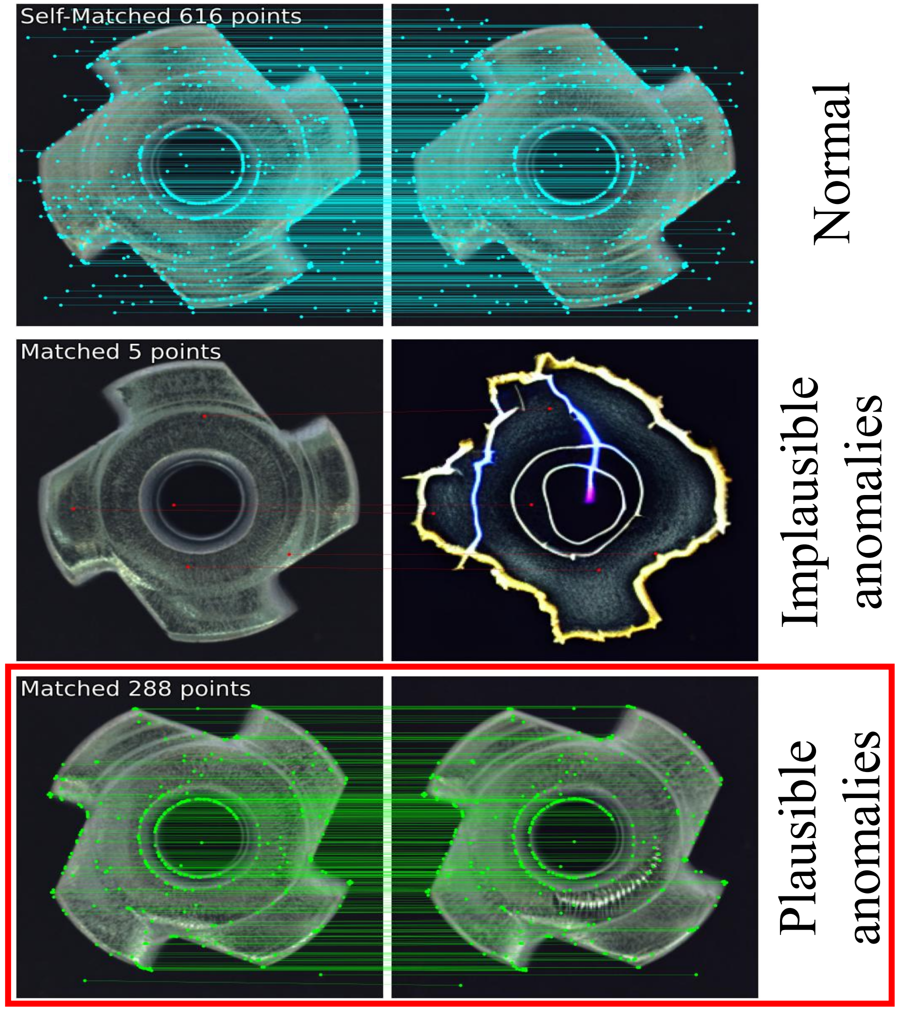
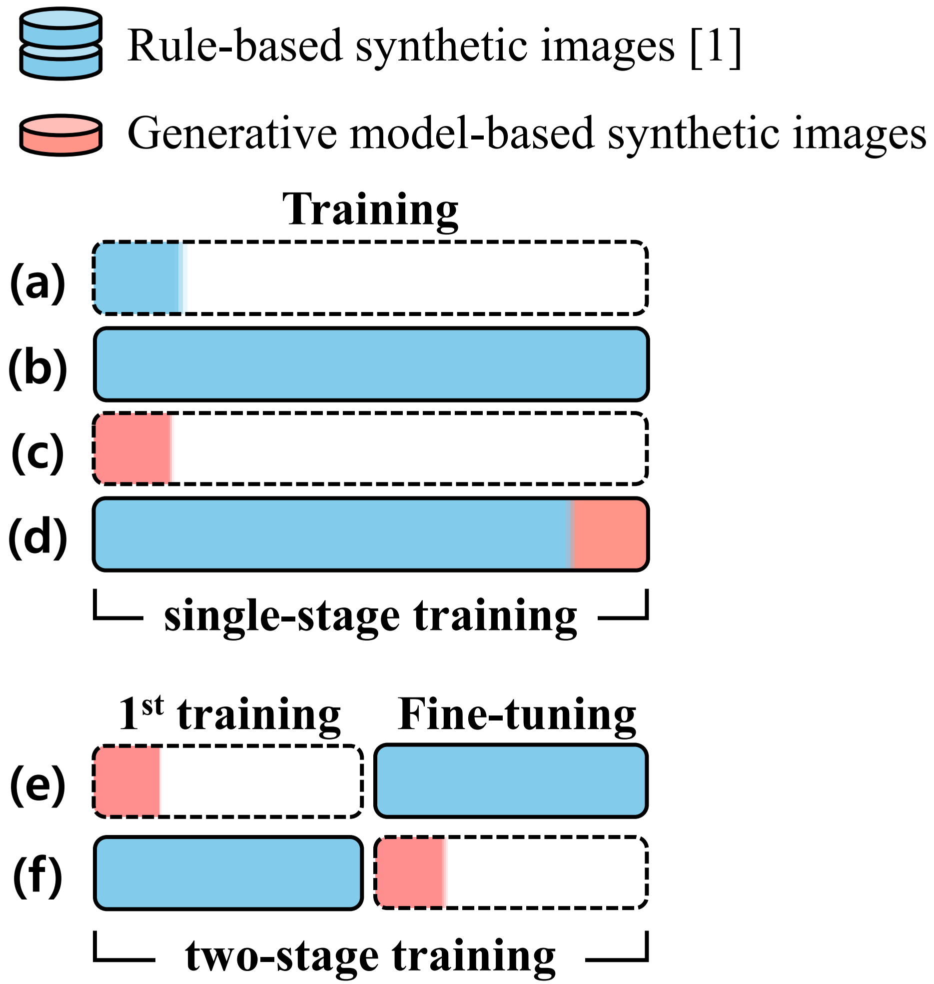




Experiment results

- Evaluating the training strategy under six experimental settings



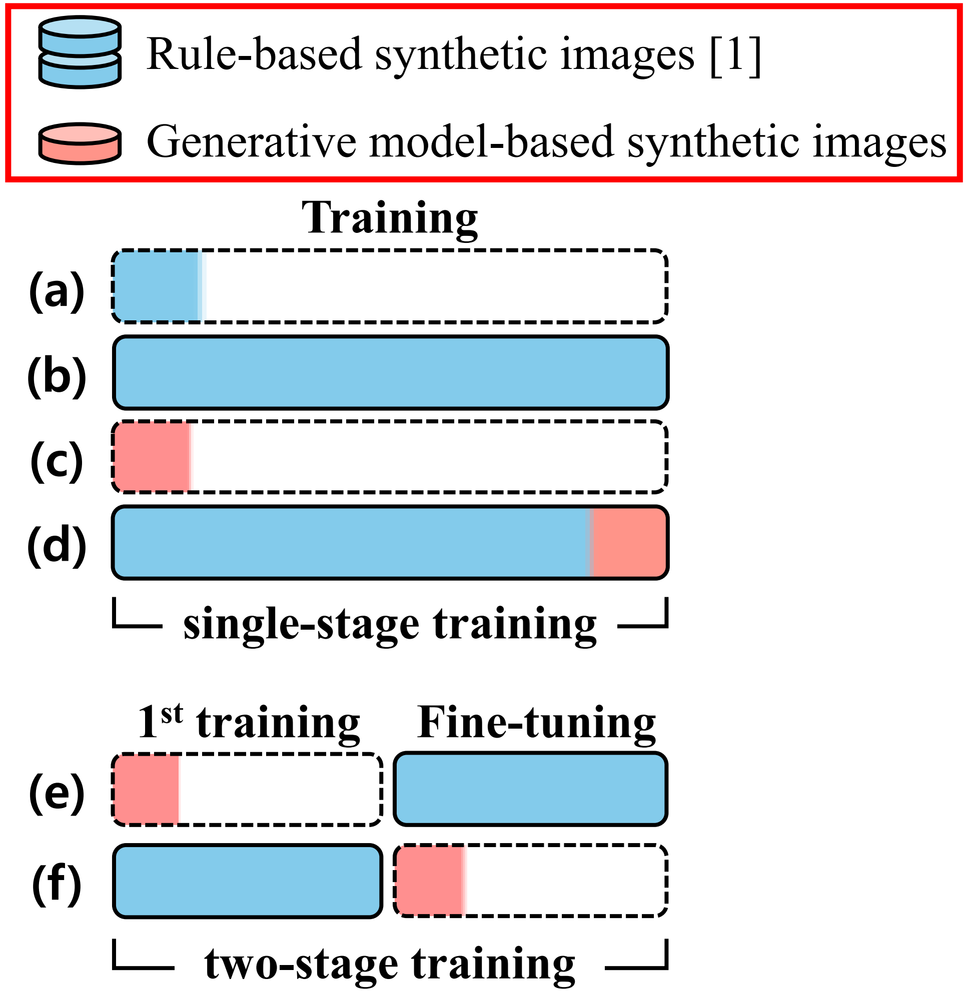
AUROC

class \ setting	(a)	(b)	(c)	(d)	(e)	(f)
capsule	84.1	97.3	87.1	97.4	54.2	**98.7**
bottle	93.8	96.7	94.8	96.3	96.1	**99.0**
pill	83.2	98.2	81.8	97.0	76.2	**98.4**
transistor	75.9	93.1	89.8	92.1	83.1	**95.9**
cable	84.1	91.8	70.4	92.2	80.9	**97.1**
toothbrush	97.2	99.7	99.4	99.4	77.8	**100**
metal nut	91.2	98.7	84.4	97.5	64.1	**99.1**
hazelnut	**93.2**	**100**	88.0	**100**	94.3	**100**
screw	80.3	93.9	89.5	96.2	70.3	**99.5**
avg	86.6	96.6	87.2	96.5	77.4	**98.7**

[1] V. Zavrtanik *et al.*, "DRÆM - A Discriminatively Trained Reconstruction Embedding for Surface Anomaly Detection," ICCV 2021.

Experiment results

- Evaluating the training strategy under six experimental settings



AUROC

class \ setting	(a)	(b)	(c)	(d)	(e)	(f)
capsule	84.1	97.3	87.1	97.4	54.2	**98.7**
bottle	93.8	96.7	94.8	96.3	96.1	**99.0**
pill	83.2	98.2	81.8	97.0	76.2	**98.4**
transistor	75.9	93.1	89.8	92.1	83.1	**95.9**
cable	84.1	91.8	70.4	92.2	80.9	**97.1**
toothbrush	97.2	99.7	99.4	99.4	77.8	**100**
metal nut	91.2	98.7	84.4	97.5	64.1	**99.1**
hazelnut	**93.2**	**100**	88.0	**100**	94.3	**100**
screw	80.3	93.9	89.5	96.2	70.3	**99.5**
avg	86.6	96.6	87.2	96.5	77.4	**98.7**

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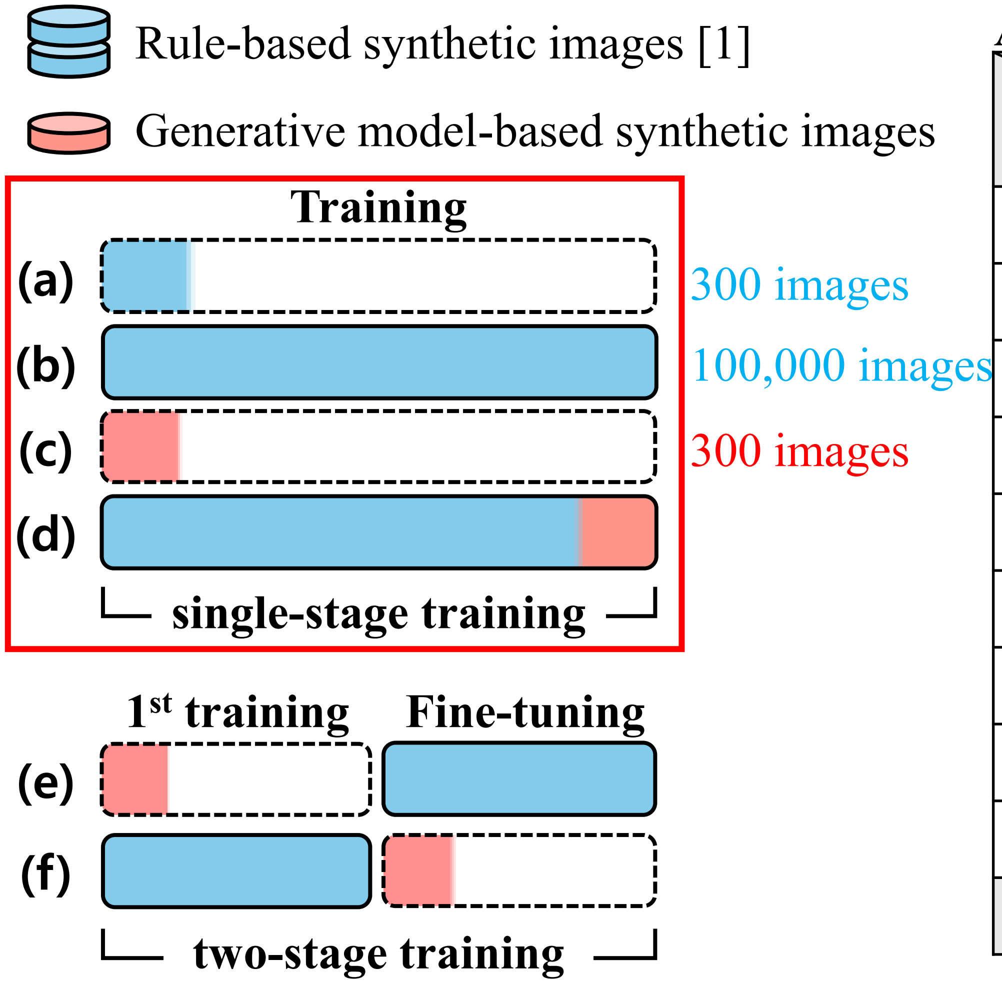

AUROC

class \ setting	(a)	(b)	(c)	(d)	(e)	(f)
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Experiment results

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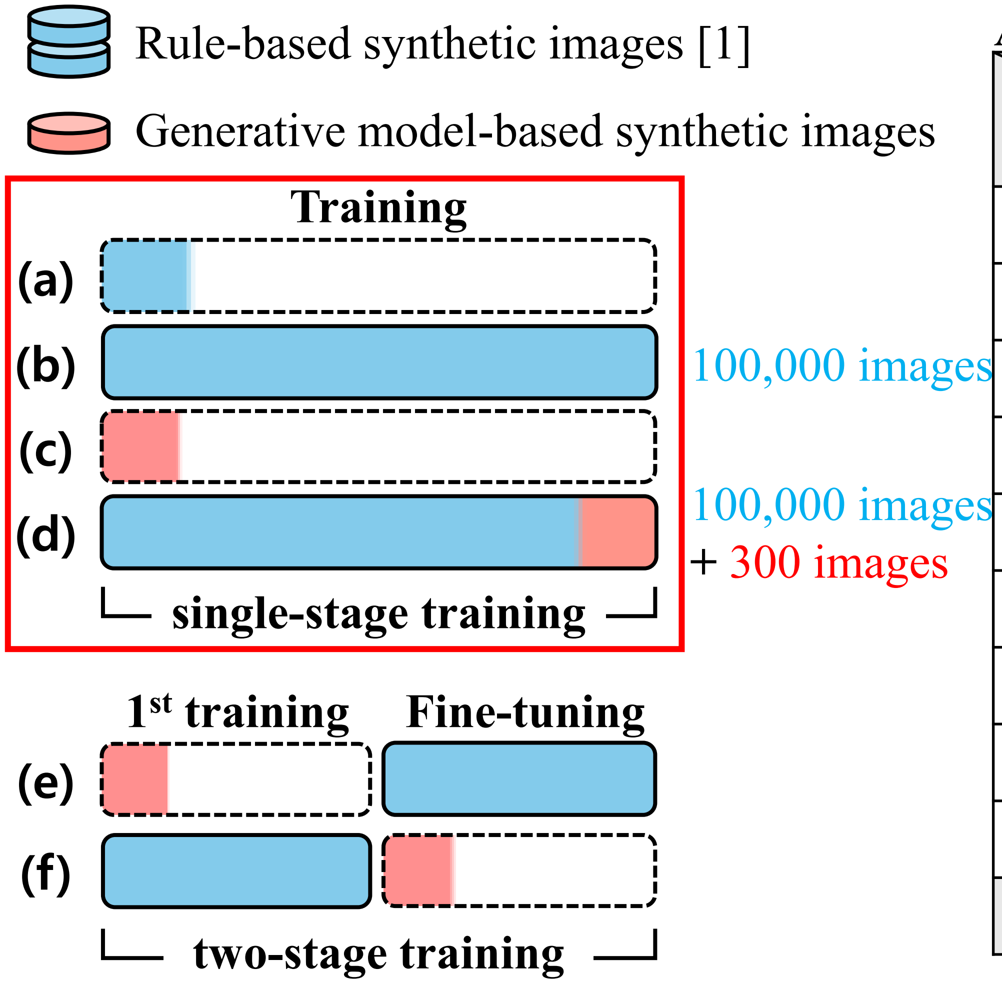

AUROC

setting / class	(a)	(b)	(c)	(d)	(e)	(f)
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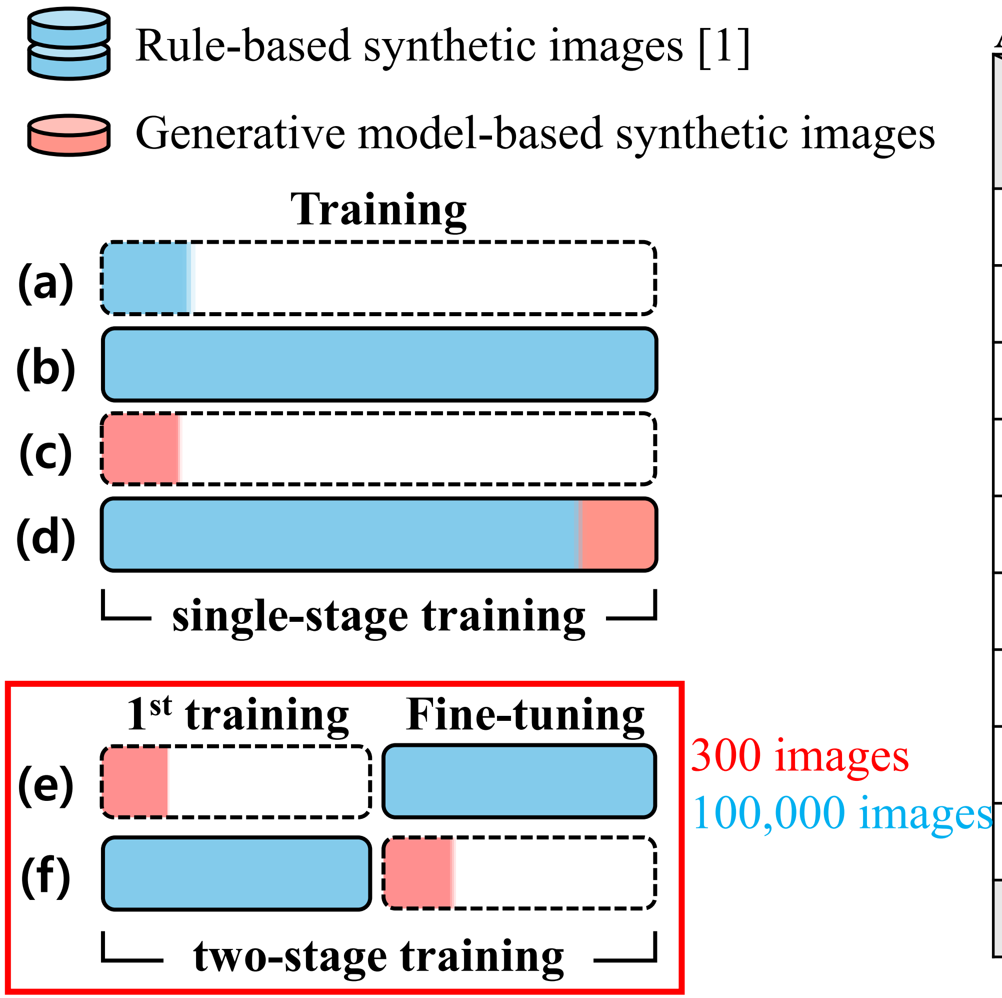
Experiment results

- Evaluating the training strategy under six experimental settings



AUROC

setting / class	(a)	(b)	(c)	(d)	(e)	(f)
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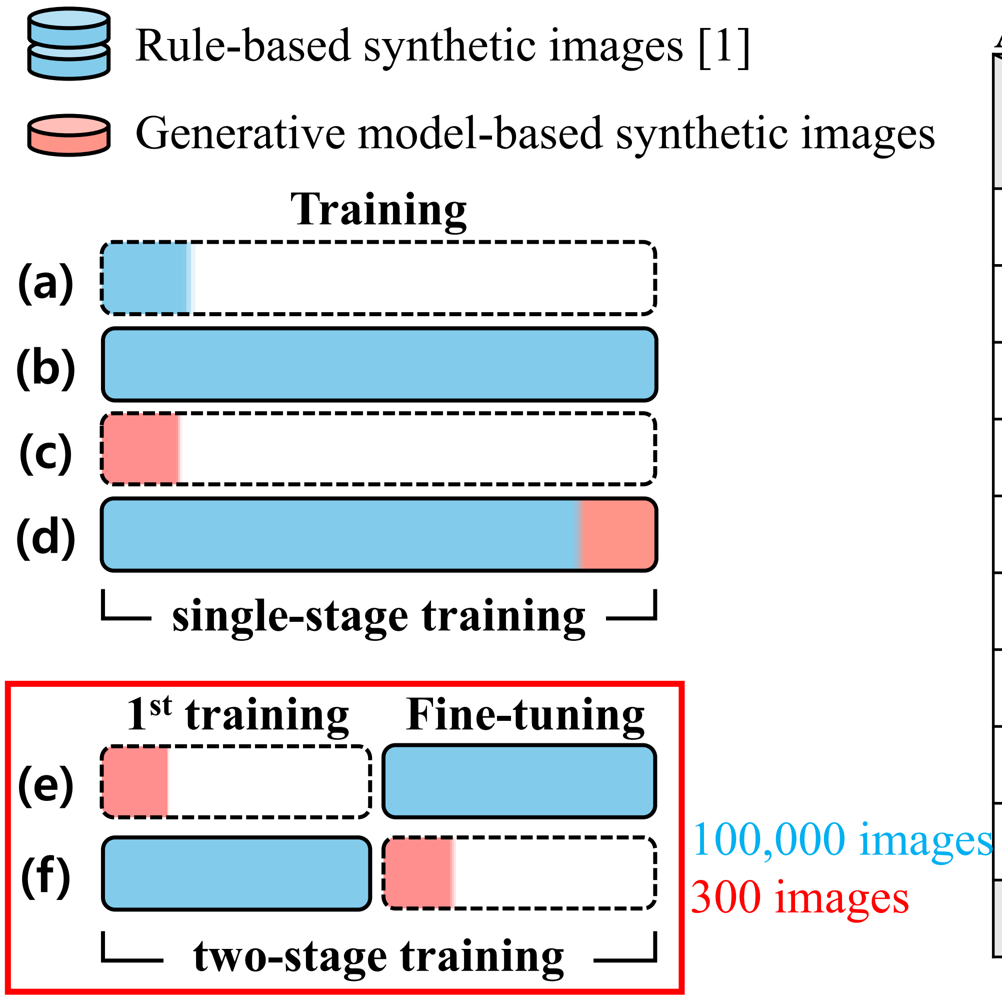
Experiment results

- Evaluating the training strategy under six experimental settings



AUROC

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[1] V. Zavrtanik *et al.*, "DRÆM - A Discriminatively Trained Reconstruction Embedding for Surface Anomaly Detection," ICCV 2021.

Conclusions

Contributions

- A training-free framework exploiting two pre-trained networks to effectively generate anomalies
- A cost-aware training strategy that utilized both rule-based synthesis and generative model-based synthesis

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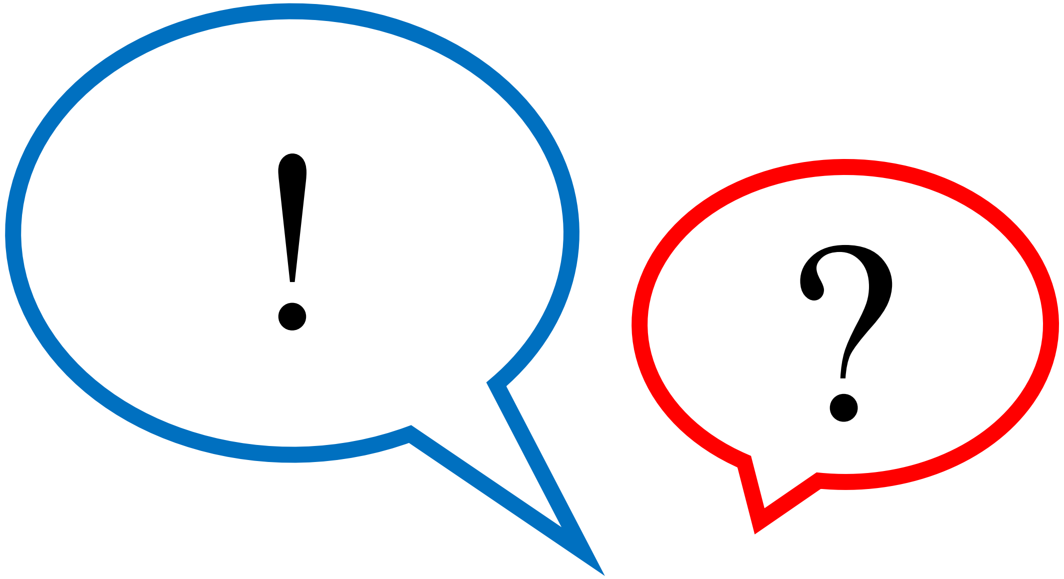
- A training-free framework exploiting two pre-trained networks to effectively generate anomalies
- A cost-aware training strategy that utilized both rule-based synthesis and generative model-based synthesis

Future research

- Investigating Classifier-Free Guidance [10] for efficient anomaly synthesis
- Exploring the relationship between anomaly types and the required amount of training data

[8] J. Ho *et al.*, "Classifier-free diffusion guidance," NeurIPS workshop 2021.

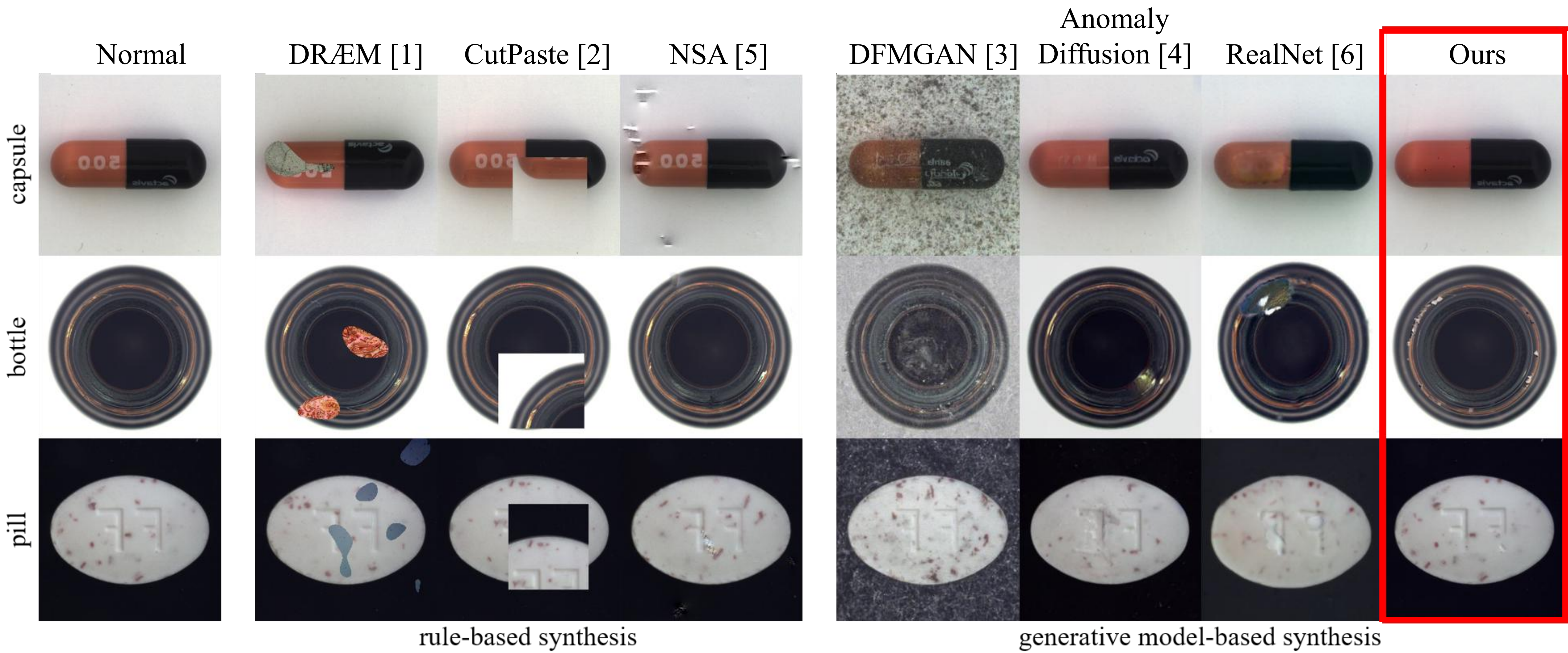


If you are interested in our research, please contact me.

Sungho Kang
sungho369@skku.edu

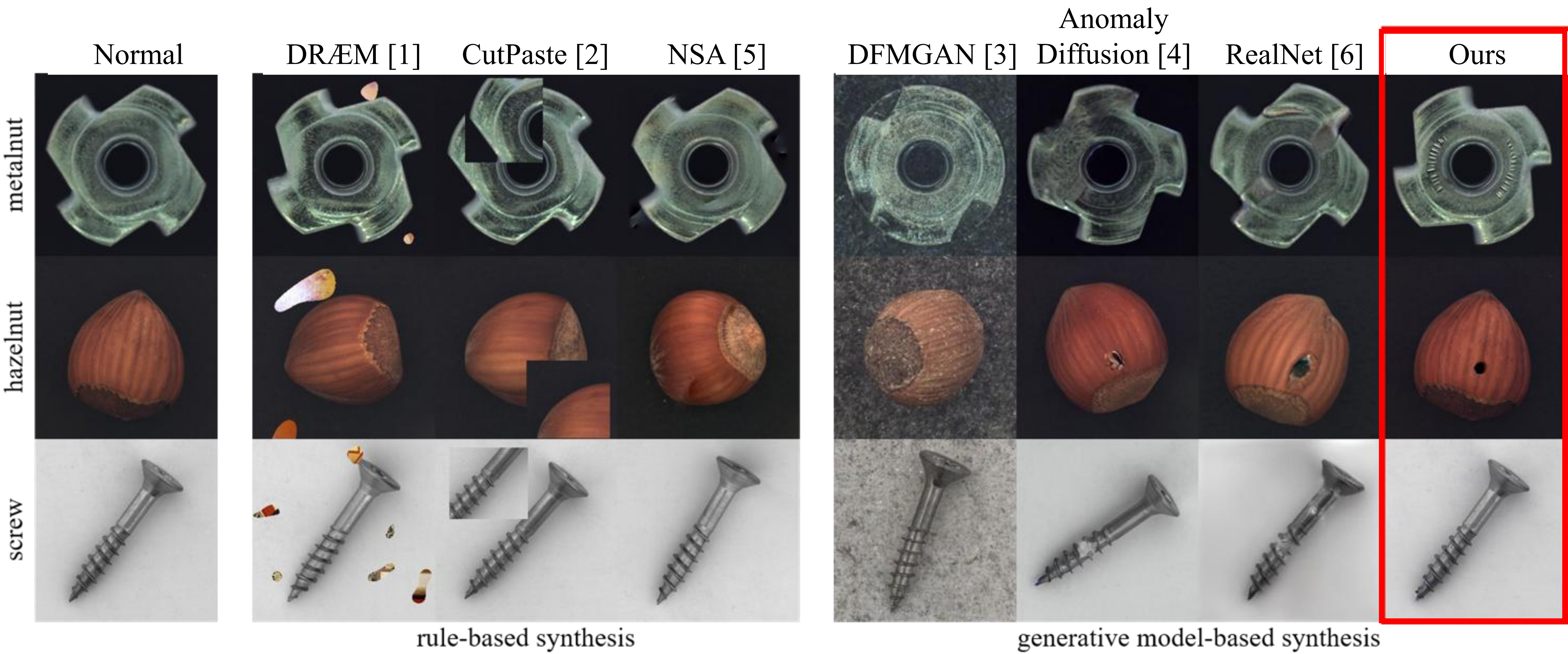
Appendix. A1

- Extra qualitative results



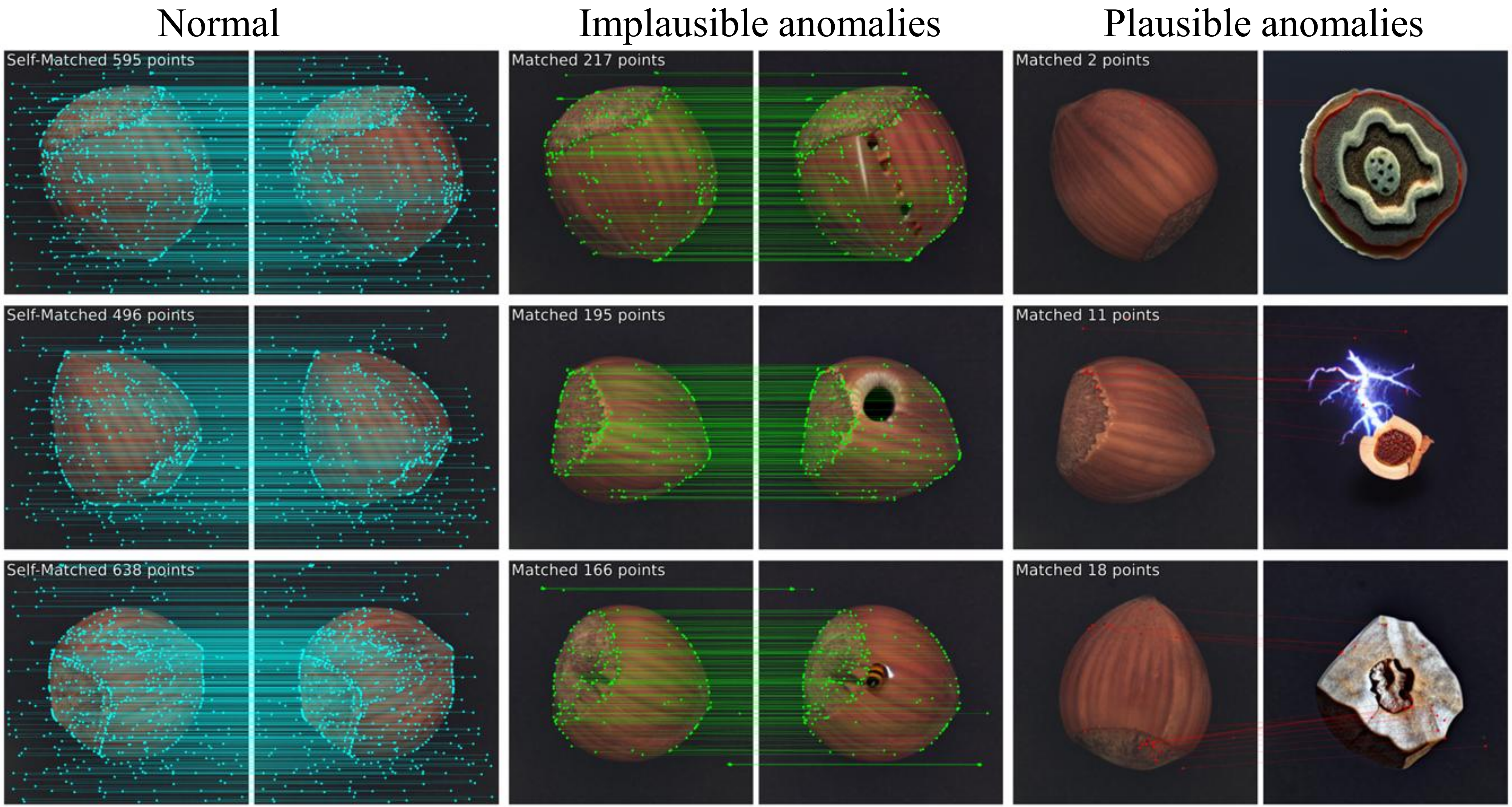
Appendix. A1

- Extra qualitative results



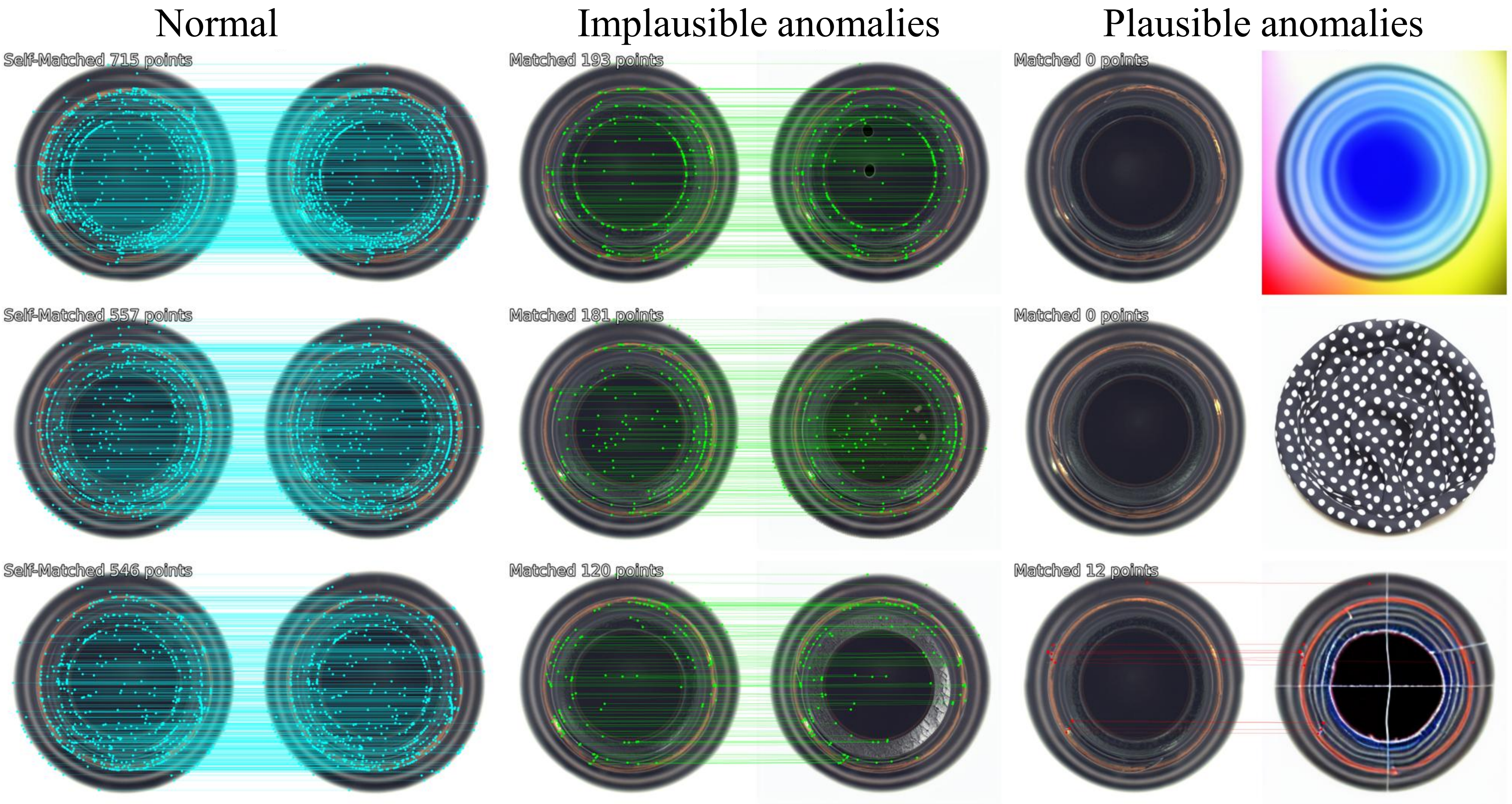
Appendix. B1

- Qualitative examples of matching-point-based filtering



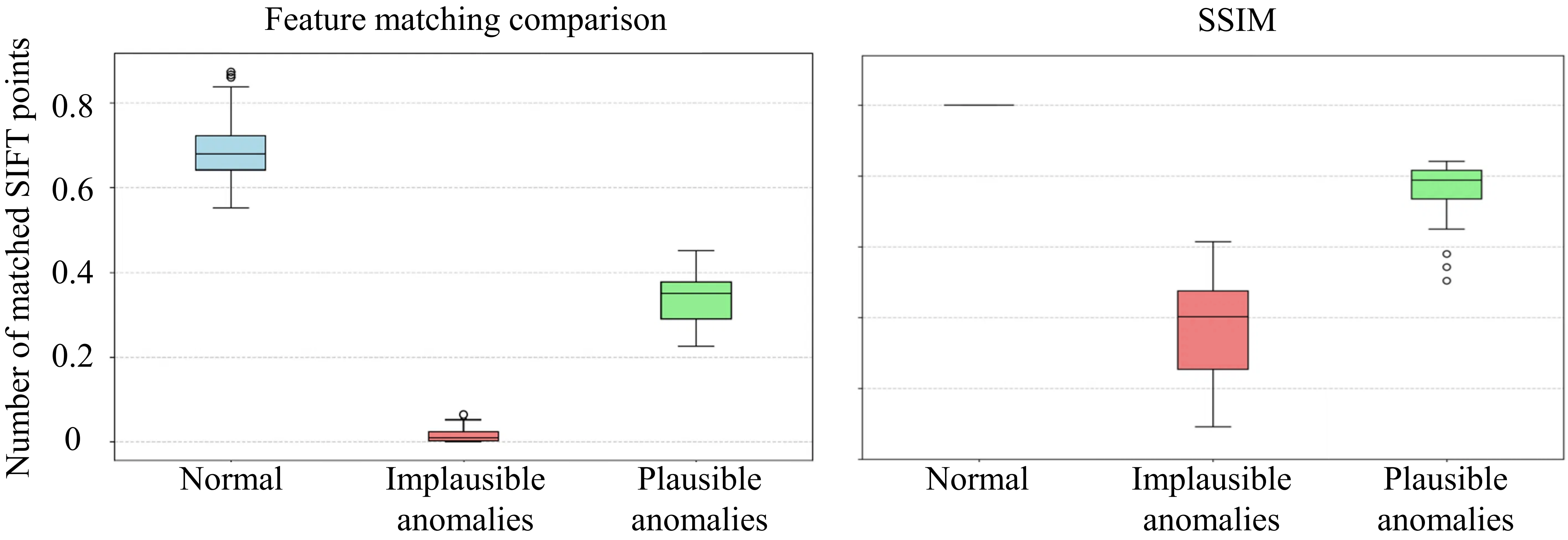
Appendix. B2

- Qualitative examples of matching-point-based filtering



Appendix. C

- Feature matching comparison VS. SSIM



Appendix. C

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