Friedrich-Alexander-Universität
Technische Fakultät

DRÆM - Pitch Presentation

A Discriminatively Trained Reconstruction Embedding for Surface Anomaly Detection

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Introduction

Surface Anomaly Detection: Why It Matters

- Where applied, surface anomaly detection often outperforms humans in both specififity and sensitivity while simulatniously reducing costs

[1] ZKS21.

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- **Paper:** “DRÆM – A Discriminatively Trained Reconstruction Anomaly Embedding Model for Surface Anomaly Detection”[1]

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- **Paper:** "DRÆM – A Discriminatively Trained Reconstruction Anomaly Embedding Model for Surface Anomaly Detection"[1]
- **Why Surface Anomaly Detection Matters:**
  - **Healthcare:** Detecting skin lesions, tissue abnormalities in medical imaging
  - **Manufacturing:** Identifying defects in circuit boards, scratches on automotive parts
  - **Infrastructure:** Finding cracks in bridges, corrosion on pipelines
  - **Food Industry:** Spotting contamination on produce, foreign objects in packaging
  - **Textiles, Pharmaceutical Industry, . . .**

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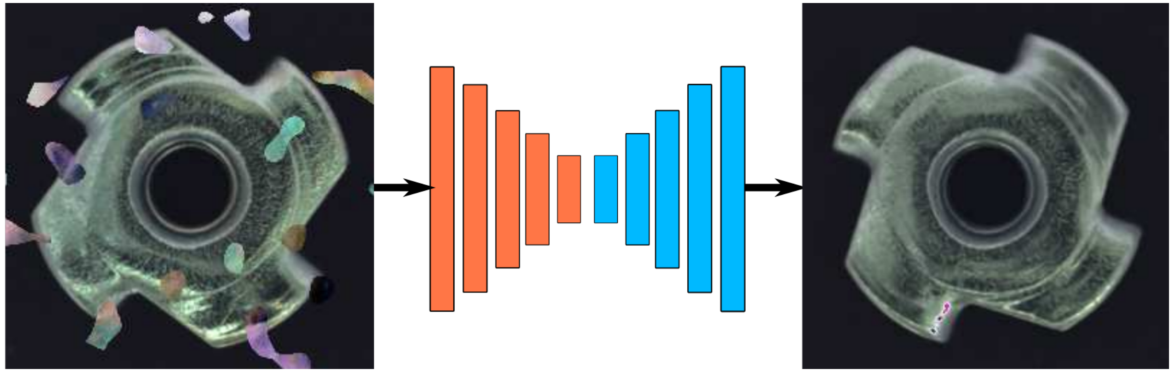

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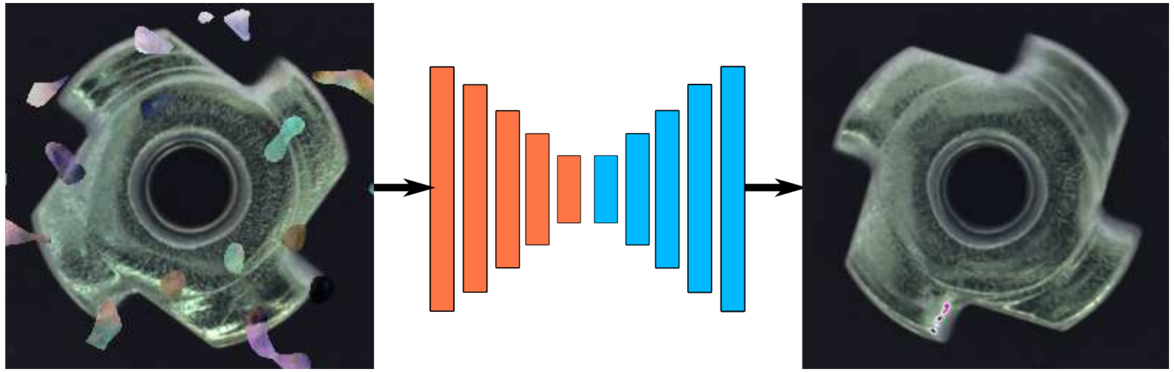

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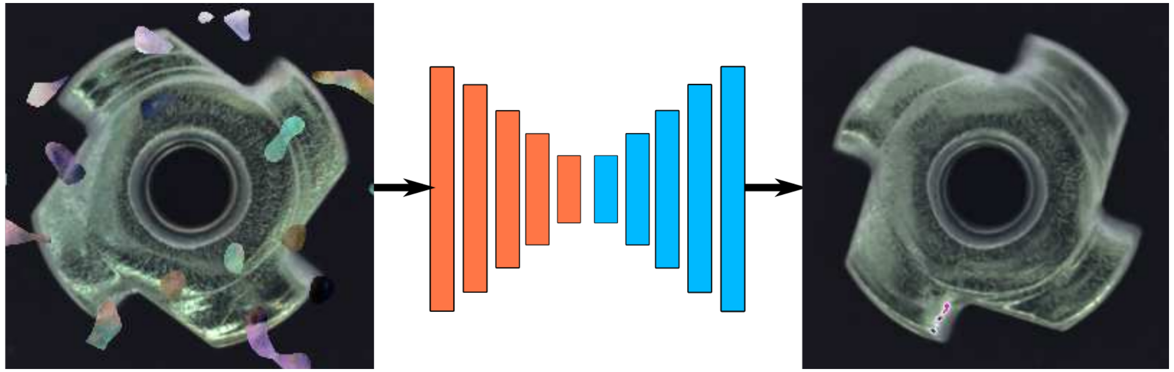

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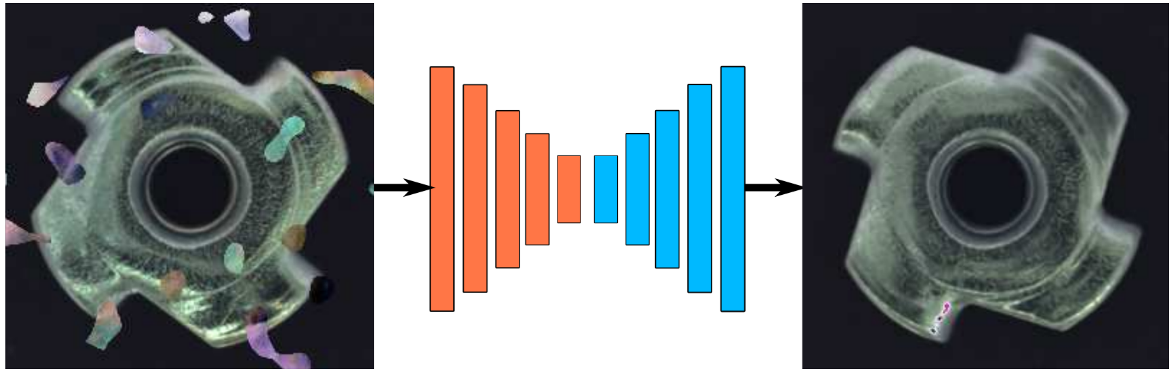
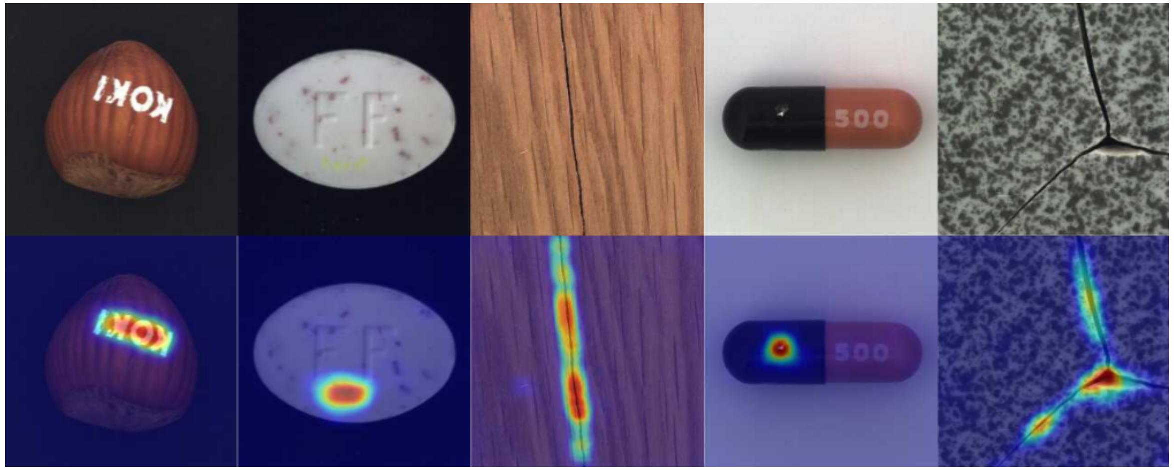
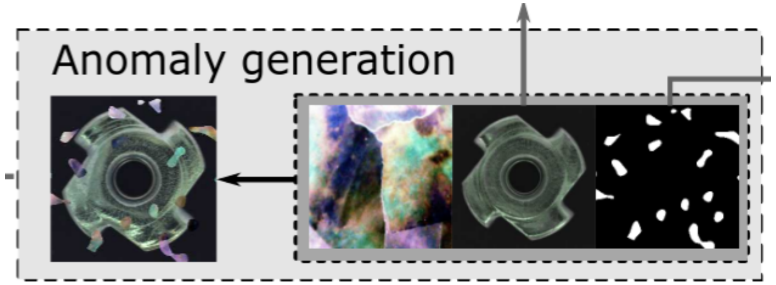
   - ▶ These often suffer from unsharp segmentation maps





Framework Overview
How it Works



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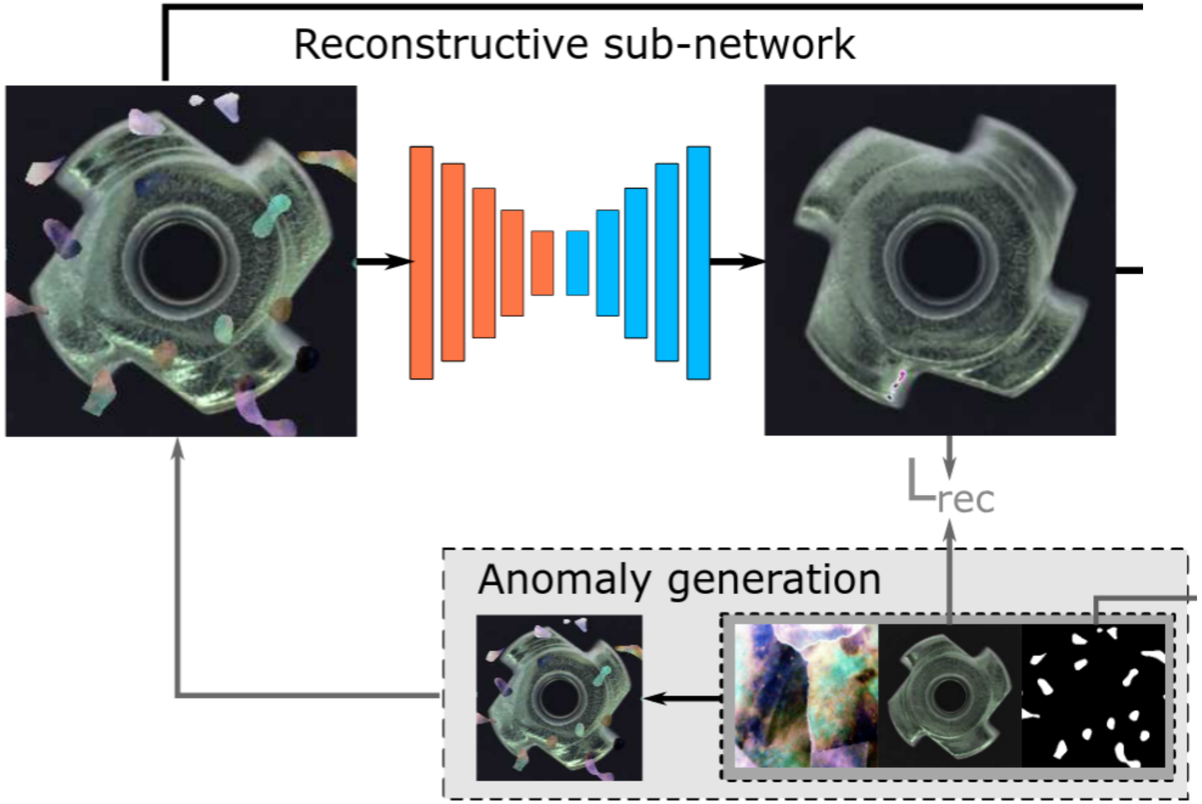

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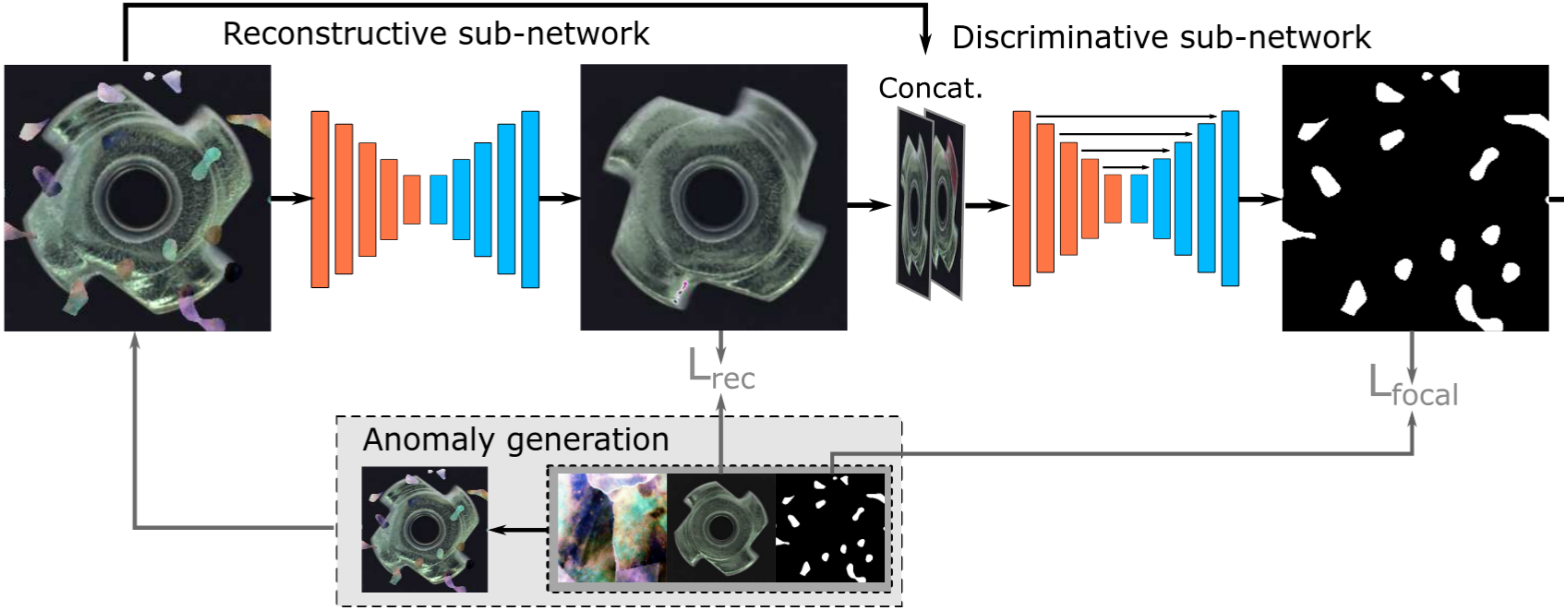

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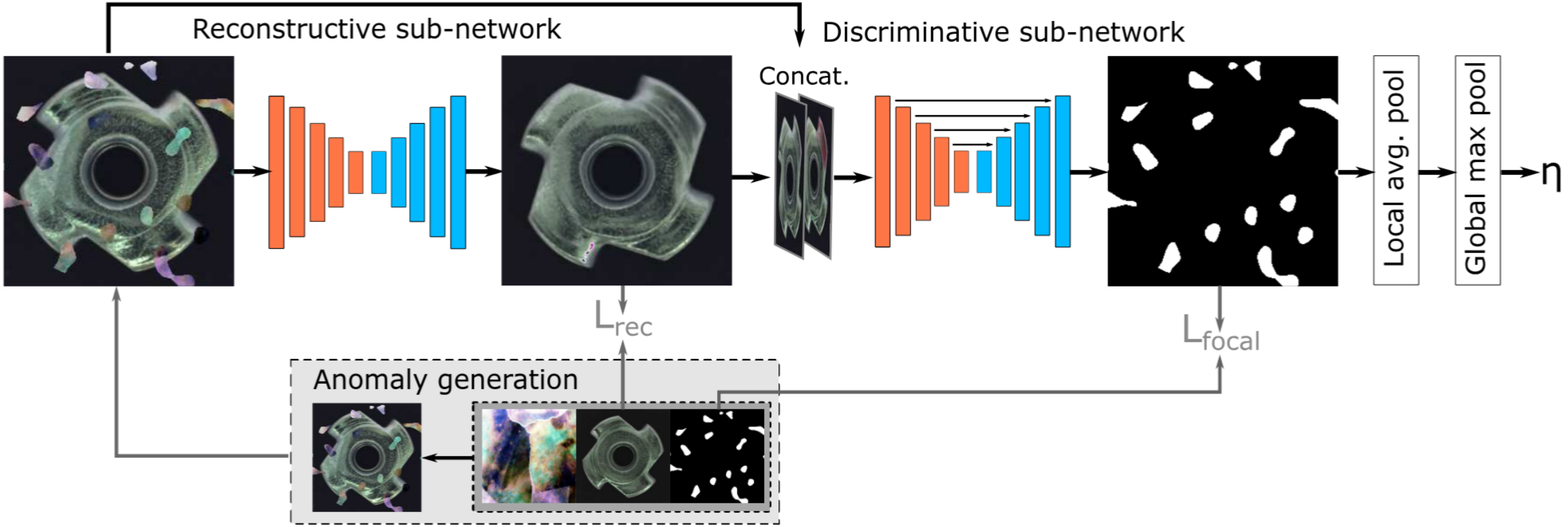

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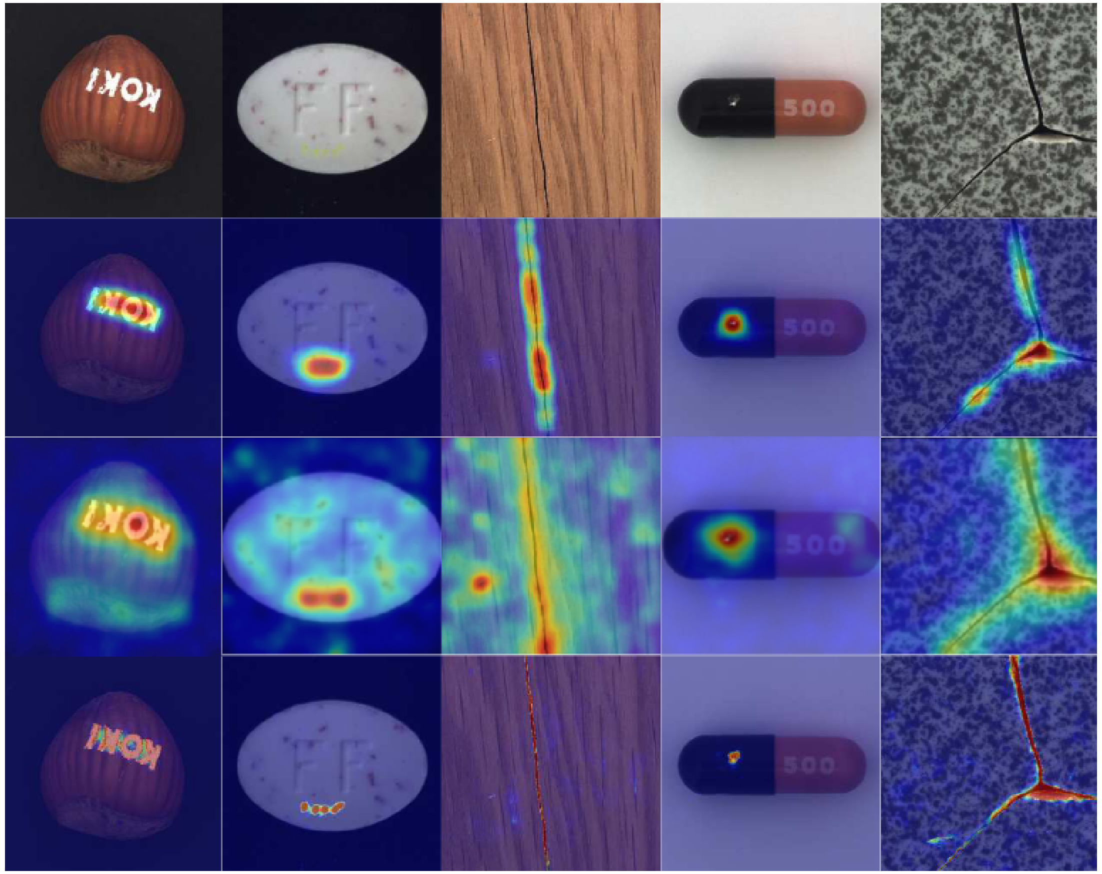

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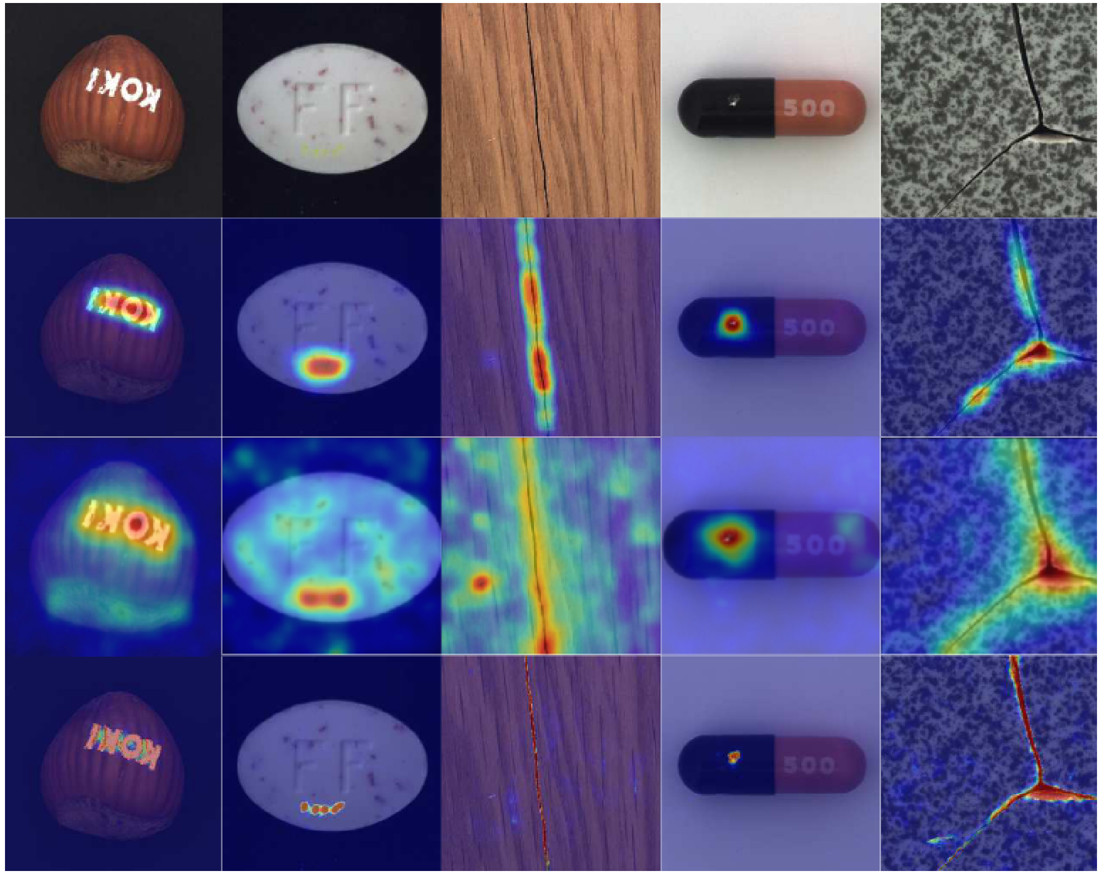

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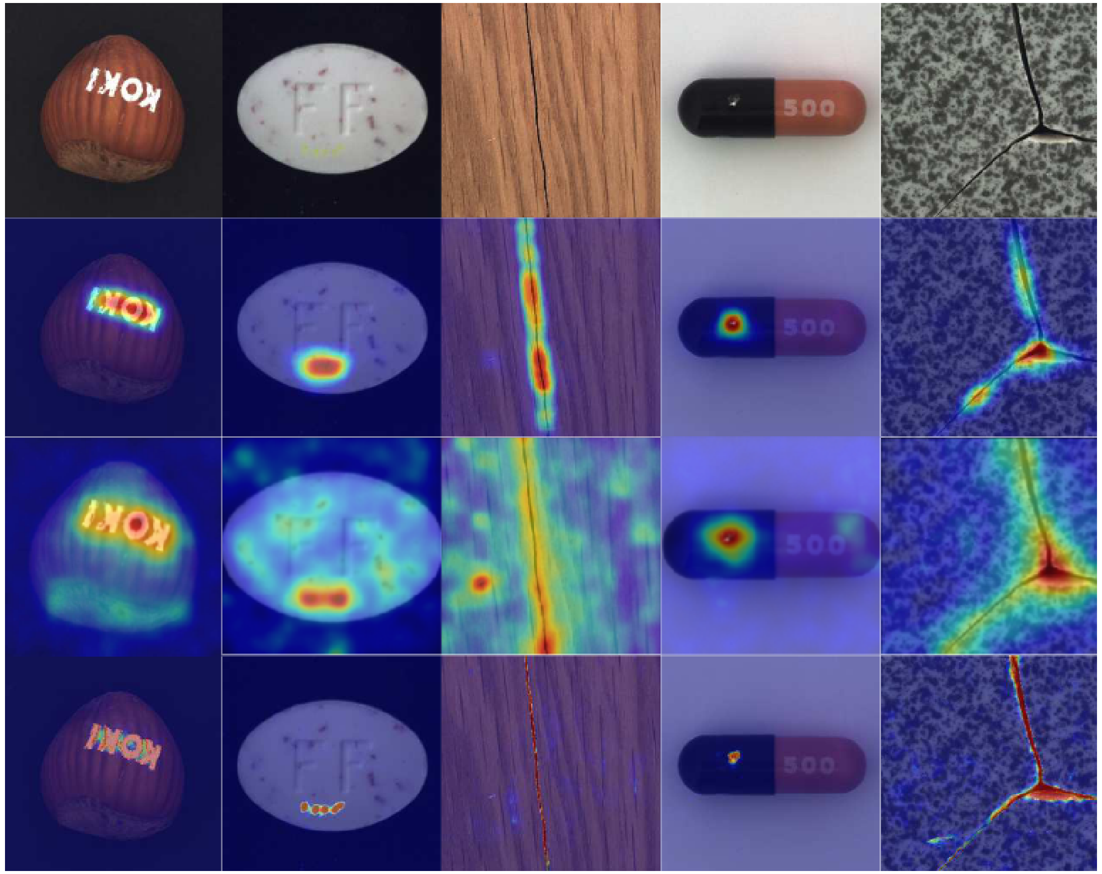

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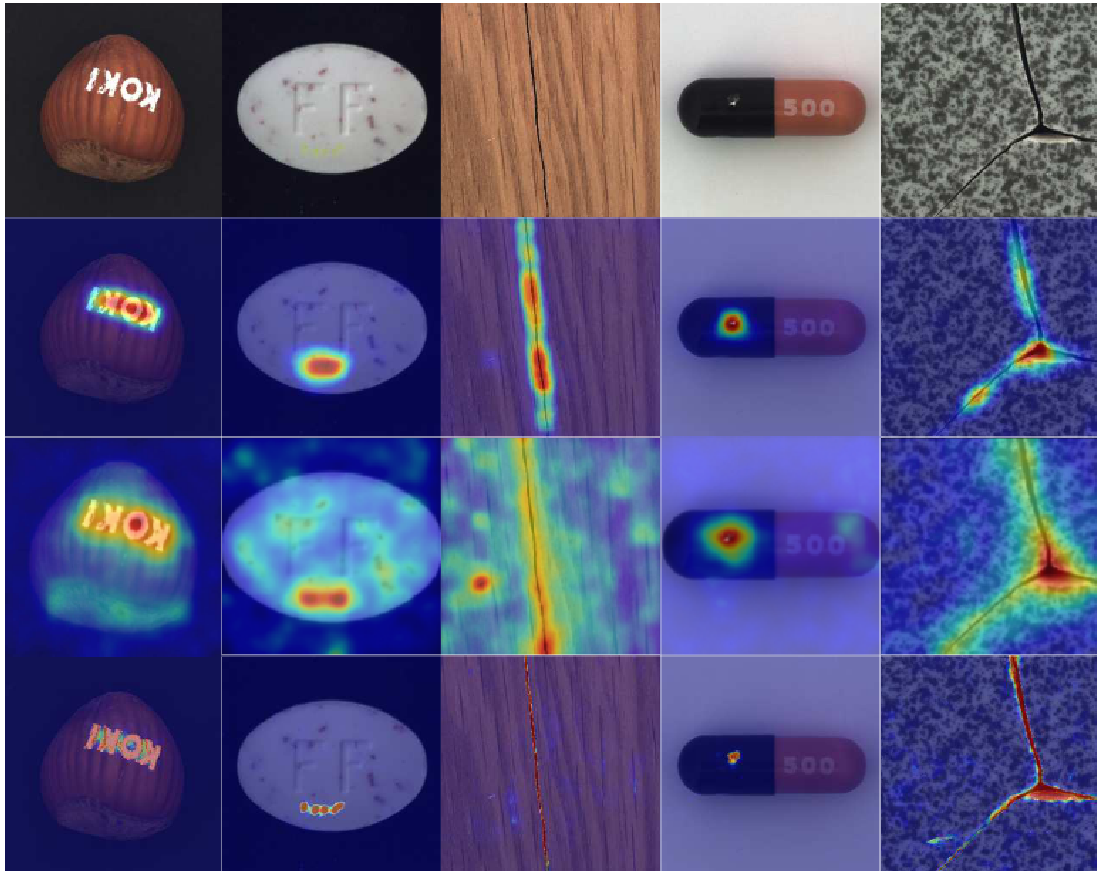

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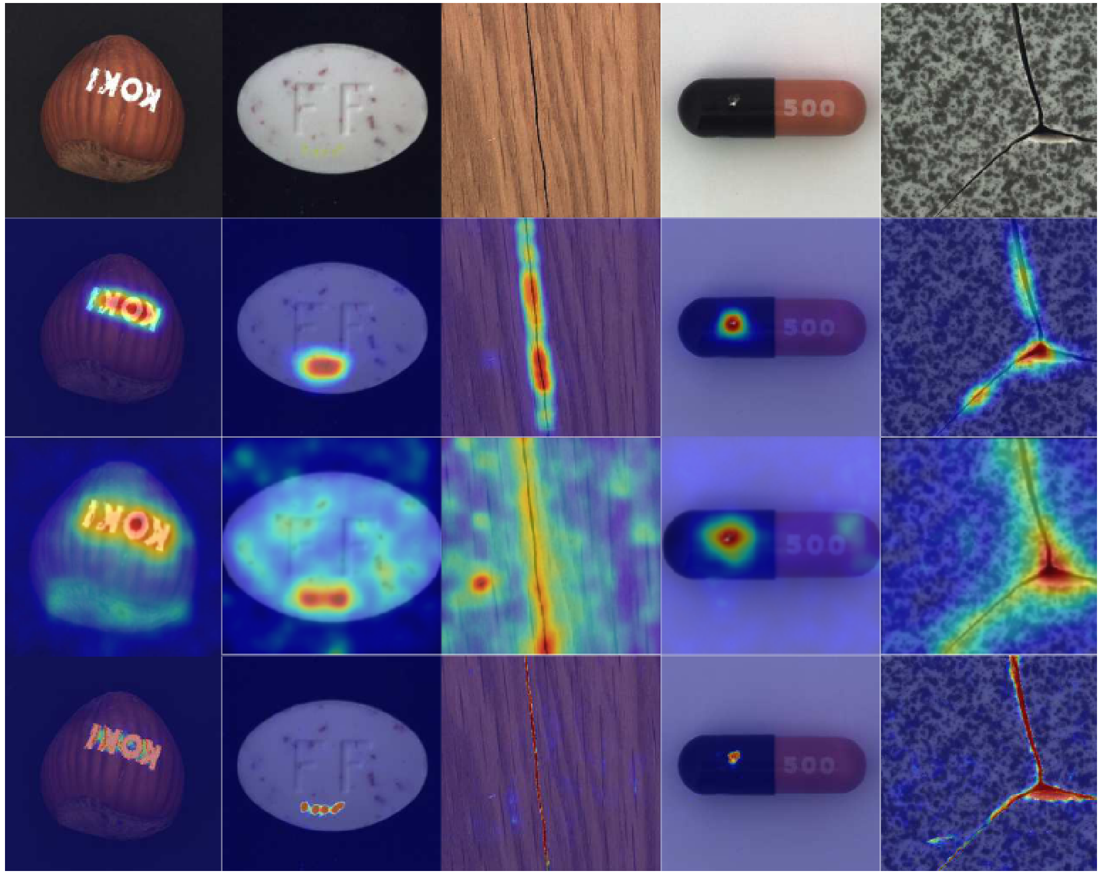
- We only need just-out-of-distribution patters for anomaly generation



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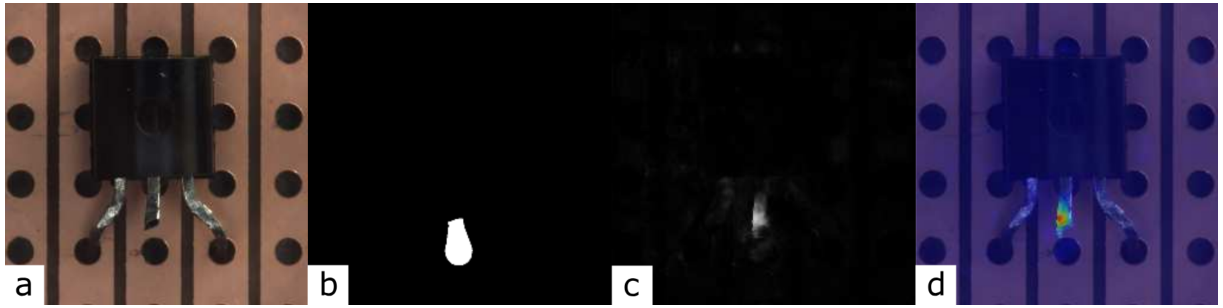

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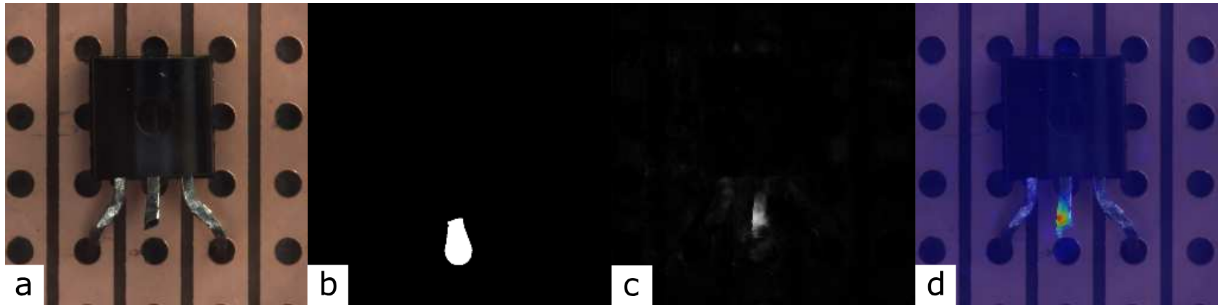

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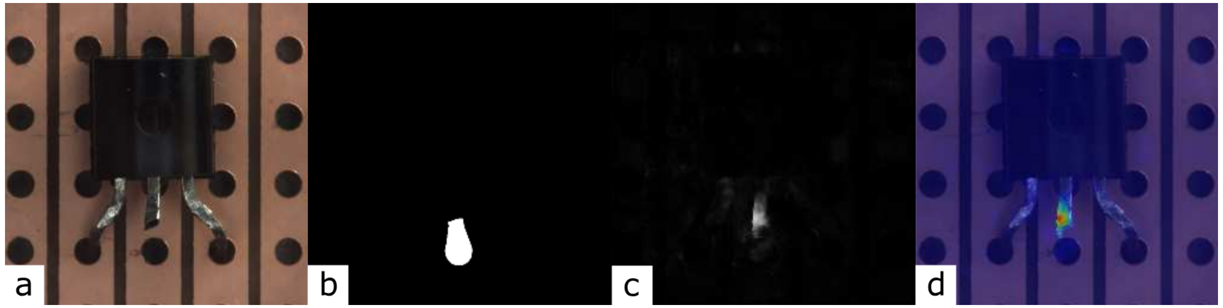

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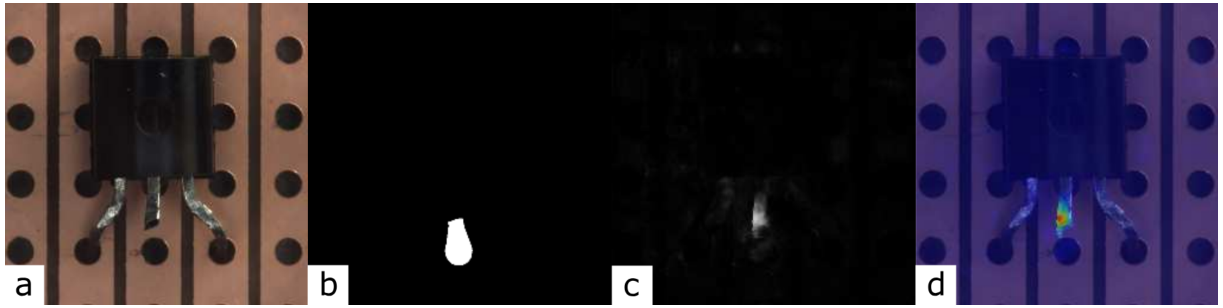

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  - DRÆM may detect stains on walls as anomalies, while only structural damange should be detected
  - In these cases finetuning the discriminative network may improve performance

Thank you for your attention