Friedrich-Alexander-Universität
Technische Fakultät

DRÆM - Pitch Presentation

A Discriminatively Trained Reconstruction Embedding for Surface Anomaly Detection

Christopher Roßbach[1]

[1]Friedrich-Alexander-Universität Erlangen-Nürnberg, Technische Fakultät

October 24, 2025

Introduction

Surface Anomaly Detection: Why It Matters

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

[1] ZKS21.

Introduction

Surface Anomaly Detection: Why It Matters

- Where applied, surface anomaly detection often outperforms humans in both specificity and sensitivity while simultaneously reducing costs
  - Why is it not applied everywhere?

[1] ZKS21.

Introduction
Surface Anomaly Detection: Why It Matters

- Where applied, surface anomaly detection often outperforms humans in both specificity and sensitivity while simultaneously reducing costs
  - Why is it not applied everywhere?
  - One problem is the availability of data, especially of rare anomalies

[1] ZKS21.

Introduction
Surface Anomaly Detection: Why It Matters

- Where applied, surface anomaly detection often outperforms humans in both specificity and sensitivity while simultaneously reducing costs
  - Why is it not applied everywhere?
  - One problem is the availability of data, especially of rare anomalies
- **Paper:** “DRÆM – A Discriminatively Trained Reconstruction Anomaly Embedding Model for Surface Anomaly Detection”[1]

[1] ZKS21.

Introduction
Surface Anomaly Detection: Why It Matters

- Where applied, surface anomaly detection often outperforms humans in both specificity and sensitivity while simultaneously reducing costs
  - Why is it not applied everywhere?
  - One problem is the availability of data, especially of rare anomalies
- **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, . . .**

[1] ZKS21.

Problem Statement
Current Situation and Related Work

- OOD-Samples are often rare and diverse

Problem Statement
Current Situation and Related Work

- OOD-Samples are often rare and diverse
- Data collection for pixel accurate anomaly detection is hard

Problem Statement
Current Situation and Related Work

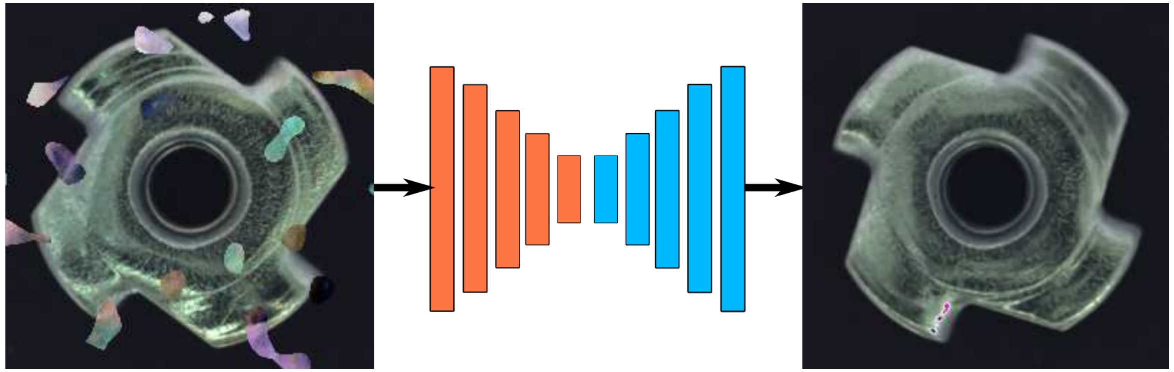
- OOD-Samples are often rare and diverse
- Data collection for pixel accurate anomaly detection is hard
- Reliance on only normal data is preferred

Problem Statement

Current Situation and Related Work

- OOD-Samples are often rare and diverse
- Data collection for pixel accurate anomaly detection is hard
- Reliance on only normal data is preferred

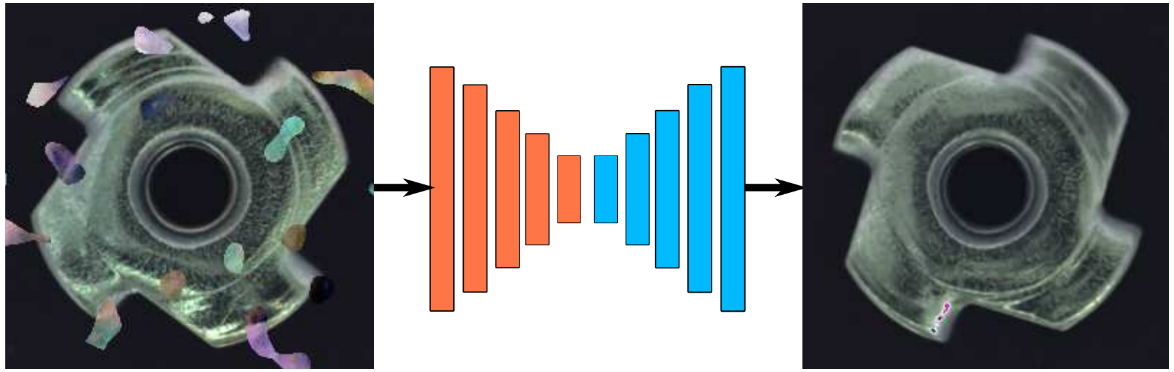
1. Methods try to either learn compression and decompression (e.g. auto-encoders) of normal data and measure reconstruction error



Problem Statement

Current Situation and Related Work

- OOD-Samples are often rare and diverse
- Data collection for pixel accurate anomaly detection is hard
- Reliance on only normal data is preferred

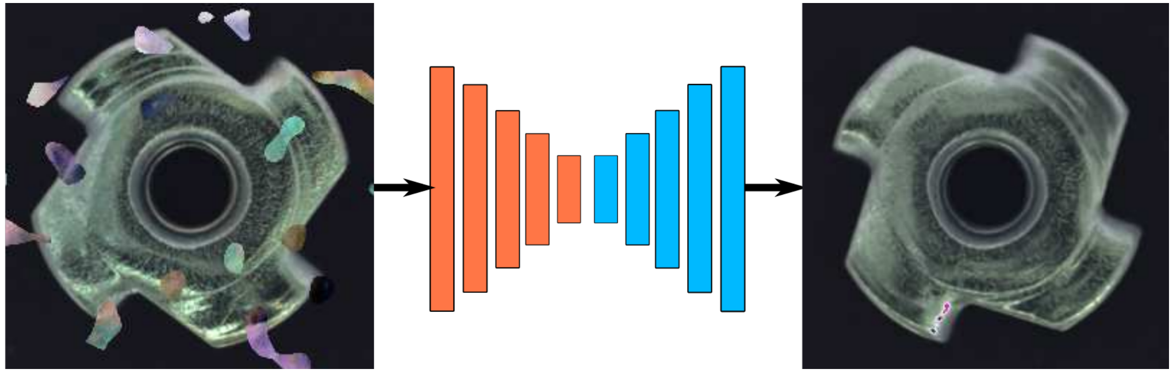


1. Methods try to either learn compression and decompression (e.g. auto-encoders) of normal data and measure reconstruction error
   - Hand-crafting difference functions for the first one is hard, the second suffers from less sharp anomaly borders

Problem Statement

Current Situation and Related Work

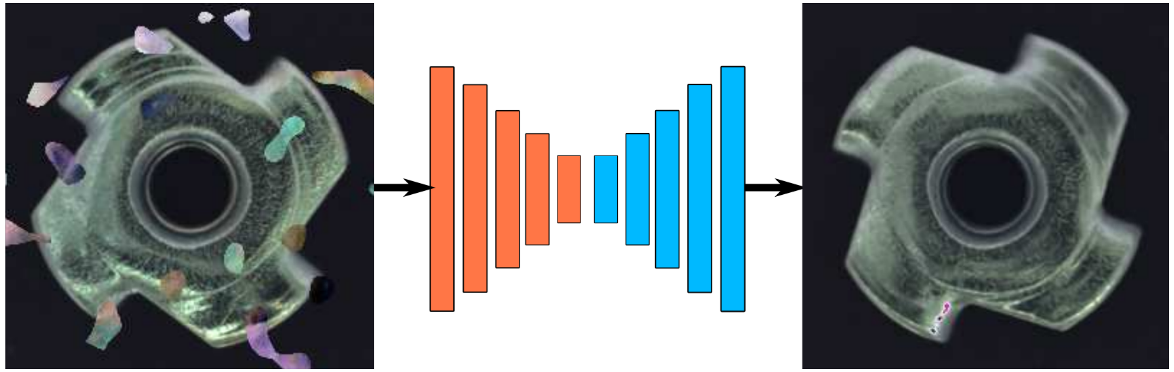
- OOD-Samples are often rare and diverse
- Data collection for pixel accurate anomaly detection is hard
- Reliance on only normal data is preferred

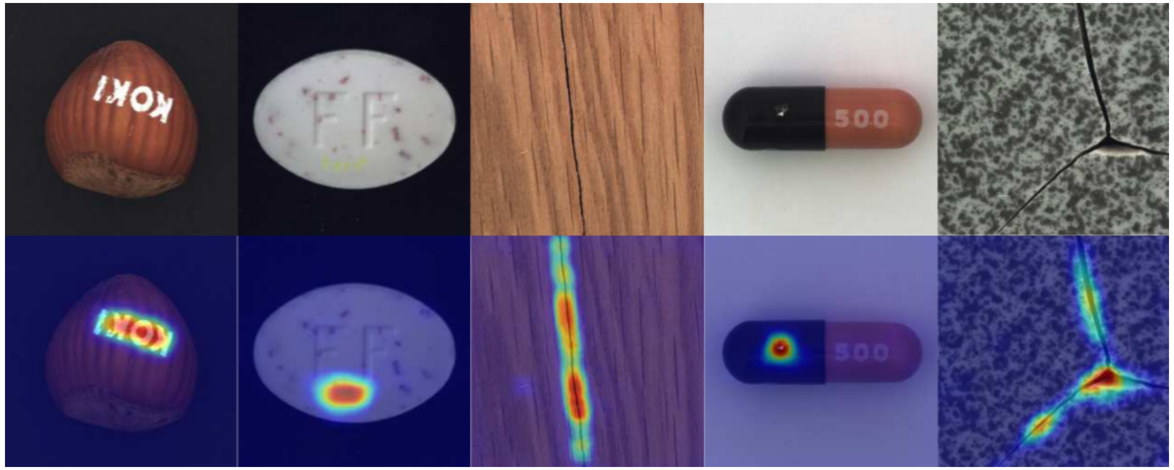


1. Methods try to either learn compression and decompression (e.g. auto-encoders) of normal data and measure reconstruction error
   - Hand-crafting difference functions for the first one is hard, the second suffers from less sharp anomaly borders
2. Or perform patchwise analysis of (deep) feature (e.g. CNNs) distribution deviation

Problem Statement
Current Situation and Related Work

- OOD-Samples are often rare and diverse
- Data collection for pixel accurate anomaly detection is hard
- Reliance on only normal data is preferred

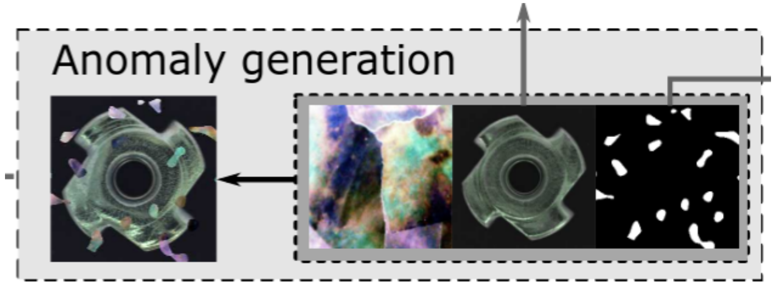




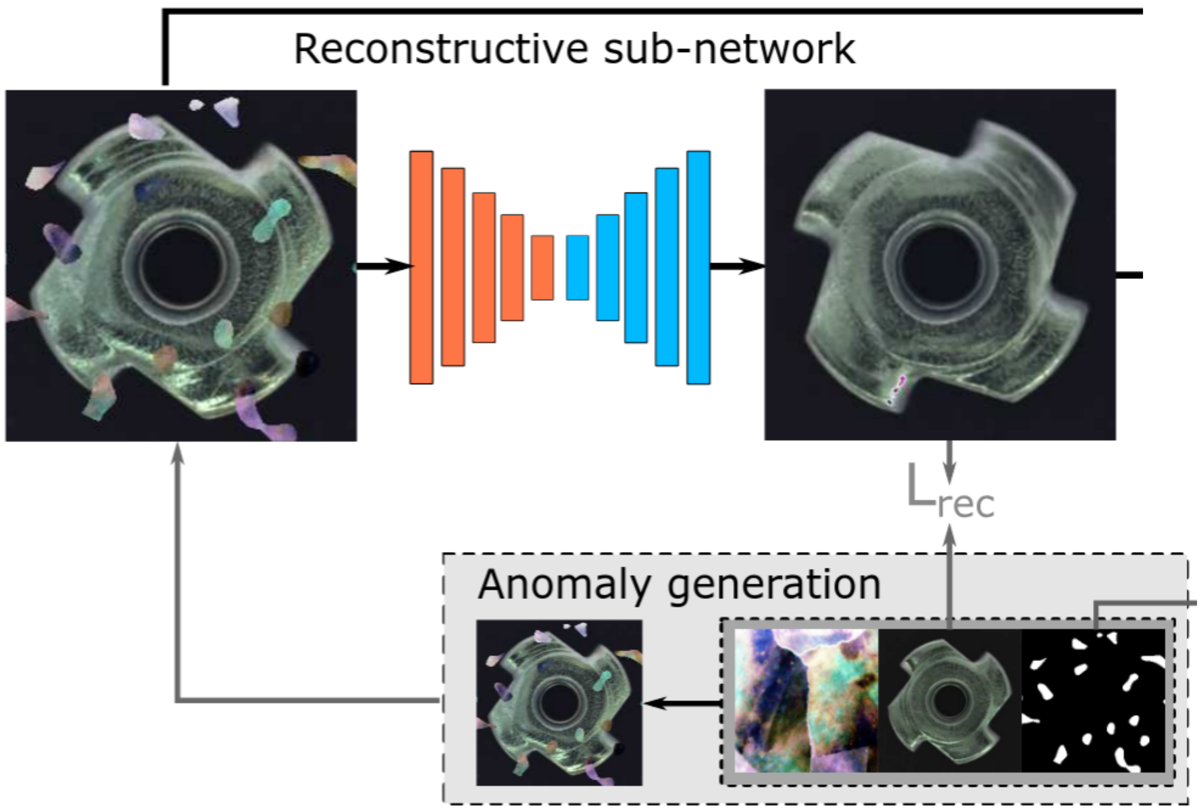
1. Methods try to either learn compression and decompression (e.g. auto-encoders) of normal data and measure reconstruction error
   - Hand-crafting difference functions for the first one is hard, the second suffers from less sharp anomaly borders
2. Or perform patchwise analysis of (deep) feature (e.g. CNNs) distribution deviation
   - These often suffer from unsharp segmentation maps

Framework Overview

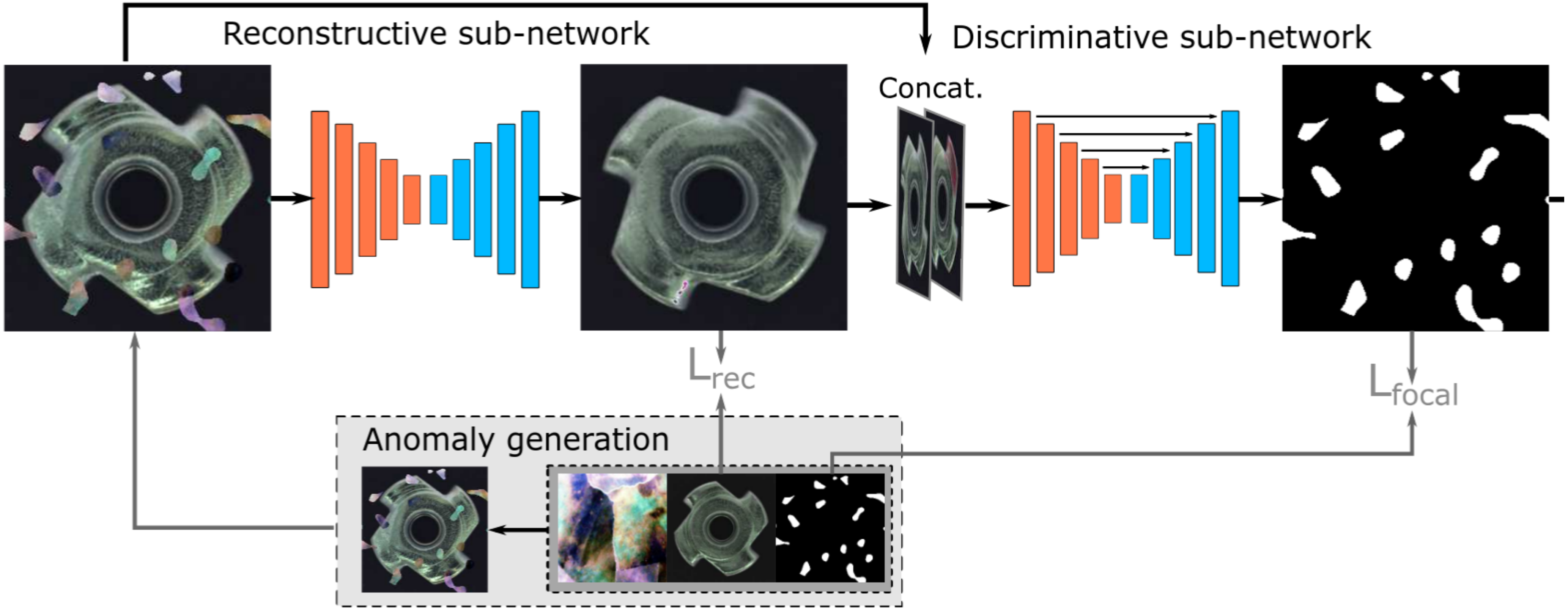
How it Works



Framework Overview
How it Works

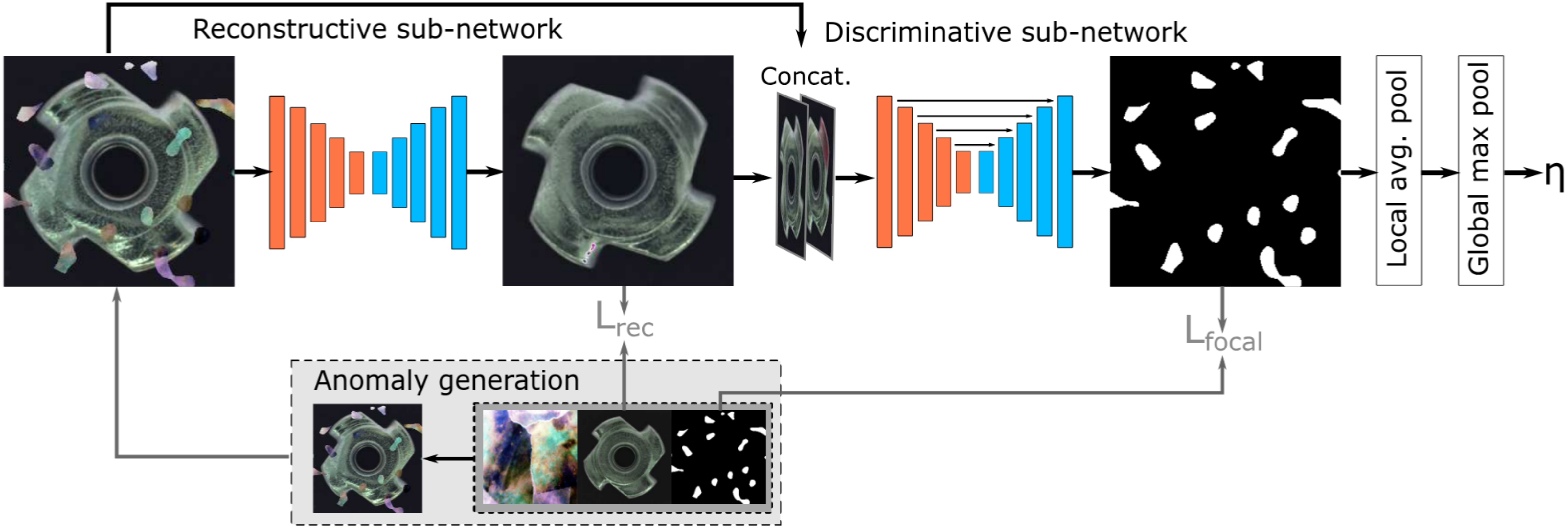


Framework Overview
How it Works



Framework Overview

How it Works



Key Findings & Application & Conclusion

The Value of DRÆM

- Outperforms unsupervised SOTA methods

Key Findings & Application & Conclusion

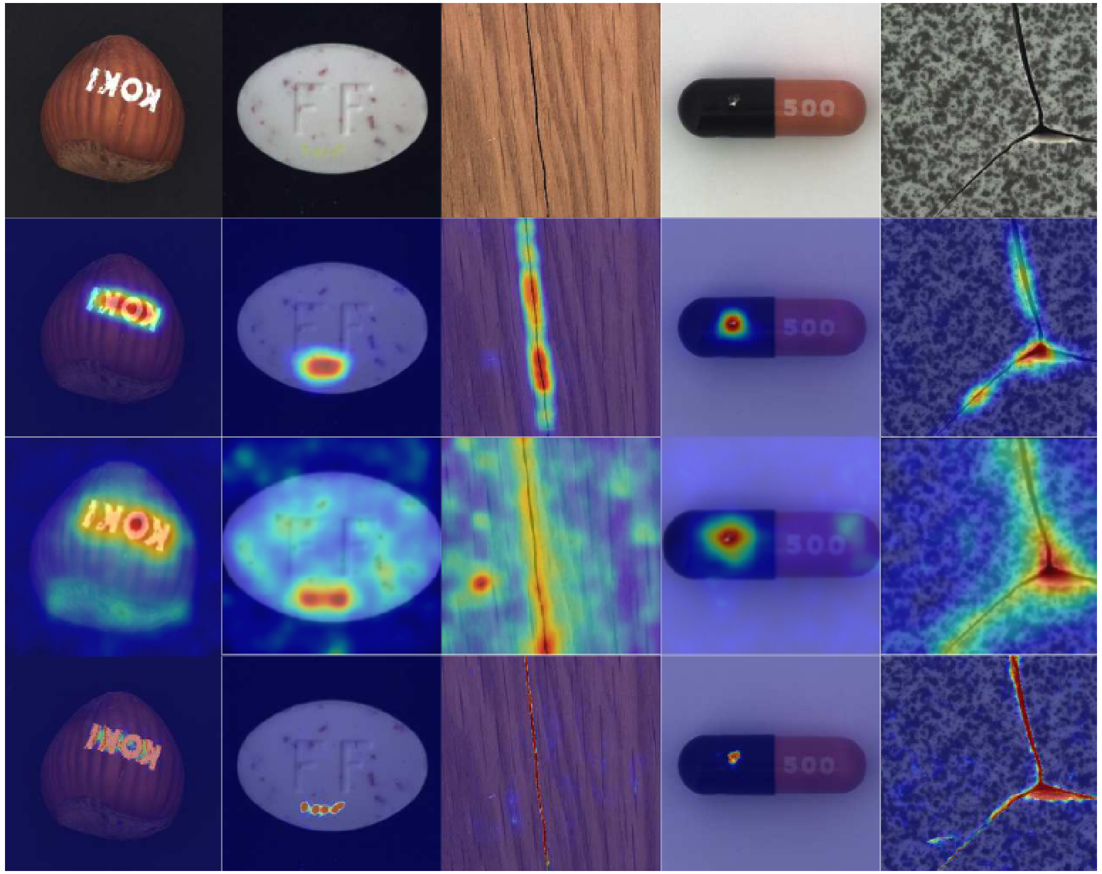
The Value of DRÆM

- Outperforms unsupervised SOTA methods
- Similar performance to supervised SOTA methods

Key Findings & Application & Conclusion

The Value of DRÆM

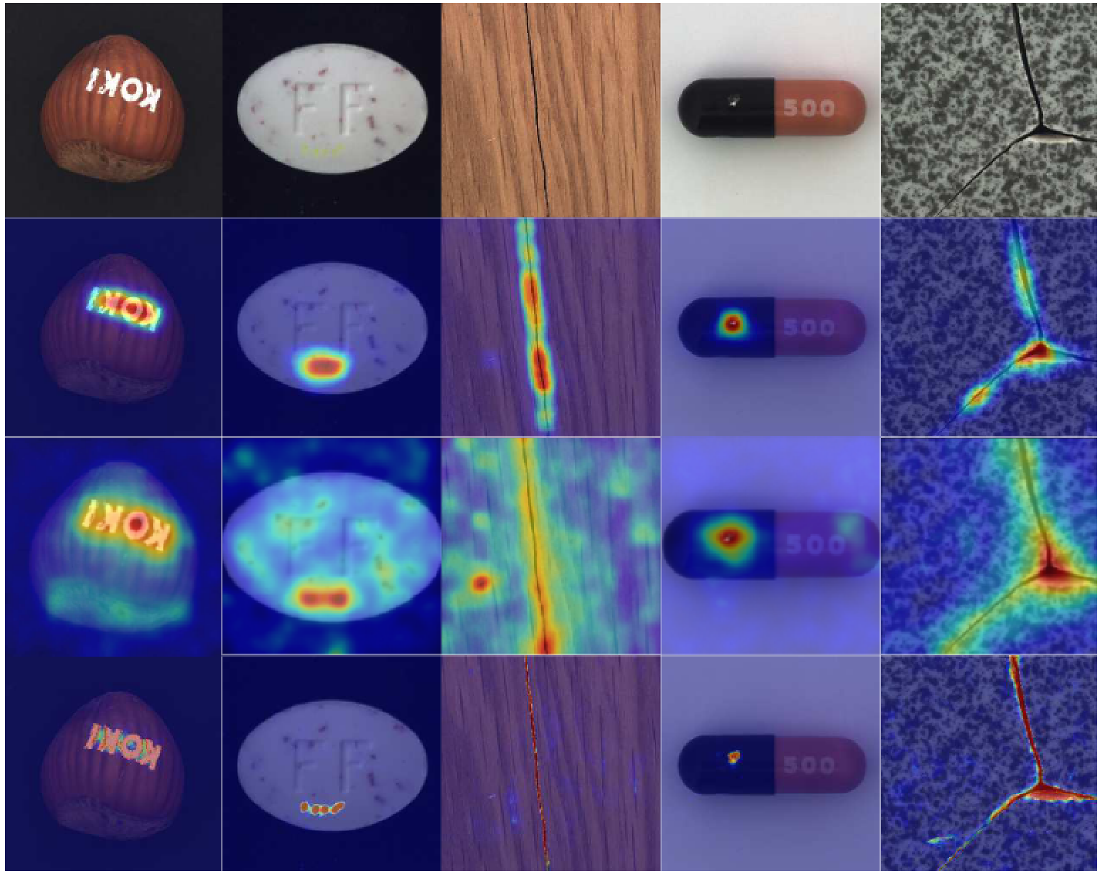
- Outperforms unsupervised SOTA methods
- Similar performance to supervised SOTA methods
- High quality segmentation can help downstream tasks



Key Findings & Application & Conclusion

The Value of DRÆM

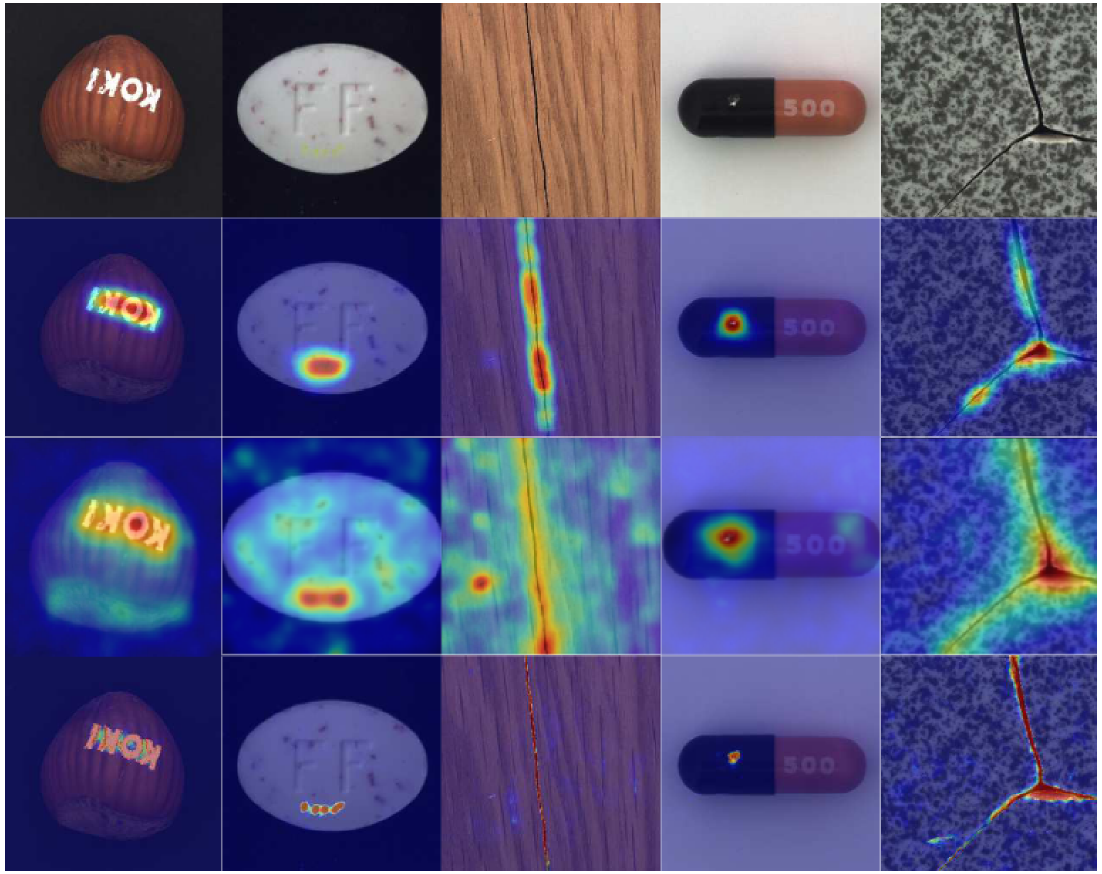
- Outperforms unsupervised SOTA methods
- Similar performance to supervised SOTA methods
- High quality segmentation can help downstream tasks
  - Estimate the size of impacted area



Key Findings & Application & Conclusion

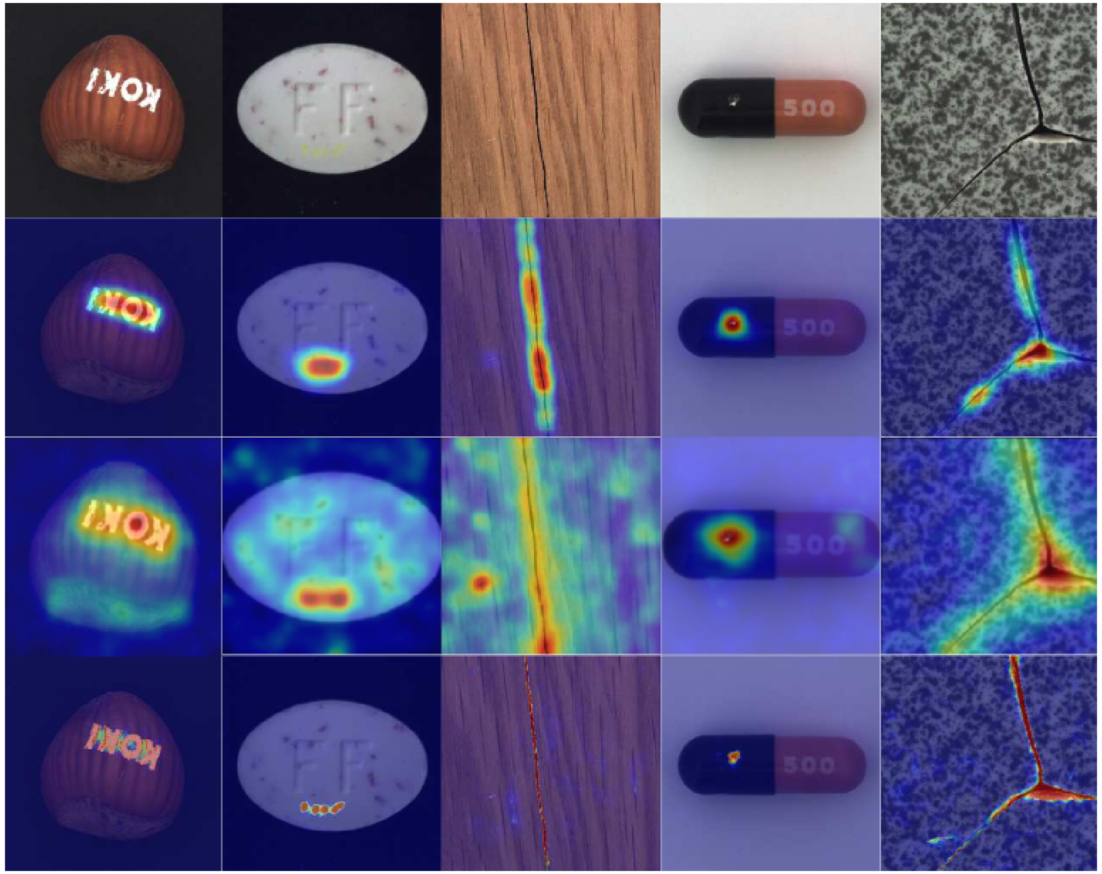
The Value of DRÆM

- Outperforms unsupervised SOTA methods
- Similar performance to supervised SOTA methods
- High quality segmentation can help downstream tasks
  - Estimate the size of impacted area
  - Distinguish between crack, corrosion or just paint



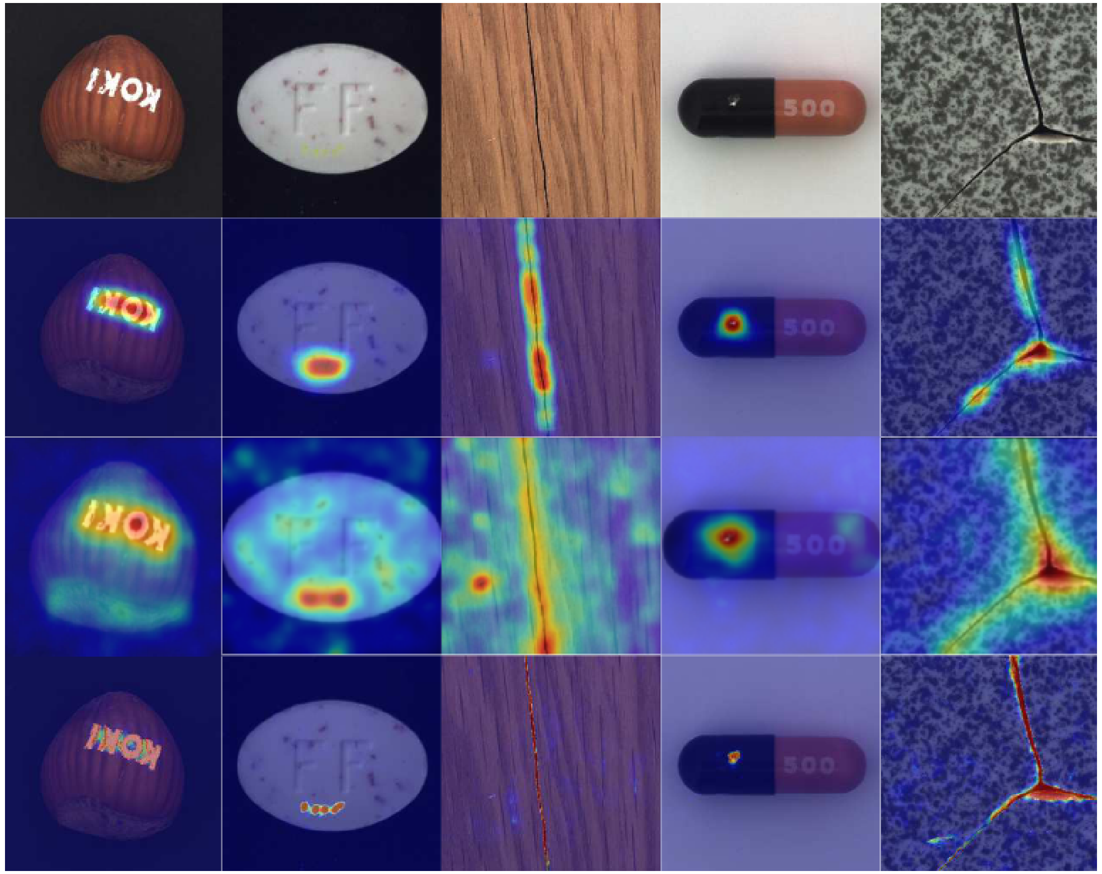
Key Findings & Application & Conclusion
The Value of DRÆM

- Outperforms unsupervised SOTA methods
- Similar performance to supervised SOTA methods
- High quality segmentation can help downstream tasks
  - Estimate the size of impacted area
  - Distinguish between crack, corrosion or just paint
- We don't need expensive hand-labeled data



Key Findings & Application & Conclusion
The Value of DRÆM

- Outperforms unsupervised SOTA methods
- Similar performance to supervised SOTA methods
- High quality segmentation can help downstream tasks
  - Estimate the size of impacted area
  - Distinguish between crack, corrosion or just paint
- We don't need expensive hand-labeled data
- We only need just-out-of-distribution patterns for anomaly generation



Limitation & Extension

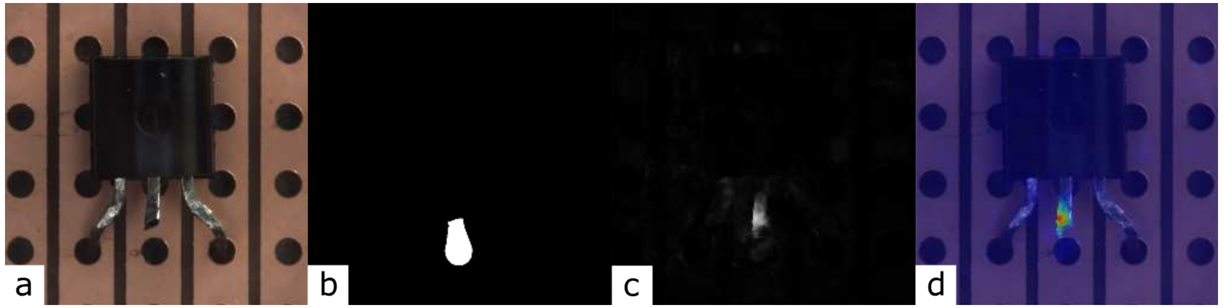
Where to go from Here

- The method lacks performance in cases where domain knowledge is necessary to perform well

Limitation & Extension

Where to go from Here

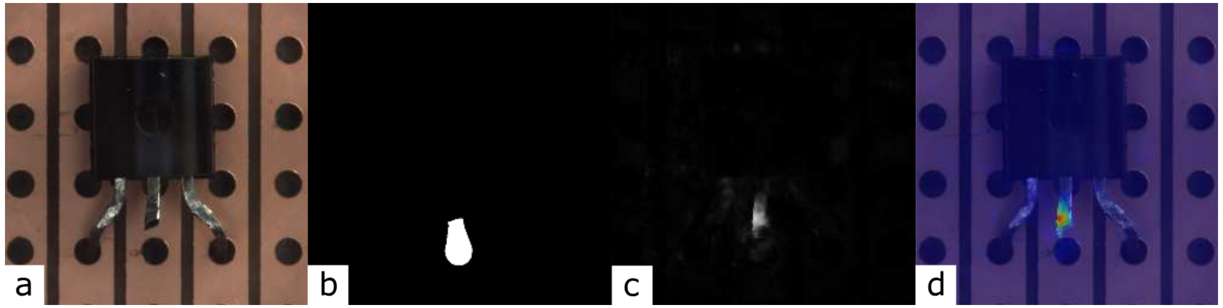
- The method lacks performance in cases where domain knowledge is necessary to perform well
- For example here the whole lead of the transistor is cut off, but it only marks the position of the cut



Limitation & Extension

Where to go from Here

- The method lacks performance in cases where domain knowledge is necessary to perform well
- For example here the whole lead of the transistor is cut off, but it only marks the position of the cut

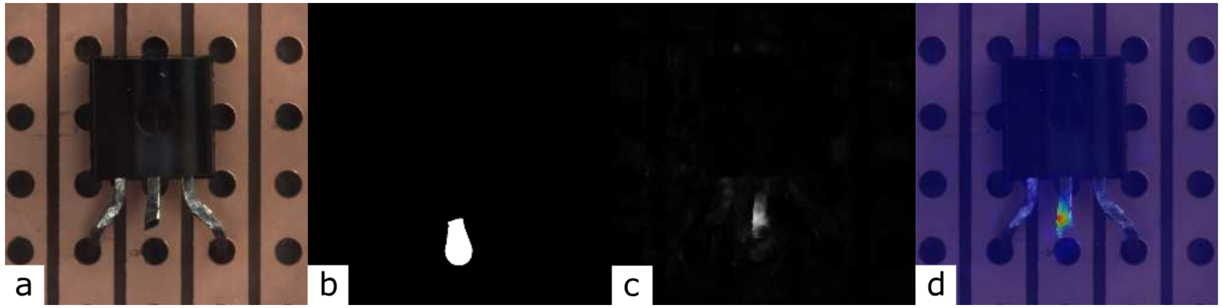


- Another example could be when certain "normalities" are underrepresented in the training data

Limitation & Extension

Where to go from Here

- The method lacks performance in cases where domain knowledge is necessary to perform well
- For example here the whole lead of the transistor is cut off, but it only marks the position of the cut

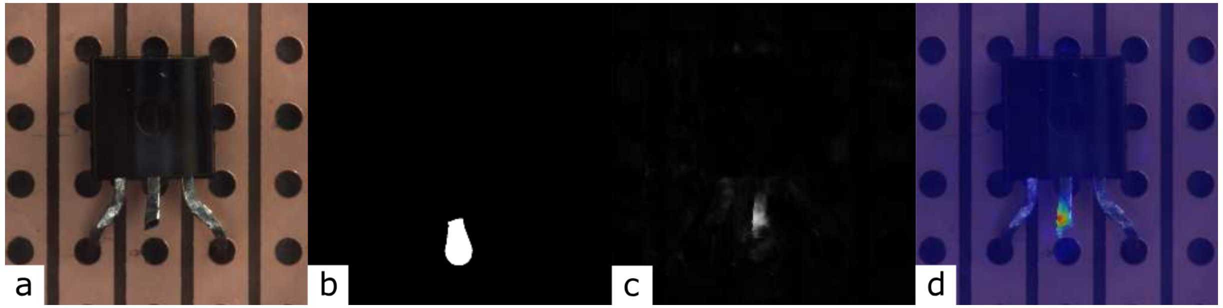


- Another example could be when certain "normalities" are underrepresented in the training data
  - DRÆM may detect stains on walls as anomalies, while only structural damage should be detected

Limitation & Extension

Where to go from Here

- The method lacks performance in cases where domain knowledge is necessary to perform well
- For example here the whole lead of the transistor is cut off, but it only marks the position of the cut



- Another example could be when certain "normalities" are underrepresented in the training data
  - DRÆM may detect stains on walls as anomalies, while only structural damage should be detected
  - In these cases finetuning the discriminative network may improve performance

Thank you for your attention