

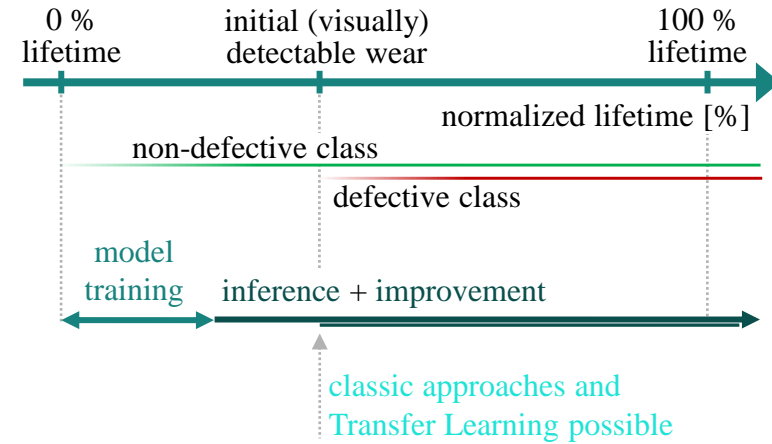
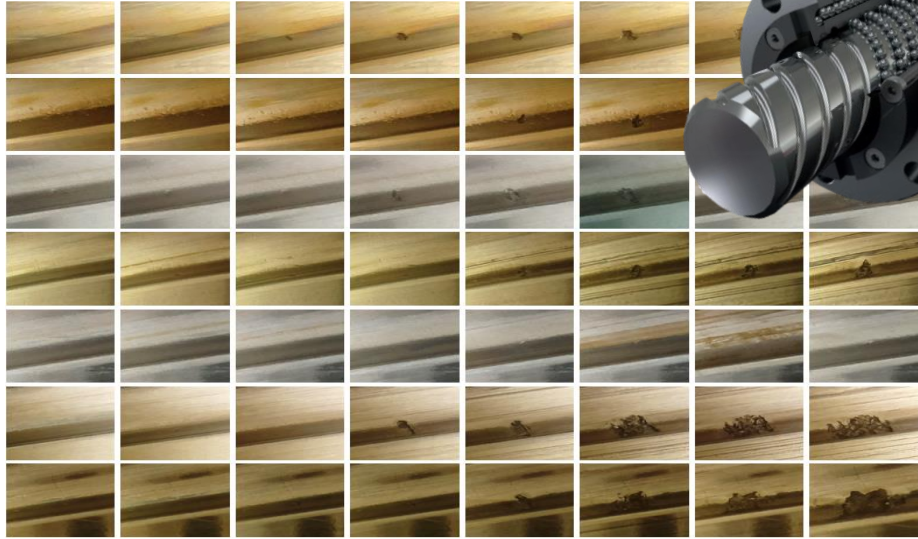
Cross-domain Transfer of Defect Features in Technical Domains Based on Partial Target Data

T. Schlagenhauf and T. Scheurenbrand, "Cross-domain Transfer of Defect Features in Technical Domains Based on Partial Target Data," International Journal of Prognostics and Health Management, vol. 14, no. 1, May 2023.

Dr. Tobias Schlagenhauf, Robert Bosch GmbH Cognitive Production

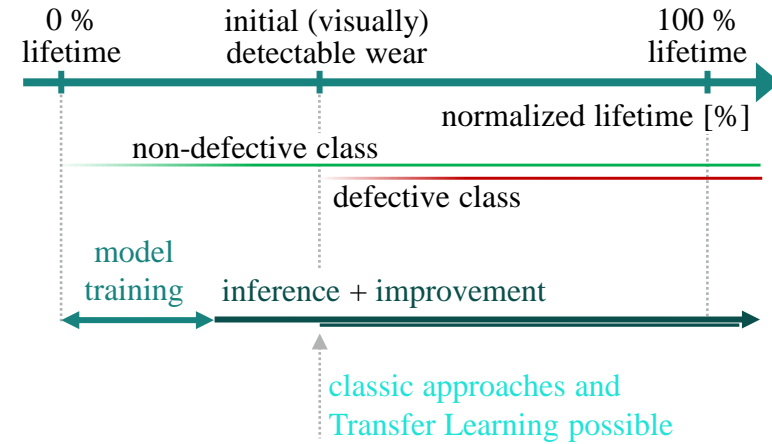


Background & Motivation



Classic Transfer-Learning is **possible** when defective data of the target class is available.

Background & Motivation



Classic Transfer-Learning is **not possible** when **no** defective data of the target class is available.
What to do?

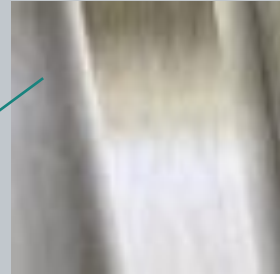
Background & Motivation

Target Domain



Defect
Features

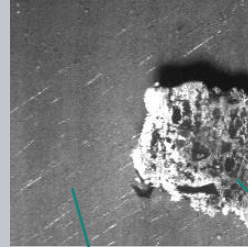
Background



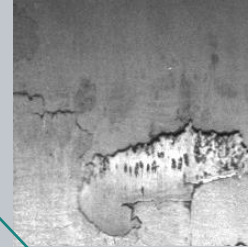
We only have this

Defects on Ball Screw Drives

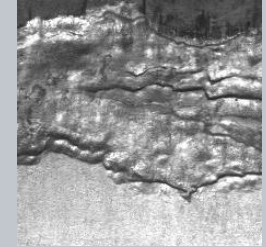
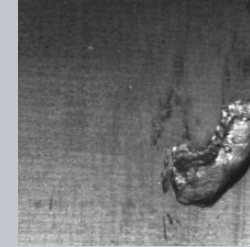
Source Domain



Background



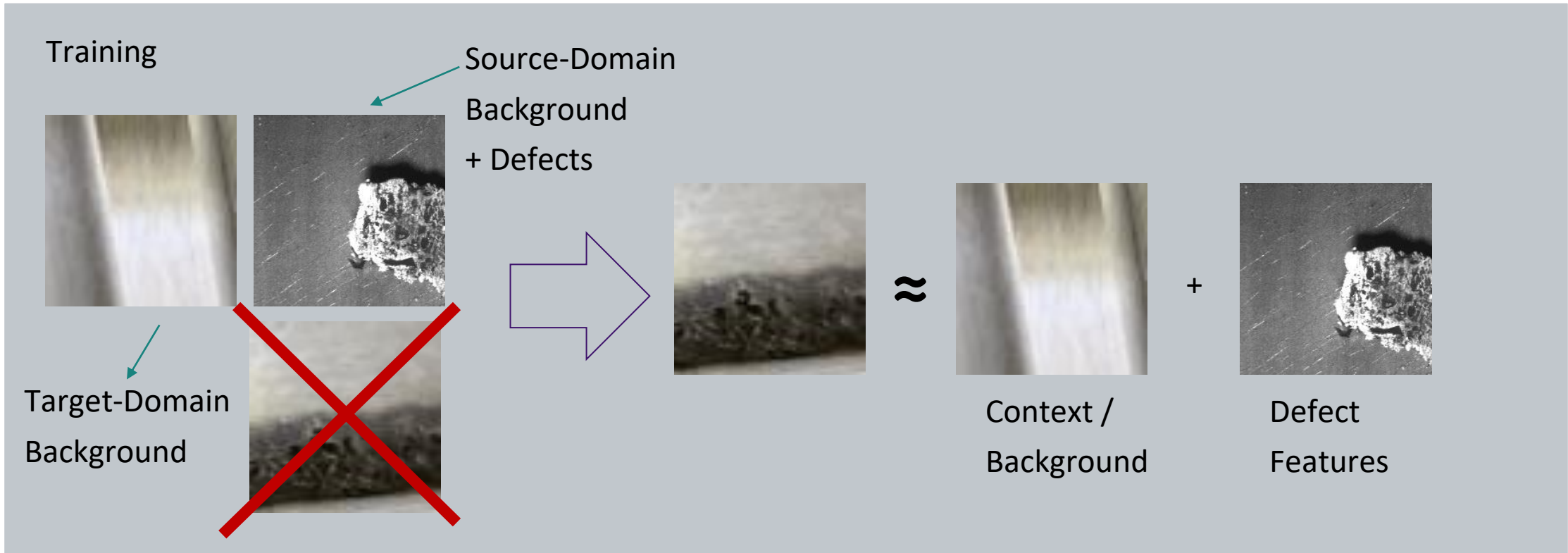
Defect
Features



Defects on metallic Surfaces

Defect features are similar. Though, background is different.

Background & Motivation



How to combine the Defect Features from the known Source Domain with the Background Features of the Target Domain?

Agenda

Background & Motivation

1

Data of interest is often underrepresented during training.



Approach

3

Data from different contexts with related features can be used to bridge the gap.



Results & Discussion

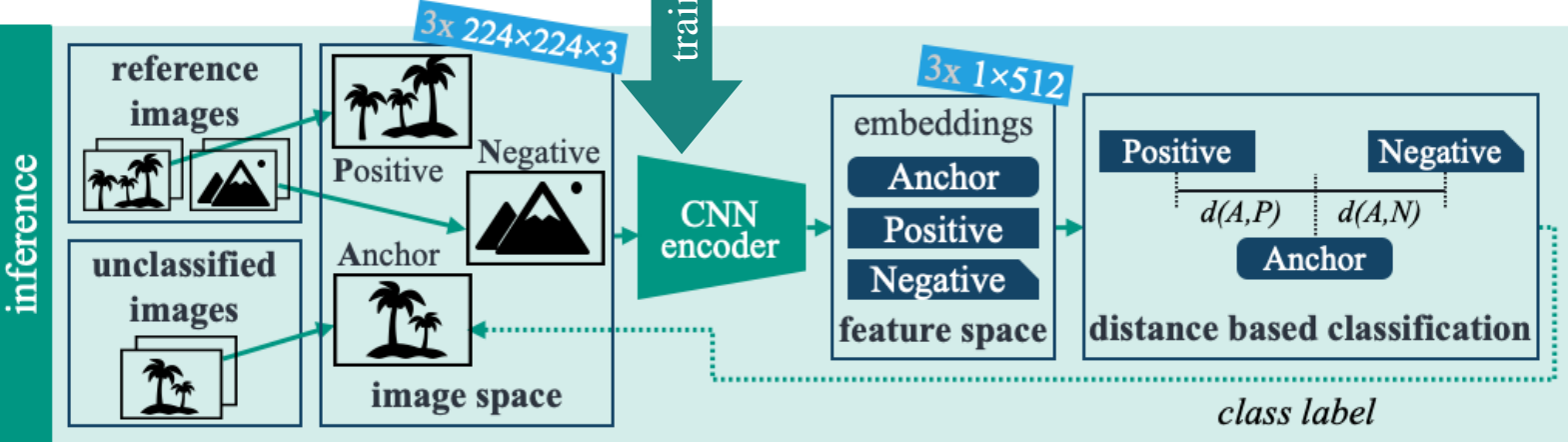
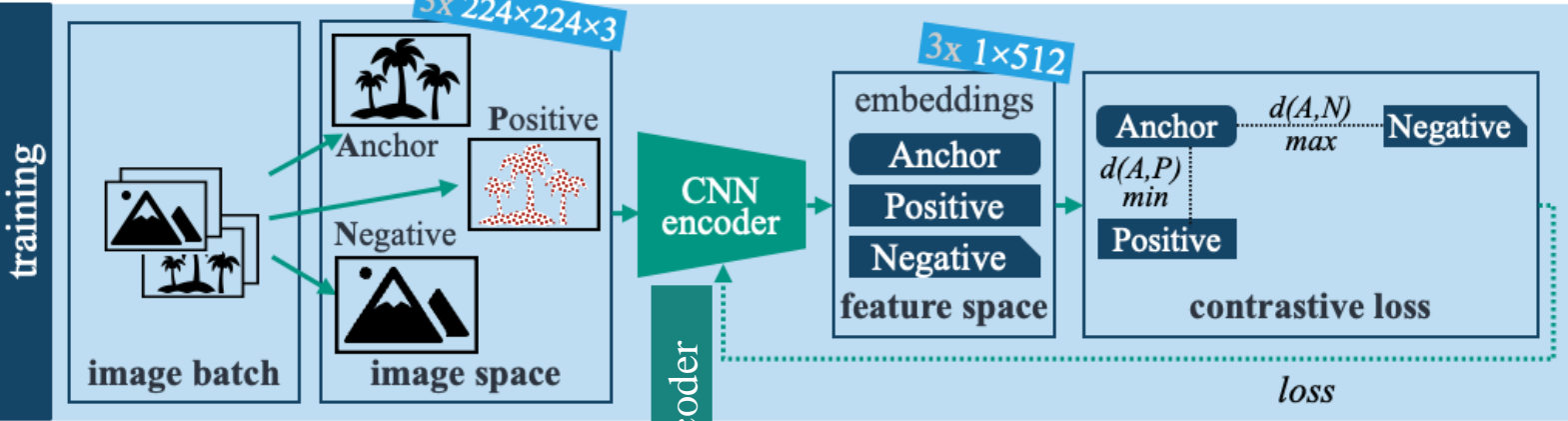
4

Helpful for different domains.

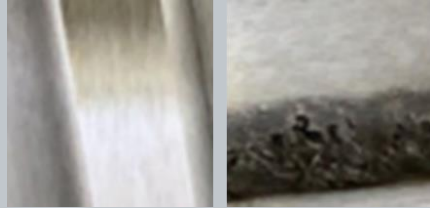


Approach

Contrastive Learning



What we should have


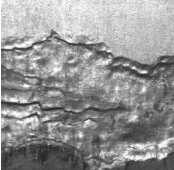


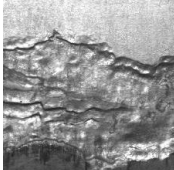



What we have









Approach

Transfer for Defects on **Steel Surfaces**

training	Anchor	 Severstal, noDefect	Negative	 Severstal, defect
	Positive	 BSD, noDefect		
	Anchor	 BSD, unknown	Negative	 Severstal, defect
	Positive	 BSD, noDefect		

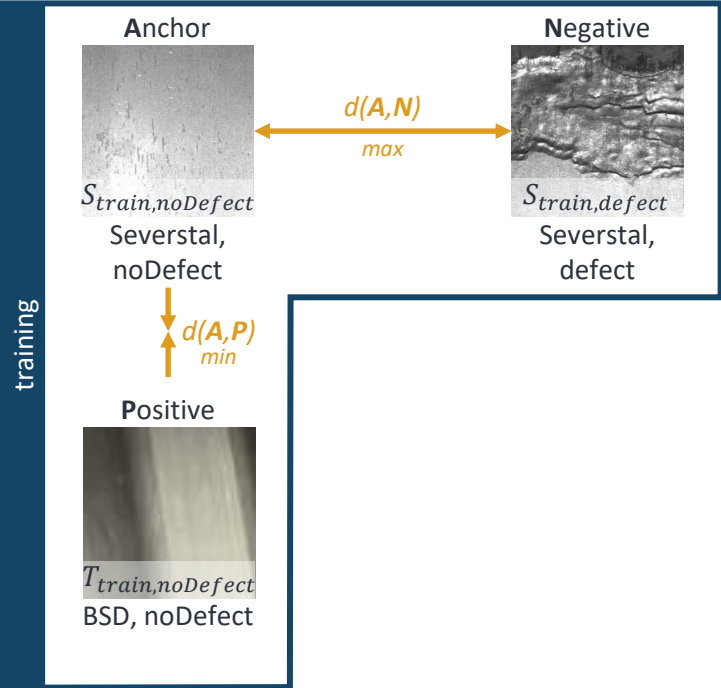
Transfer for Defects on **Leafes**

training	Anchor	 bean, healthy	Negative	 bean, diseased
	Positive	 apple, healthy		
	Anchor	 apple, unknown	Negative	 bean, diseased
	Positive	 bean, healthy		

How to combine the Defect Features from the known Source Domain with the Background Features of the Target Domain?

Approach

Adapted Contrastive Learning



Adaption of Loss Function

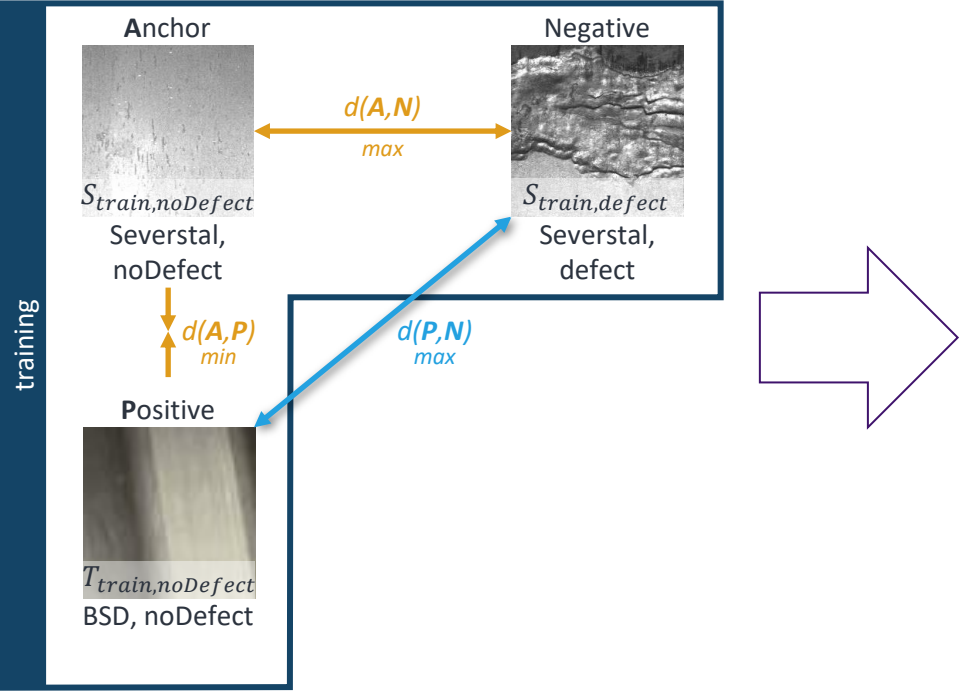
Original Loss Function

$$Loss = \max(d(A, P) - d(A, N) + m_1, 0)$$

How to combine the Defect Features from the known Source Domain with the Background Features of the Target Domain?

Approach

Adapted Contrastive Learning



Adaption of Loss Function

Original Loss Function

$$Loss = \max(d(A, P) - d(A, N) + m_1, 0)$$

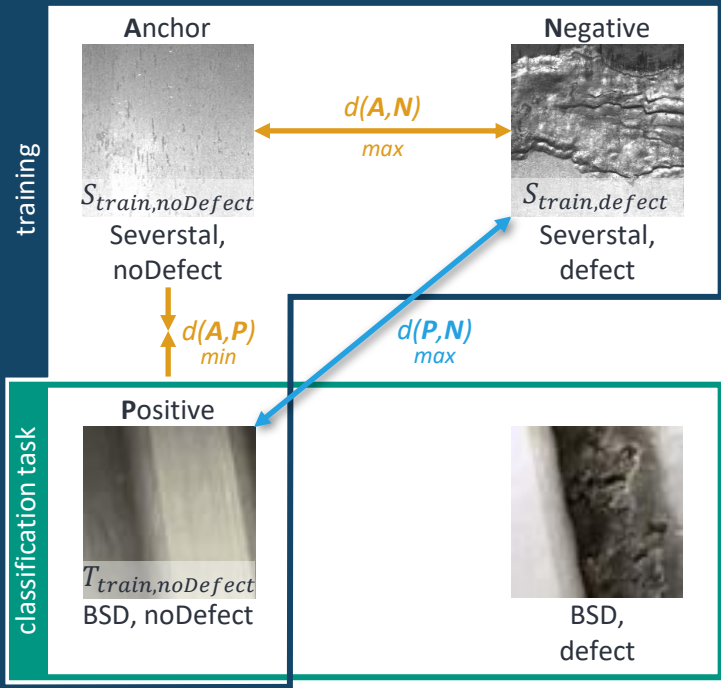
Adapted Loss Function

$$Loss = \max(d(A, P) - d(A, N) + m_1, 0) + \max(d(A, P) - d(P, N) + m_2, 0)$$

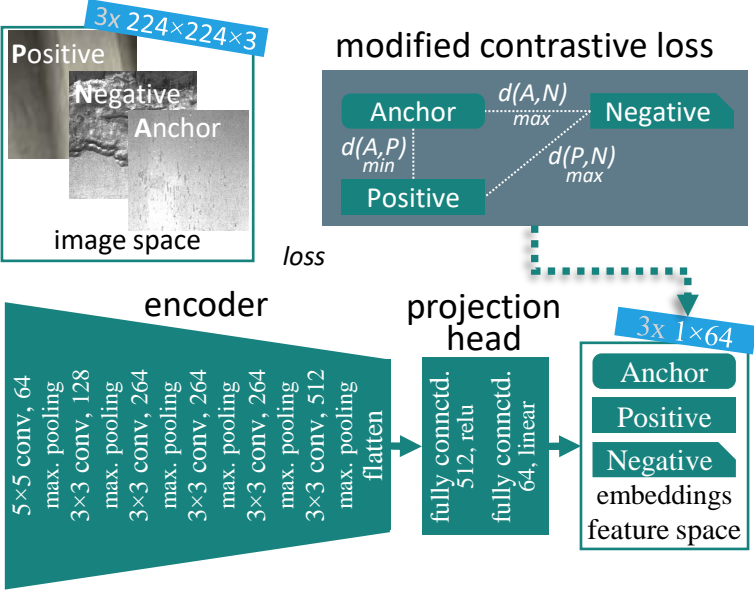
Adapting the loss function bridges the gap between domains.

Approach

Adapted Contrastive Learning



Feature Extractor Trained with Adapted Loss Function



Agenda

Background & Motivation

1

Data of interest is often underrepresented during training.



Approach

3

Data from different contexts with related features can be used to bridge the gap.



Results & Discussion

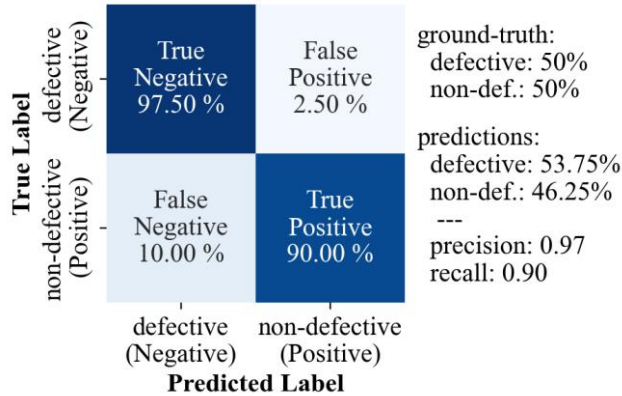
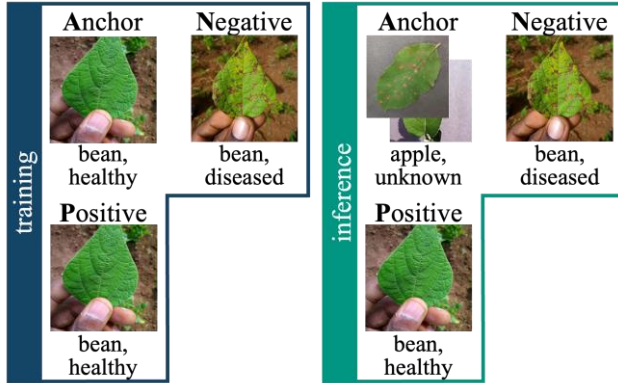
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Helpful for different domains.

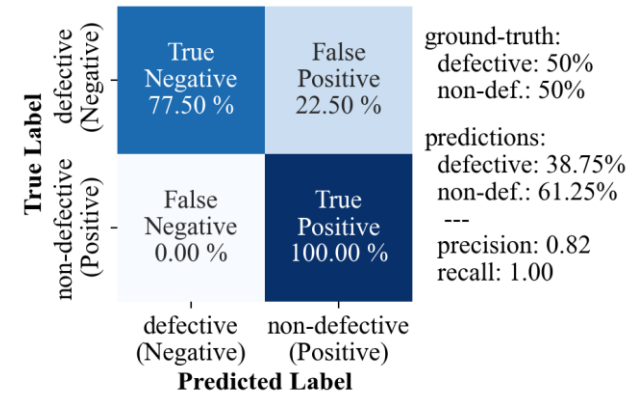
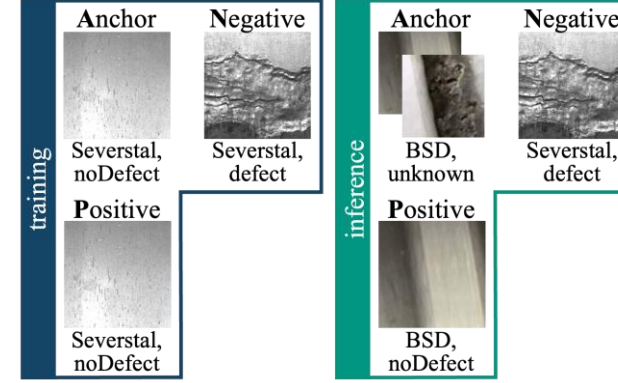


Results – Baseline: Domain Transfer

Domain Transfer from Bean to Apple



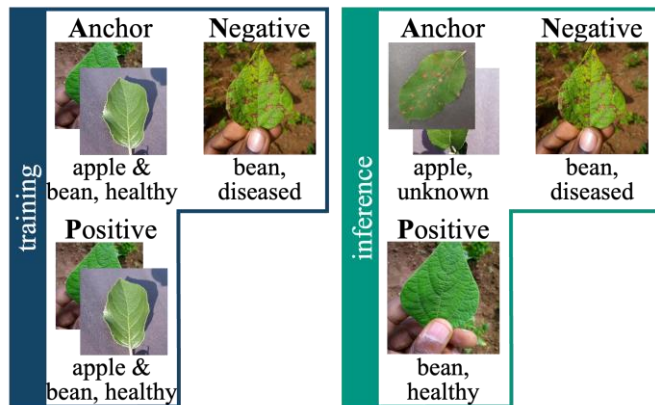
Domain Transfer from Severstal to BSD



Domain Transfer works, when the domains are closely related.

Results – Baseline: Mixed Datasets

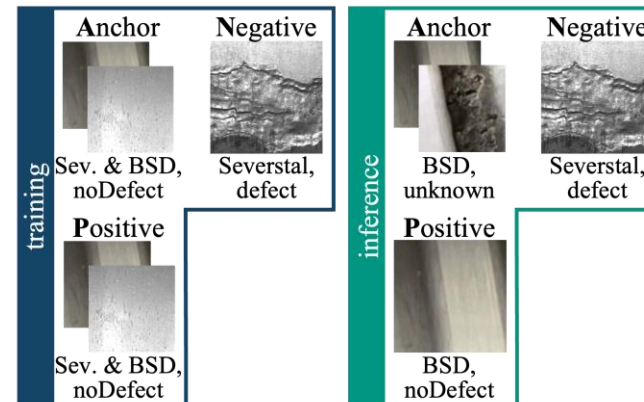
Mixed Datasets Healthy Bean and Apple



True Label	defective (Negative)	True Negative 22.50 %	False Positive 77.50 %	ground-truth: defective: 50% non-def.: 50%
	non-defective (Positive)	False Negative 0.00 %	True Positive 100.00 %	
		defective (Negative)	non-defective (Positive)	

Predicted Label

Mixed Datasets Healthy Severstal and BSD



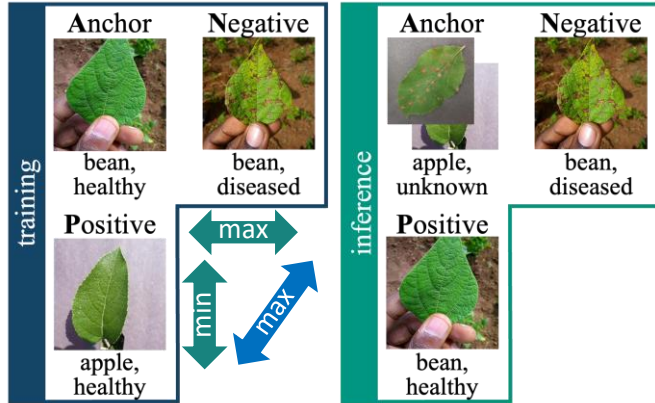
True Label	defective (Negative)	True Negative 25.00 %	False Positive 75.00 %	ground-truth: defective: 50% non-def.: 50%
	non-defective (Positive)	False Negative 2.50 %	True Positive 97.50 %	
		defective (Negative)	non-defective (Positive)	

Predicted Label

Mixed datasets confuse the model and do not lead to a domain transfer.

Results – New Loss

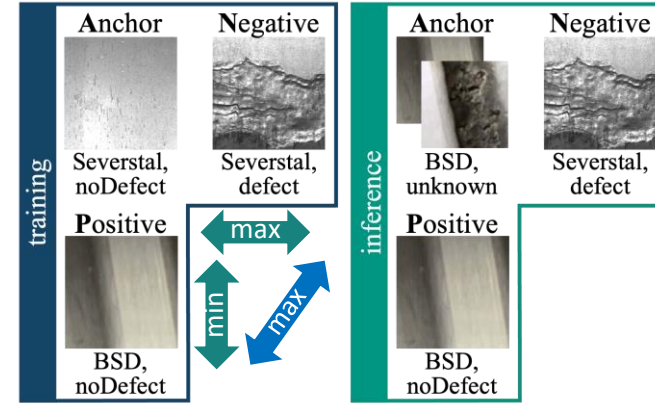
Cross domain transfer Bean, Apple



True Label	defective (Negative)	<table border="1"> <tr> <td>True Negative 97.50 %</td> <td>False Positive 2.50 %</td> </tr> </table>	True Negative 97.50 %	False Positive 2.50 %	ground-truth: defective: 50% non-def.: 50% predictions: defective: 48.75% non-def.: 51.25% --- precision: 0.98 recall: 1.00
	True Negative 97.50 %	False Positive 2.50 %			
non-defective (Positive)	<table border="1"> <tr> <td>False Negative 0.00 %</td> <td>True Positive 100.00 %</td> </tr> </table>	False Negative 0.00 %	True Positive 100.00 %		
False Negative 0.00 %	True Positive 100.00 %				
		defective (Negative) non-defective (Positive)			

Predicted Label

Cross domain transfer Severstal, BSD



True Label	defective (Negative)	<table border="1"> <tr> <td>True Negative 100.00 %</td> <td>False Positive 0.00 %</td> </tr> </table>	True Negative 100.00 %	False Positive 0.00 %	ground-truth: defective: 50% non-def.: 50% predictions: defective: 50.00% non-def.: 50.00% --- precision: 1.00 recall: 1.00
	True Negative 100.00 %	False Positive 0.00 %			
non-defective (Positive)	<table border="1"> <tr> <td>False Negative 0.00 %</td> <td>True Positive 100.00 %</td> </tr> </table>	False Negative 0.00 %	True Positive 100.00 %		
False Negative 0.00 %	True Positive 100.00 %				
		defective (Negative) non-defective (Positive)			

Predicted Label

Domain Adaption is possible: Defective Data is successfully classified during inference.

Summary and Outlook

Key Findings

- Loss function seems to be the key.
- We can identify defective instances without defective data during training by transfer of features across domains.
- Especially useful if features of interest are similar while background is different.



Outlook

- How to use this approach in the context of object detection?
- Can this be used for e.g. federated learning to combine feature spaces?
- Can this be applied on time series data as well?

