Few-Shot Anomaly Detection with Adversarial Loss for Robust Feature Representations

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Introduction

❖ Background

- Anomaly detection methods shifted from traditional statistical to advanced deep learning-based techniques
- in the industrial field's pre-mass production phase, limited sample availability often necessitates the implementation of few-shot anomaly detection technique
- Highlight of reconstruction-based methods, embedding similarity-based methods, and few-shot methods

Objective

Introduce adversarial loss in the context of domain adaptation to enhance the performance of Few-Shot Anomaly Detection (FSAD).

Proposed Method

1. Problem Formulation

- Train with normal samples across n categories : $D_{train} = \bigcup_{i=1}^{n} D_i$
- Test with image from unknown target category c_t & K normal samples.

2. Loss Function and Training

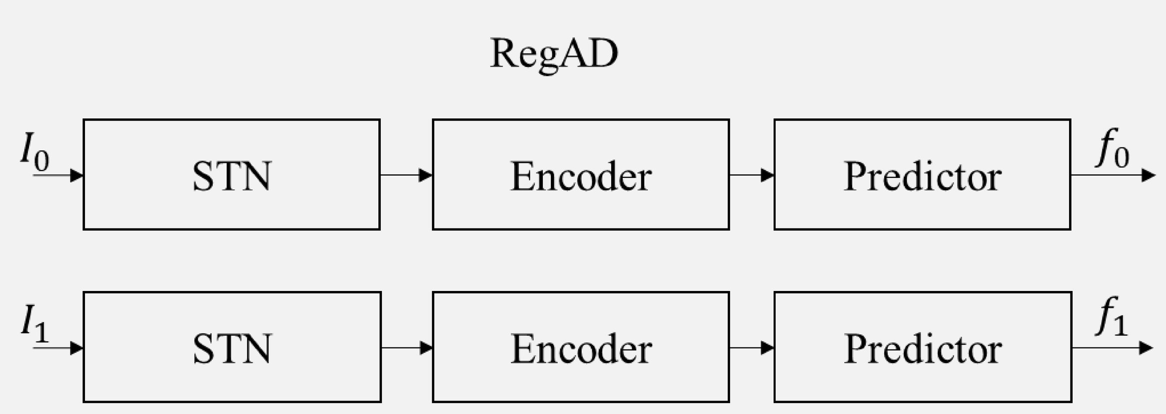
- Main Model M : Potential models include RegAD, UniAD.
- Discriminator D : Auxiliary network trained with M using adversarial loss.

3. Key Formulations

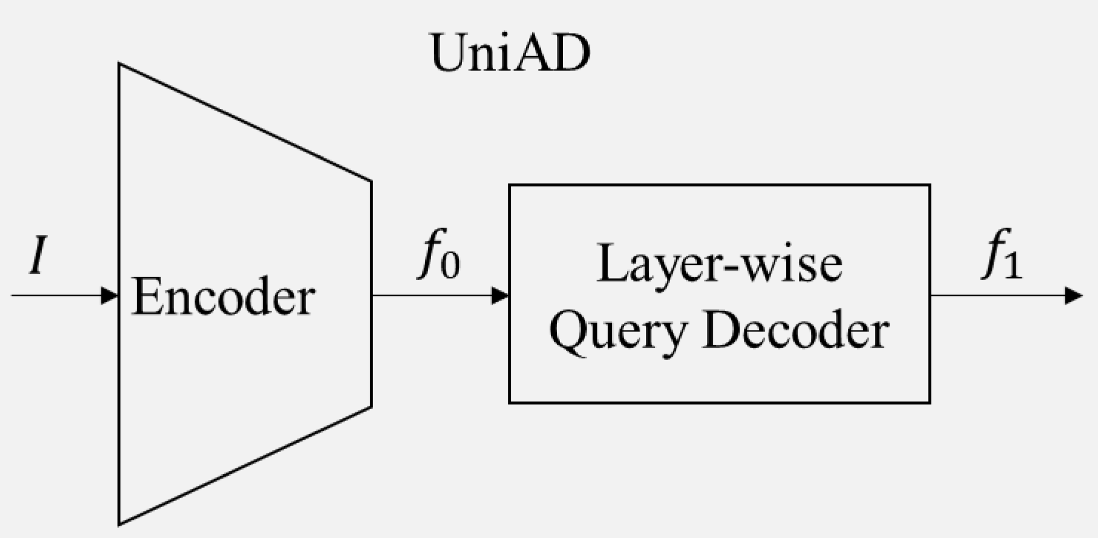
- Discriminator Training Loss : $\mathcal{L}_{DT} = \mathcal{L}_D(\boldsymbol{f_0}, 0) + \mathcal{L}_D(\boldsymbol{f_1}, 1)$
- Main Model Training Loss : $\mathcal{L}_{MT} = \mathcal{L}_D(f_0, 1)$

4. Integration with RegAD & UniAD

- **RegAD**
  - Siamese network with two branches
  - Branches process images I_0 and I_1 from same category
  - Feature I_0 and I_1 extracted from predictor



- **UniAD**
  - Comprises encoder & layer-wise query decoder.
  - Input-output pairs of the layer-wise query decoder used as features $f_0$and f_1



Result

1. MvTec AD

Metric	Shot	Method	Bottle	Cable	Capsule	Carpet	Grid	Hazelnut	Leather	MetalNut	Pill	Screw	Tile	Toothbrush	Transistor	Wood	Zipper	Average
Image Level AUC	$K=2$	TDG	69.3	68.3	55.1	66.2	83.8	67.2	93.6	67.1	69.2	98.8	86.3	54.4	55.9	98.4	64.4	73.2
		DifferNet	99.3	85.3	73.0	78.4	62.1	94.9	90.7	61.9	83.2	73.4	97.0	60.8	61.8	98.1	89.2	81.0
		RegAD	99.4	65.1	67.5	96.5	84.0	96.0	99.4	91.4	81.3	52.5	94.3	86.6	86.0	99.2	86.3	85.7
		+ Ours	99.8	65.9	70.2	96.9	77.0	96.3	100.0	94.9	80.7	66.0	99.4	83.2	82.6	99.7	86.6	86.6
		UniAD	99.9	60.1	65.7	100.0	90.6	90.4	100.0	63.0	62.5	75.3	99.4	91.4	67.9	98.1	90.6	83.7
		+ Ours	100.0	58.5	64.7	99.9	94.3	91.9	100.0	64.6	63.0	73.1	99.2	91.1	68.4	97.9	91.1	83.8
	$K=4$	TDG	69.6	70.3	47.6	68.7	86.2	71.2	93.2	69.2	64.7	98.8	87.2	57.8	67.7	98.3	65.3	74.4
		DifferNet	99.3	85.2	80.3	78.6	60.5	95.8	91.2	67.3	84.0	72.5	98.0	62.5	62.2	96.4	84.8	81.0
		RegAD	99.4	76.1	72.4	97.9	91.2	95.8	100.0	94.6	80.8	56.6	95.5	90.9	85.2	98.6	88.5	88.2
		+ Ours	99.6	77.0	77.5	98.5	83.4	96.6	100.0	94.3	85.9	60.2	99.2	91.2	85.0	99.6	91.5	89.3
		UniAD	99.9	60.2	70.1	99.8	93.1	94.5	100.0	60.7	66.5	76.3	99.5	98.6	72.1	98.2	90.8	85.4
		+ Ours	100.0	71.2	71.4	99.9	94.7	94.1	100.0	76.5	78.5	74.9	99.5	98.1	79.4	97.9	91.9	88.5
	$K=8$	TDG	70.3	74.7	44.7	78.2	87.6	82.8	93.5	68.7	67.9	99.0	87.4	57.6	71.5	98.4	66.3	76.6
		DifferNet	99.4	87.9	78.6	78.5	78.5	97.9	92.2	67.7	82.1	75.0	99.6	60.8	63.3	99.4	87.3	83.0
		RegAD	99.8	80.6	76.3	98.5	91.5	96.5	100.0	98.3	80.6	63.4	97.4	98.5	93.4	99.4	94.0	91.2
		+ Ours	99.9	85.1	80.6	96.7	87.3	96.8	100.0	94.5	84.4	70.1	99.9	98.7	90.9	99.2	94.7	91.9
		UniAD	99.9	65.7	70.4	100.0	94.8	94.4	100.0	76.5	73.1	76.3	99.6	96.9	71.0	98.2	91.5	87.2
		+ Ours	99.9	59.5	71.5	97.1	93.2	95.1	99.0	76.3	85.5	92.1	99.5	97.5	87.6	93.6	94.5	89.4
Pixel Level AUC	$K=2$	RegAD	98.0	91.7	97.3	98.9	77.4	98.1	98.0	96.9	93.6	94.4	94.3	98.2	93.4	93.5	95.1	94.6
		+ Ours	98.6	93.9	97.5	98.9	80.0	98.4	99.4	97.8	97.8	94.8	96.3	96.6	94.3	96.8	97.4	95.9
		UniAD	95.4	83.9	95.4	99.6	92.8	95.0	99.0	72.4	82.7	91.4	90.6	96.0	81.7	93.3	94.3	90.9
		+ Ours	95.9	85.0	95.5	98.6	93.3	94.1	99.1	73.2	84.5	91.7	90.2	96.8	79.6	93.0	94.0	91.0
	$K=4$	RegAD	98.4	92.7	97.6	98.9	85.7	98.0	99.1	97.8	97.4	95.0	94.9	98.5	93.8	94.7	94.0	95.8
		+ Ours	98.6	96.1	98.3	98.9	83.0	98.7	99.5	96.8	97.8	96.3	95.7	97.9	93.8	96.6	97.6	96.4
		UniAD	97.4	91.3	71.4	98.7	93.7	95.3	99.1	81.5	88.7	92.0	91.1	97.9	91.5	93.7	93.7	91.8
		+ Ours	97.4	90.7	71.8	98.6	93.7	95.3	99.1	82.8	90.8	91.8	90.9	98.1	92.7	96.9	94.6	92.3
	$K=8$	RegAD	97.5	94.9	98.2	98.9	88.7	98.5	98.9	96.9	97.8	97.1	95.2	98.7	96.8	94.6	97.4	96.7
		+ Ours	98.5	96.8	98.4	98.8	86.2	98.8	99.2	98.0	98.1	97.4	96.2	98.9	96.5	94.9	96.7	96.9
		UniAD	96.6	88.4	96.8	98.5	93.2	95.1	99.0	76.3	85.5	92.1	90.9	97.5	87.6	93.6	94.5	92.4
		+ Ours	96.5	88.1	96.8	96.9	92.7	95.3	99.1	77.8	87.1	96.4	96.8	97.4	88.3	96.9	93.8	93.3

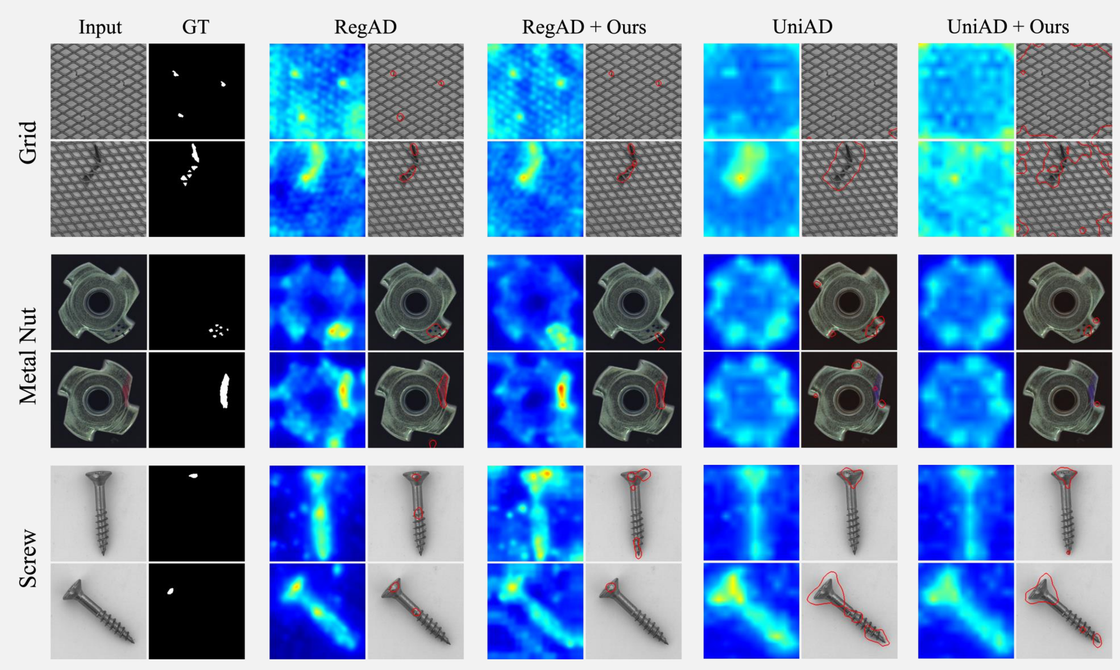
Table 1: RegAD + Ours outperforms RegAD, showcasing improvements between 0.4 to 1.4 percentage points in the image level AUC. Similarly, UniAD combined with our method achieves up to 3.1 percentage points boost.

2. DAGM2007

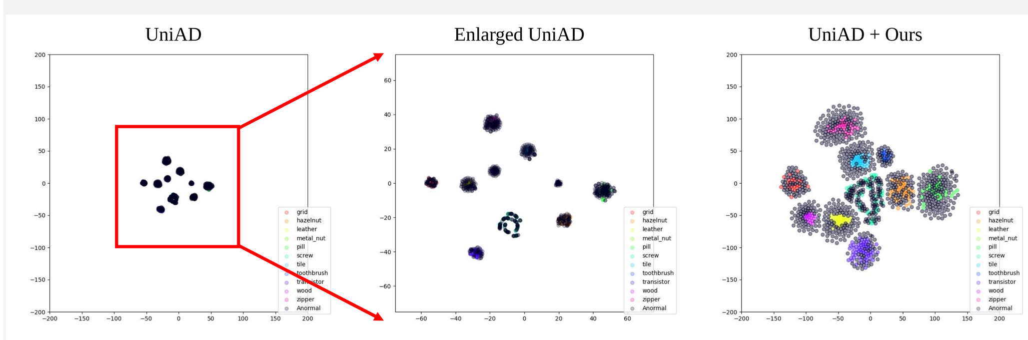
- Image & Pixel Level AUC

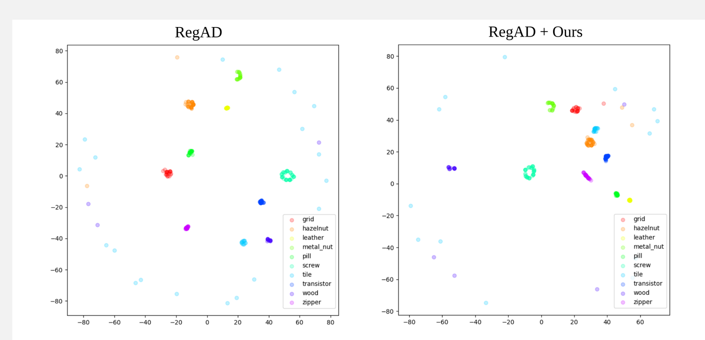
Shot	Method	Image-level Class1	Class2	Class3	Class4	Class5	Average	Pixel-level Class1	Class2	Class3	Class4	Class5	Average
$K=2$	RegAD	56.1	67.6	76.8	93.5	73.7	73.5	73.0	89.7	90.0	97.7	82.1	86.5
	+ Ours	64.8	60.6	83.4	96.8	76.6	75.2	78.6	79.5	89.5	97.3	78.3	84.7
	UniAD	58.3	98.1	74.2	64.5	69.7	72.9	84.1	99.7	89.1	91.2	82.3	89.3
	+ Ours	60.0	98.0	74.8	66.4	70.6	74.0	84.1	99.8	88.9	91.9	82.9	89.5
$K=4$	RegAD	89.8	73.1	76.0	80.5	64.8	76.9	88.5	90.2	88.9	95.5	76.6	87.9
	+ Ours	90.0	78.6	81.3	97.8	78.1	85.1	88.0	95.1	89.4	96.4	82.8	90.3
	UniAD	59.4	98.1	74.1	78.6	70.4	76.1	85.0	99.8	88.8	93.7	82.3	89.9
	+ Ours	59.1	98.1	75.8	79.4	70.9	76.7	85.1	99.8	89.6	94.0	82.5	90.2
$K=8$	RegAD	71.5	77.8	84.6	90.0	69.0	78.6	71.0	93.4	91.0	97.8	80.4	86.7
	+ Ours	73.1	96.9	84.8	97.7	73.9	85.3	87.1	99.2	89.1	98.2	82.5	91.2
	UniAD	59.1	98.1	75.7	88.3	71.0	78.4	85.1	99.8	89.9	95.5	82.7	90.6
	+ Ours	59.3	98.0	76.1	93.2	72.2	79.8	85.3	99.8	90.0	96.2	83.1	90.9

Table 2: Results on the **DAGM2007** dataset reveal our proposed method **generally enhances** RegAD and UniAD performance, despite occasional exceptions in certain classes.



Comparison of RegAD / UniAD vs. **RegAD + Ours / UniAD + Ours** varied results across categories like grid, metal_nut, and screw.





- UniAD + Ours broadens feature space, enhancing separation of sample types.

- RegAD + Ours offers better feature clustering, reducing misclassifications.

Conclusion

- Our method proposed a novel FSAD method incorporating adversarial loss for enhanced generalization.
- We demonstrated overall performance improvement on MVTec AD and DAGM datasets.

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