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ROADS: Robust Prompt-driven Multi-Class Anomaly Detection under Domain Shift

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Challenges in Traditional Methods

- Focus on one-class anomaly detection; limitations with scalability and handling diverse datasets.
- Environmental changes and varied data collection settings reduce model accuracy.

Contributions

Unified framework with prompt-driven learning and domain adaptation. Key Contributions of ROADS Framework:

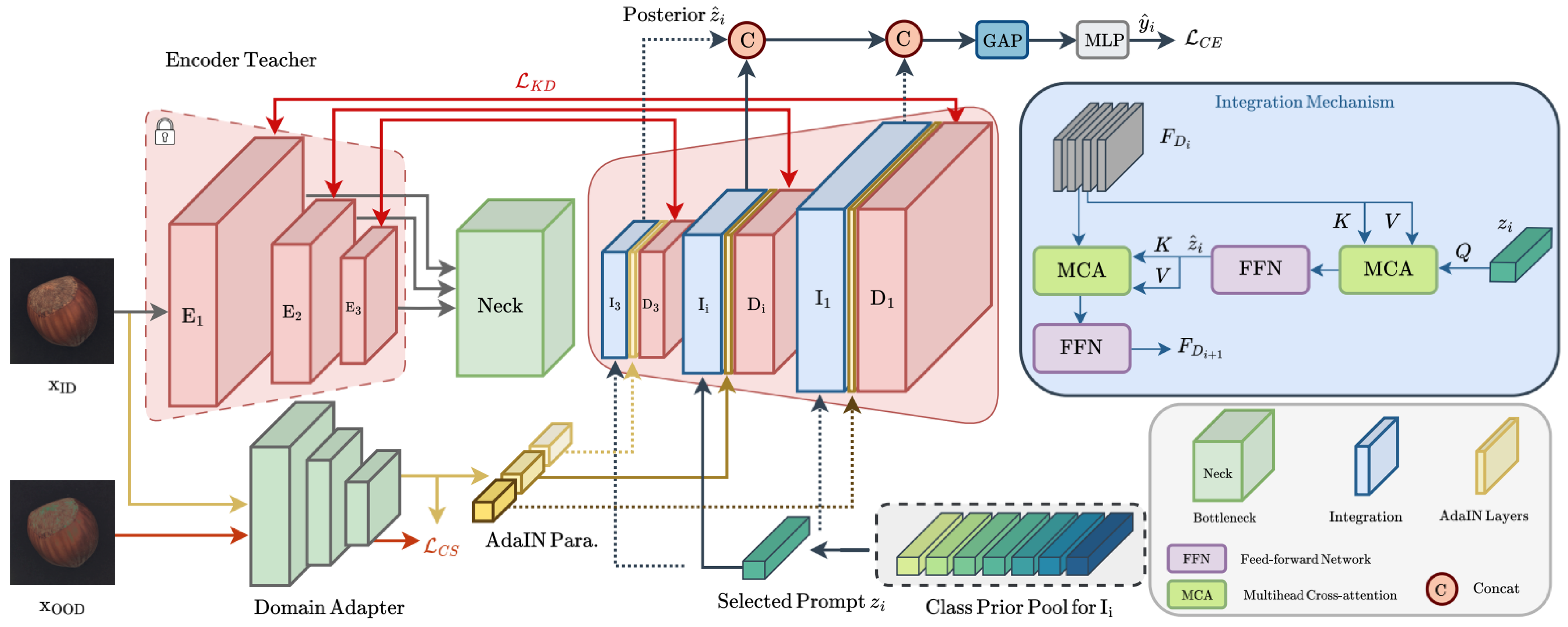
- **Class-Aware Prompt Integration:** Enhances differentiation by encoding class-specific prompts.
- **Domain Adapter:** Adapts to domain shifts via domain-invariant style codes and style consistency loss.
- **Comprehensive Benchmarking:** Validated on MVTec-AD and VISA datasets with state-of-the-art results.

Problem Definition

Domains and Data: Defines In-Distribution (ID) source domain and Out-of-Distribution (OOD) target domain, training on normal data from source domain and testing on mixed data from source domain and target domains.

Objective: The main goal is to effectively detect anomalies in mixed class data in target domain regardless of their domain origin, challenging due to varying feature distributions and inter-class interference.

ROADS Framework



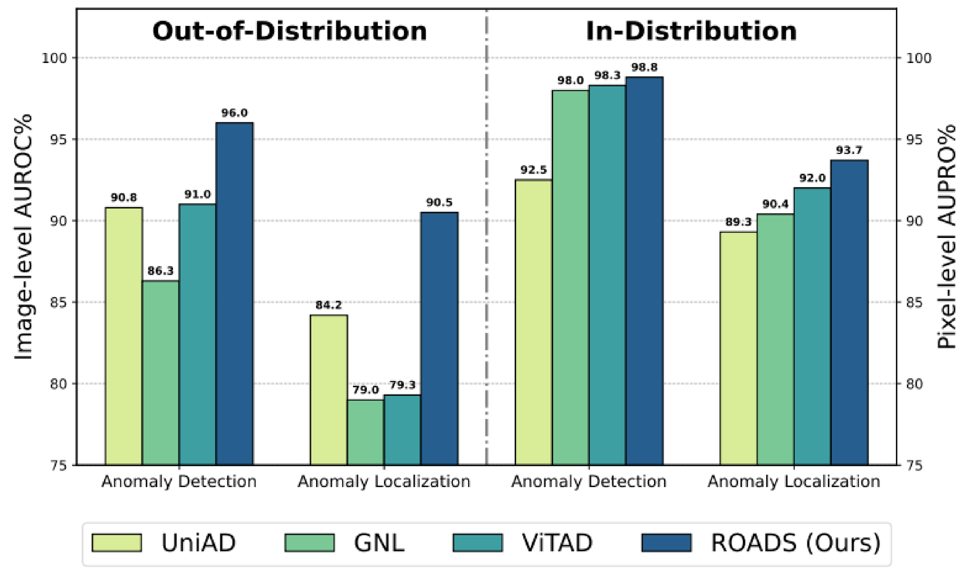
- **Challenges in the Multi-class Anomaly Detection**: Inter-class interference between different anomaly classes.
- ✓ **Hierarchical Class-Aware Prompt Integration**: It dynamically learns and incorporates class-specific prompt tokens directly from diverse anomaly classes into our anomaly detector to mitigate inter-class interference challenge.
- **Challenges in the Multi-class Anomaly Detection**: Neglecting distribution shifts training and test domains that can severely impair model performance.
- ✓ **Domain Adapter**: To enhance the robustness of our model to distribution shifts, we propose a novel domain adapter ξ that aligns the styles of Out-of-Distribution target domains with the In-Distribution source domain.

Experimental Results on MVTec-AD

Quantitative comparison with SOTA methods on MVTec-AD benchmark under ID setting.

	Category/Method	PaDiM [14]	MKD [55]	DRAEM [79]	PatchCore [52]	SimpleNet [39]	UniAD [76]	OmniAL [86]	DiAD [25]	ROADS (Ours)
Object	Bottle	97.9 / 96.1	98.7 / 91.8	97.5 / 87.6	**100** / 98.4	86.5 / 88.1	99.7 / 98.1	**100 / 99.2**	99.7 / 98.4	**100** / 99.1
	Cable	70.9 / 81.0	78.2 / 89.3	57.8 / 71.3	99.2 / 97.3	71.5 / 79.3	95.2 / 97.3	98.2 / 97.3	94.8 / 96.8	**99.3 / 99.0**
	Capsule	73.4 / 96.9	68.3 / 88.3	65.3 / 50.5	85.6 / 95.2	77.8 / 89.4	86.9 / 98.5	95.2 / 96.9	89.0 / 97.1	**96.0 / 99.1**
	Hazelnut	85.5 / 96.3	97.1 / 91.2	93.7 / 96.9	100 / 98.9	94.3 / 95.9	99.8 / 98.1	95.6 / 98.4	99.5 / 98.3	**100 / 98.9**
	Metal Nut	88.0 / 84.8	64.9 / 64.2	72.8 / 62.2	**99.9** / 98.4	87.8 / 87.0	99.2 / 94.8	99.2 / **99.1**	99.1 / 97.3	99.7 / 98.2
	Pill	68.8 / 87.7	79.7 / 69.7	82.2 / 94.4	93.3 / 95.7	80.2 / 90.7	93.7 / 95.0	**97.2 / 98.9**	95.7 / 95.7	96.2 / 98.0
	Screw	56.9 / 94.1	75.6 / 92.1	92.0 / 95.5	82.9 / 95.9	72.8 / 85.7	87.5 / 98.3	88.0 / 98.0	90.7 / 97.9	**98.5 / 99.6**
	Toothbrush	95.3 / 95.6	75.3 / 88.9	90.6 / 97.7	88.9 / 98.2	87.8 / 96.4	94.2 / 98.4	**100 / 99.4**	99.7 / 99.0	99.2/ 98.7
	Transistor	86.6 / 92.3	73.4 / 71.7	74.8 / 64.5	96.7 / 89.3	79.7 / 83.3	**99.8 / 97.9**	93.8 / 93.3	**99.8** / 95.1	96.3 / 95.8
	Zipper	79.7 / 94.8	87.4 / 86.1	98.8 / 98.3	91.9 / 95.5	88.5 / 84.3	95.8 / 96.8	**100 / 99.5**	95.1 / 96.2	99.6 / 98.5
Texture	Carpet	93.8 / 97.6	69.8 / 95.5	98.0 / 98.6	96.1 / 98.7	87.6 / 89.5	**99.8** / 98.5	98.7 / **99.4**	99.4 / 98.6	99.4 / 99.2
	Grid	73.9 / 71.0	83.8 / 82.3	99.3 / 98.7	97.1 / 96.6	79.1 / 69.9	98.2 / 96.5	99.9 / **99.4**	98.5 / 96.6	**100** / 99.3
	Leather	99.9 / 84.8	93.6 / 96.7	98.7 / 97.3	**100** / 99.4	95.2 / 96.6	**100** / 98.8	99.0 / 99.3	99.8 / 98.8	**100 / 99.5**
	Tile	93.3 / 80.5	89.5 / 85.3	99.8 / 98.0	99.9 / 95.7	97.9 / 91.6	99.3 / 91.8	**99.6 / 99.0**	96.8 / 92.4	99.2 / 96.5
	Wood	98.4 / 89.1	93.4 / 80.5	99.8 / 96.0	98.4 / 93.5	97.5 / 87.0	98.6 / 93.2	93.2 / **97.4**	99.7 / 93.3	**99.1** / 96.0
	Total Average	84.2 / 89.5	81.9 / 84.9	88.1 / 87.2	95.3 / 96.4	85.6 / 87.6	96.5 / 96.80	97.1 / 98.3	97.2 / 96.8	**98.83 / 98.36**

Experimental results on the the MVTec-AD dataset under both ID and OOD settings



Experiments

- We validate our method across two different settings: In-Distribution Evaluation and Out-of-Distribution Evaluation.
- Our experiments utilize MVTec-AD and VISA benchmarks. We applied four corruption types (Brightness, Contrast, Defocus Blur, Gaussian noise) at severity 5 to generate Out-of-Distribution datasets.

Experimental Results on VISA

- Experimental results on the VISA dataset under both ID and OOD settings.

Category	ID	Brightness	Contrast	Blur	Gaussian Noise
UniAD [32]	90.33 / 86.99	81.19 / 80.87	78.16 / 78.27	90.61 / 85.88	85.68 / 81.82
ViTAD [36]	90.58 / 84.77	68.73 / 61.55	77.79 / 70.98	89.92 / 81.62	75.53 / 50.54
DiAD [14]	90.52 / 44.36	76.14 / 32.95	72.41 / 29.56	88.23 / 41.03	83.48 / 37.89
RD++ [27]	93.94 / 91.79	73.89 / 75.16	81.92 / 84.36	92.58 / 88.52	75.19 / 76.56
SimpleNet [20]	87.94 / 82.66	61.35 / 46.34	56.51 / 55.91	79.28 / 72.00	61.52 / 42.93
ROADS (Ours)	**95.42 / 92.27**	**85.98 / 78.07**	**83.88 / 85.27**	**94.62 / 89.55**	**88.63 / 84.08**

- Qualitative comparison between the proposed ROADS method and UniAD on the MVTecAD dataset under both ID and OOD settings.