MILANO 2024

OneNIP Code

Tencent YouTu Lab

Learning to Detect Multi-class Anomalies with Just One Normal Image Prompt

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Introduction

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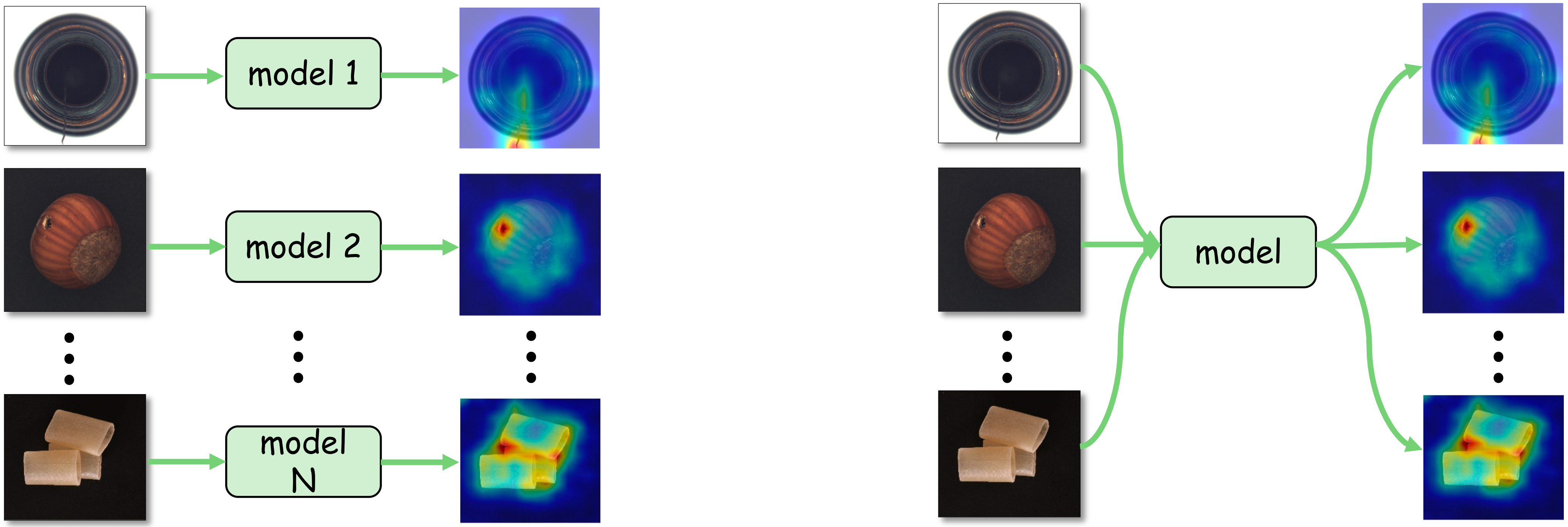
Sepereated and Unified Anomlay Detection

The unified anomaly detection attempts to detect multi-class anomalies using a single model. Compared to the separated mode, the unified AD is more challenging as it requires handling more complex data distributions.

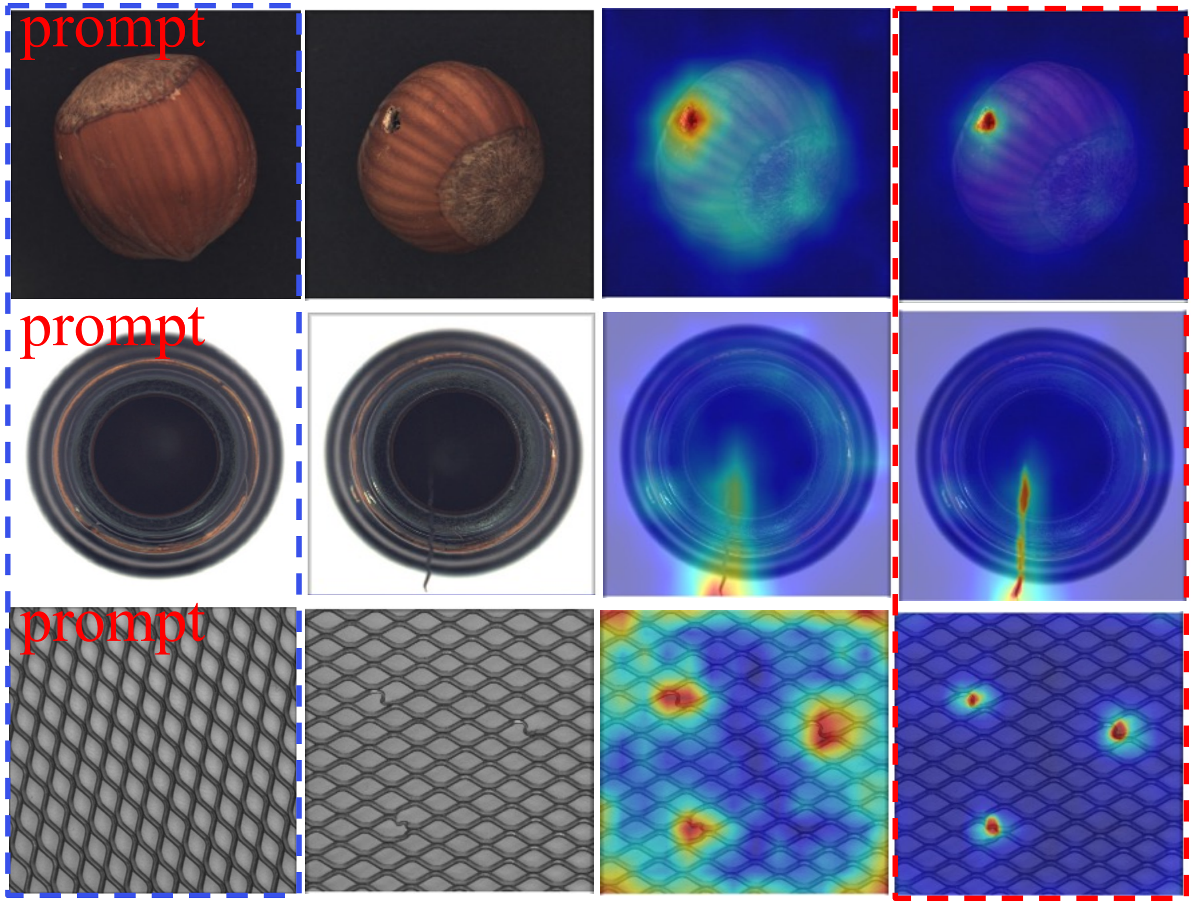


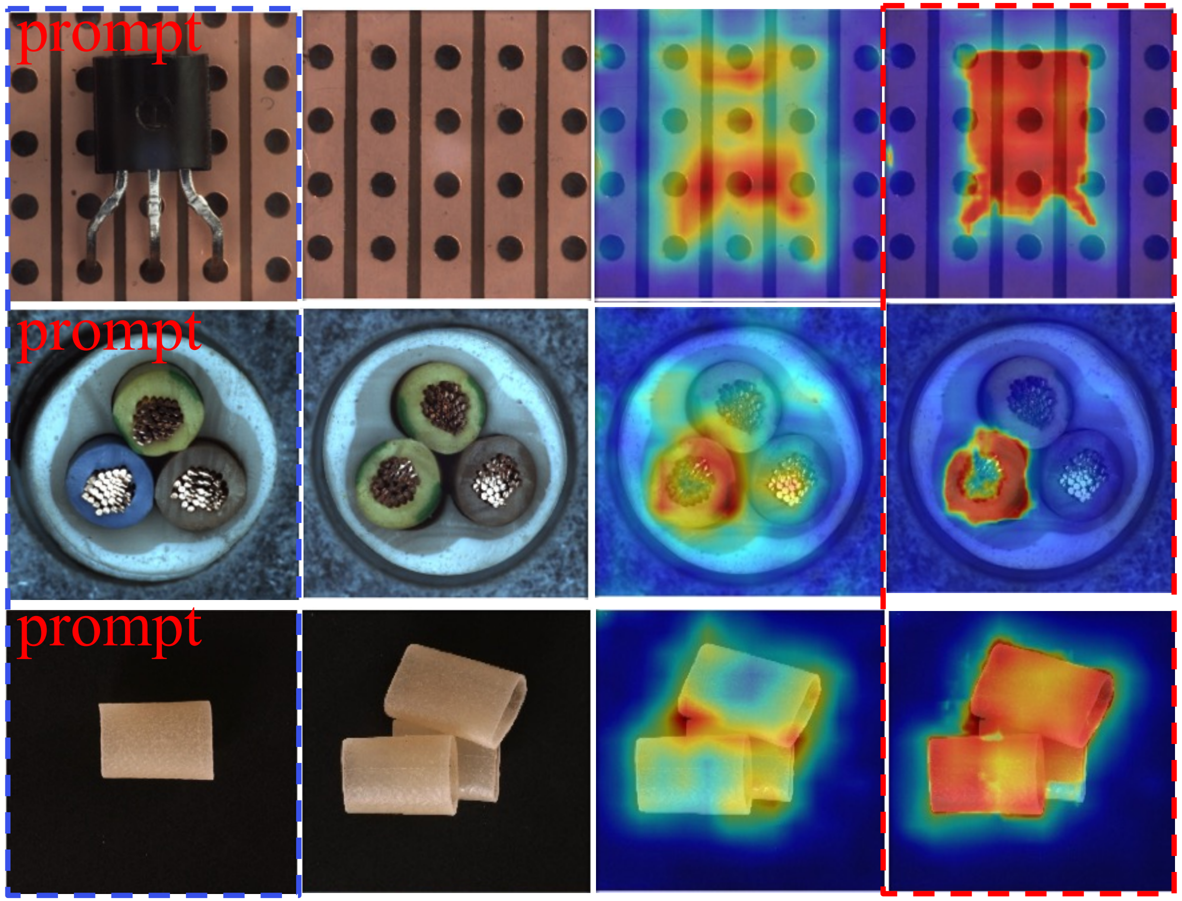
Separated Paradigm
one model for one class

Unified Paradigm
one model for all classes

Introduction

- ✓ The common anomalies can be detected using their own contextual information.
- ✓ The camouflaged anomalies are hard to detect using only query images.





How to effectively utilize the normal image prompts to improve unified anomaly detection?

Our Method

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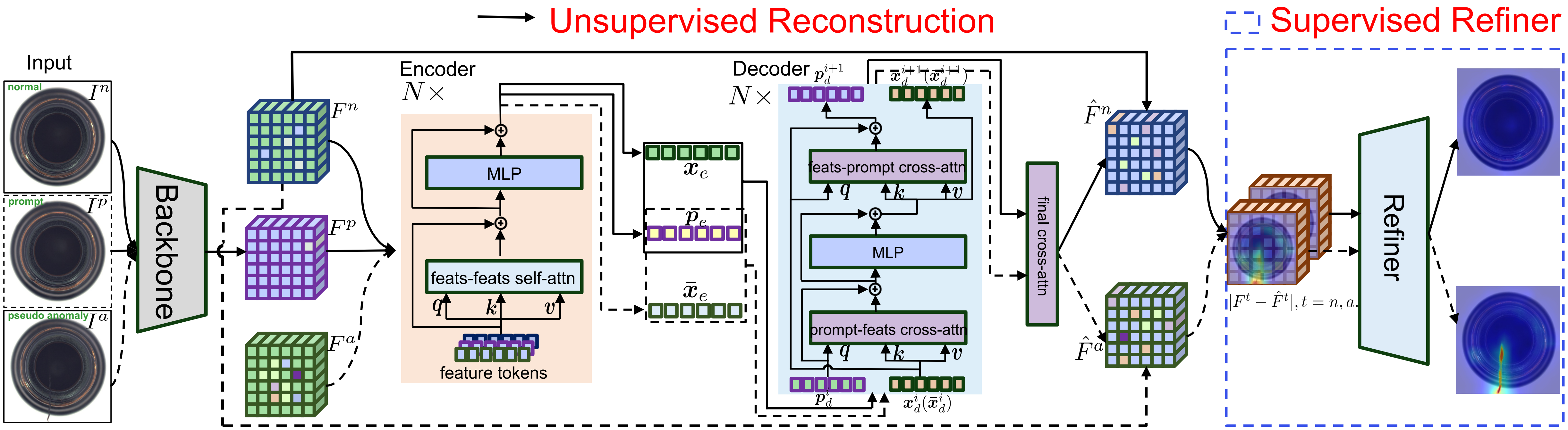
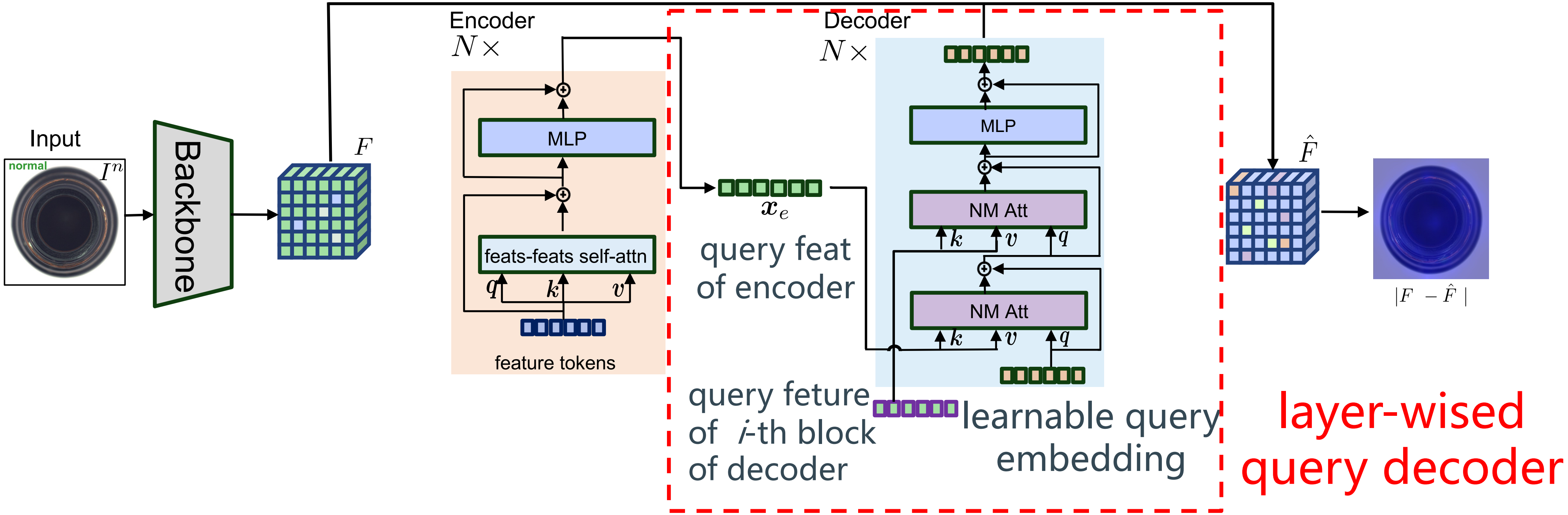
OneNIP



OneNIP is built on the state-of-the-art UniAD, which mainly consists of unsupervised reconstruction, unsupervised restoration, and supervised refiner.

Our Method

Revisiting UniAD.



UniAD is the first work to study the unified anomaly detection using a transformer reconstruction network. The layer-wised query decoder is one of core components.

Our Method

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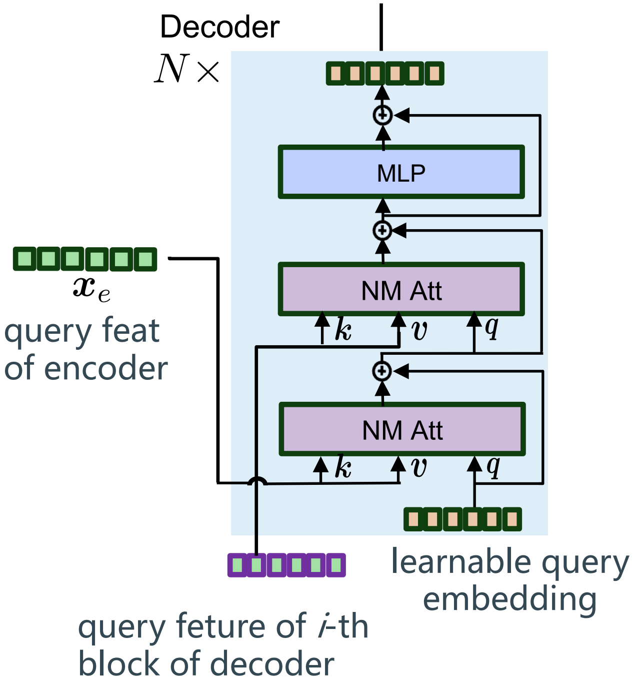
Revisiting UniAD: Layer-wised Decoder in UniAD



learnable query embedding

query token of i-th block of decoder

$$\boldsymbol{q}\prime = \mathrm{softmax}(\boldsymbol{q}^i \boldsymbol{x}_e{}^T / \sqrt{c})\boldsymbol{x}_e,$$

$$\boldsymbol{x}_d^{i+1} = \mathrm{softmax}(\boldsymbol{q}\prime \boldsymbol{x}_d^i{}^T / \sqrt{c})\boldsymbol{x}_d^i,$$

$$\boldsymbol{x}_d^0 = \boldsymbol{x}_e.$$

initalized by query output of last block of encoder

Eq.1 Layer-wise query decoder

Our Method

How to utilize normal image prompt? unidirectional decoder

A simple and naive manner is to directly replace the learnable query embedding in the LQD with the normal image prompt token from the encoder, thereby enabling the interaction between the prompt and query.

learnable query embedding

query token from i-th block of decoder

$$
\begin{aligned}
\boldsymbol{q}\prime &= \mathrm{softmax}(\boxed{\boldsymbol{q}^i}\,{\boldsymbol{x}_e}^T/\sqrt{c})\boldsymbol{x}_e, \\
\boxed{\boldsymbol{x}_d^{i+1}} &= \mathrm{softmax}(\boldsymbol{q}\prime {\boldsymbol{x}_d^i}^T/\sqrt{c})\boldsymbol{x}_d^i, \\
\boldsymbol{x}_d^0 &= \boxed{\boldsymbol{x}_e}.
\end{aligned}
$$

initalized by query token from last block of encoder

normal image token from the last block of encoder

query token from i-th block of decoder

$$
\begin{aligned}
\boldsymbol{q}\prime &= \mathrm{softmax}(\boxed{\boldsymbol{p}_e}\,{\boldsymbol{x}_e}^T/\sqrt{c})\boldsymbol{x}_e, \\
\boxed{\boldsymbol{x}_d^{i+1}} &= \mathrm{softmax}(\boldsymbol{q}\prime {\boldsymbol{x}_d^i}^T/\sqrt{c})\boldsymbol{x}_d^i, \\
\boldsymbol{x}_d^0 &= \boxed{\boldsymbol{x}_e}.
\end{aligned}
$$

initalized by query token from last block of encoder

Eq.1 layer-wise query decoder

Eq.2 unidirectional decoder with static prompt

Issue: The static prompt may not be flexible enough and may fail to align with the query token especially when the query token is continuously updated in the decoder.

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How to update normal image prompt and query token dynamically ?

bidirectional decoder

$$\boldsymbol{q}' = \mathrm{softmax}(\boldsymbol{q}^i {\boldsymbol{x}_e}^T/\sqrt{c})\boldsymbol{x}_e,$$
$$\boldsymbol{x}_d^{i+1} = \mathrm{softmax}(\boldsymbol{q}' {\boldsymbol{x}_d^i}^T/\sqrt{c})\boldsymbol{x}_d^i,$$
$$\boldsymbol{x}_d^0 = \boldsymbol{x}_e.$$

Eq.1 layer-wise query decoder

normal image token from the last block of encoder

$$\boldsymbol{q}' = \mathrm{softmax}(\boxed{\boldsymbol{p}_e} {\boldsymbol{x}_e}^T/\sqrt{c})\boldsymbol{x}_e,$$
$$\boldsymbol{x}_d^{i+1} = \mathrm{softmax}(\boldsymbol{q}' {\boldsymbol{x}_d^i}^T/\sqrt{c})\boldsymbol{x}_d^i,$$
$$\boldsymbol{x}_d^0 = \boldsymbol{x}_e.$$

Eq.2 unidirectional decoder with static prompt

prompt-to-feature $\quad \boldsymbol{p}_d^{i+1} = \mathrm{softmax}(\boldsymbol{p}_d^i {\boldsymbol{x}_d^i}^T/\sqrt{c})\boldsymbol{x}_d^i,$

feature-to-prompt $\quad \boldsymbol{x}_d^{i+1} = \mathrm{softmax}(\boldsymbol{x}_d^i {\boldsymbol{p}_d^{i+1}}^T/\sqrt{c})\boldsymbol{p}_d^{i+1},$

$$\boldsymbol{p}_d^0 = \boldsymbol{p}_e, \boldsymbol{x}_d^0 = \boldsymbol{x}_e.$$

initalized by normal image and query tokens from last block of encoder

Eq.3 bidirectional decoder with dynamic prompt

In this way, the query token reconstruction not only utilizes its contextual information but also leverages the corresponding normal prompt dynamically.

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Unsupervised Reconstruction Loss

For unsupervised reconstruction, we minimize MSE loss between the reconstructed normal tokens and original normal tokens, that is

$$\mathcal{L}_{rec} = \frac{1}{c \times h \times w} \sum_{i=1}^{c} \sum_{j=1}^{h} \sum_{k=1}^{w} (\boxed{F^n_{i,j,k}} - \boxed{\hat{F}^n_{i,j,k}})^2.$$

original normal tokens

reconstructed normal tokens

Our Method

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Unsupervised Restoration Loss

For unsupervised restoration, we minimize MSE loss between the restored pseudo anomaly tokens and the corresponding normal tokens.

$$\mathcal{L}_{res} = \frac{1}{c \times h \times w} \sum_{i=1}^{c} \sum_{j=1}^{h} \sum_{k=1}^{w} (\boxed{F^n_{i,j,k}} - \boxed{\hat{F}^a_{i,j,k}})^2 .$$

corresponding normal tokens

reconstructed pseudo anomaly tokens

Here, we generate pseudo anomaly images using CutPaste and DRAEM. (adding corruptions or disruptions to a normal training images)

Our Method

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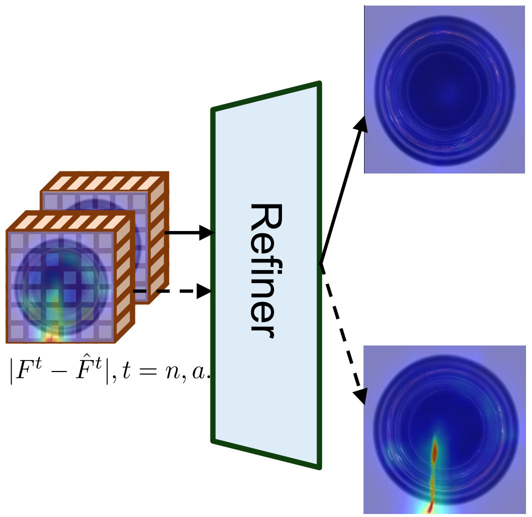
Supervised Refiner

We design a lightweight and pixel-level refiner based on reconstruction errors on normal and pseudo anomaly tokens for achieving more anomaly segmentation

Supervised Refiner



$$\mathcal{L}_{seg} = 1 - \frac{2 \cdot \sum_{i=1}^{H} \sum_{j=1}^{W} \hat{M}_{i,j}^{t} \cdot M_{i,j}^{t}}{\sum_{i=1}^{H} \sum_{j=1}^{W} (\boxed{\hat{M}_{i,j}^{t}})^2 + \sum_{i=1}^{H} \sum_{j=1}^{W} (\boxed{M_{i,j}^{t}})^2},$$

predicted anomaly map

Ground-truth anomaly mask

Experiments

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Comparisons with State-of-the-Arts

Datasets	Metric↑	Embedding-based					Discriminator-based		Reconstruction-based	
		CS-Flow [38]	PaDiM [10]	DFM [1]	PatchCore [37]	CFA [20]	DRAEM [54]	SimpleNet [25]	UniAD [52]	**OneNIP**
MVTec [4]	I-ROC/PR	81.4 / 90.2	87.5 / 92.8	69.7 / 89.8	89.8 / 96.3	80.4 / 91.0	91.4 / 95.3	78.2 / 90.0	96.5 / 98.9	97.9 / 99.3
	P-ROC/PR	93.8 / 33.8	95.5 / 37.8	96.5 / 42.4	96.4 / 50.1	90.7 / 37.1	85.2 / 49.6	81.0 / 24.8	96.8 / 44.7	97.9 / 63.7
BTAD [26]	I-ROC/PR	91.8 / 96.3	95.7 / 97.4	68.8 / 82.8	89.2 / 96.4	87.5 / 87.7	84.7 / 95.0	90.3 / 95.0	92.2 / 97.9	92.6 / 98.5
	P-ROC/PR	95.9 / 34.6	96.7 / 48.7	96.3 / 48.0	96.3 / 48.4	95.6 / 40.4	74.2 / 12.3	78.8 / 36.2	97.1 / 50.9	97.4 / 56.8
VisA [60]	I-ROC/PR	75.8 / 80.0	78.1 / 78.3	51.6 / 77.8	90.3 / 92.0	69.0 / 73.8	81.8 / 85.8	89.2 / 92.2	90.8 / 93.0	92.5 / 94.5
	P-ROC/PR	95.6 / 18.6	95.9 / 17.1	96.5 / 25.2	96.8 / 38.2	91.4 / 16.8	78.1 / 15.1	95.3 / 33.1	98.4 / 33.6	98.7 / 43.3

Results on Complex Distribution

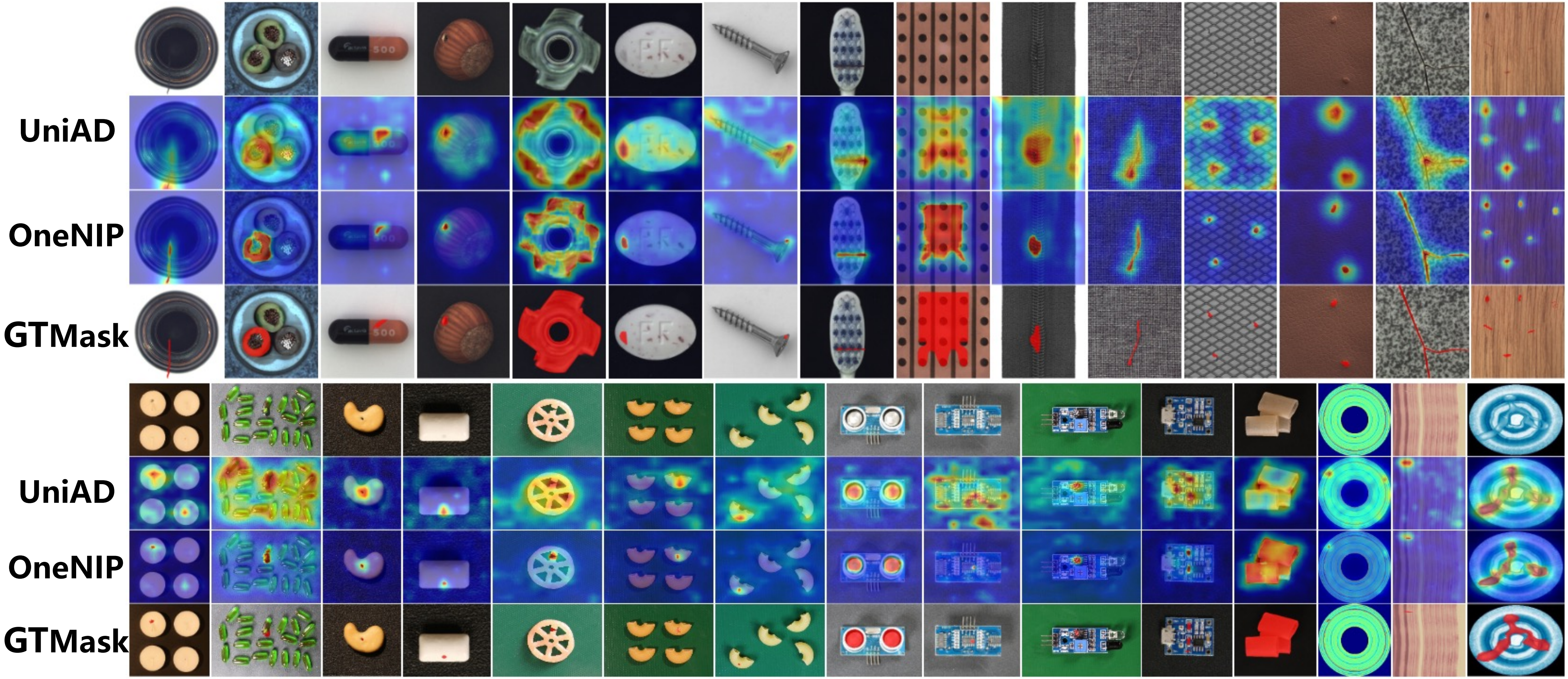
Datasets	#Classes	Metric ↑	UniAD [52]	OneNIP
MVTec [4]	15	I-ROC/PR	94.8/98.0	97.1/99.0
		P-ROC/PR	96.2/42.1	97.6/61.1
BTAD [26]	3	I-ROC/PR	92.0/97.1	92.0/97.5
		P-ROC/PR	97.1/48.0	97.9/59.0
VisA [60]	12	I-ROC/PR	89.9/92.4	91.9/93.9
		P-ROC/PR	98.3/33.2	98.6/40.6
All	30	I-ROC/PR	92.6/95.7	94.5/96.8
		P-ROC/PR	97.1/39.1	98.0/52.4

Results with Different Resolution

Datasets	Metric ↑	224×224	256×256	320×320
MVTec [4]	I-ROC/PR	97.9/99.3	97.6/99.2	97.9/99.3
	P-ROC/PR	97.9/63.7	97.8/64.7	97.9/65.9
BTAD [26]	I-ROC/PR	92.6/98.5	94.9/99.0	95.3/98.9
	P-ROC/PR	97.4/56.8	97.6/57.0	97.8/57.6
VisA [60]	I-ROC/PR	92.5/94.5	93.3/94.3	94.2/95.7
	P-ROC/PR	98.7/43.3	98.8/44.1	98.8/46.1

Experiments

Qualitative Comparisons with State-of-the-Arts



Experiments

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Ablation Studies

Table 4: Ablation studies on MVTec. Default settings are marked in blue.

(a) Prompt strategy in Reconstruction, Restoration, and Refiner

No.	Prompt	Res.	Ref.	I-ROC	P-ROC	I-PR	P-PR
0	✗	✗	✗	96.5	96.8	98.9	44.7
1	static	✗	✗	96.8	97.0	98.9	45.8
2	dynamic	✗	✗	97.5	97.1	99.2	46.0
3	✗	✓	✗	96.7	97.0	98.9	46.5
4	dynamic	✓	✗	97.4	97.3	99.1	48.4
5	dynamic	✓	✓	**97.9**	**97.9**	**99.3**	**63.7**

(b) Effects of the number of Encoder, and Decoder

Enc	Dec	I-ROC	P-ROC	I-PR	P-PR
1	1	94.8	97.0	97.9	56.0
2	2	96.7	97.4	98.9	59.4
4	4	97.9	97.9	99.3	63.7
6	6	**98.1**	**98.0**	**99.4**	**64.6**
2	4	97.0	97.6	99.0	61.2
4	2	97.1	97.6	99.0	62.1

(c) Effects of weight α

α	I-ROC	P-ROC	I-PR	P-PR
0.00	97.6	97.3	99.2	48.3
0.25	97.8	97.7	99.3	59.3
0.50	97.9	97.9	99.3	63.7
1.00	96.7	96.7	98.9	63.7

(d) Different prompt modes of the same category

Train	Test	I-ROC	P-ROC	I-PR	P-PR
rand	rand	97.85±0.01	97.86±0.00	99.27±0.01	63.71±0.01
	fixed	97.85±0.02	97.86±0.00	99.27±0.01	63.71±0.02
fixed	fixed	97.91	97.86	99.30	63.66
	rand	96.05±0.24	97.49±0.03	98.34±0.19	60.65±0.18

Conclusions

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- We propose a simple yet effective anomaly detection framework that learns to detect multi-class anomalies with one normal image prompt.
- We propose a bidirectional decoder to dynamically update the prompt and query tokens and promote their interaction.
- To enhance the prompt guidance, we introduce pseudo anomaly images and propose an unsupervised restoration stream.
- We propose a lightweight and pixel-level refiner, which greatly boosts anomaly segmentation performance.

Thanks!

OneNIP Code