Towards Open-World Object-based Anomaly Detection via Self-Supervised Outlier Synthesis

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Motivation

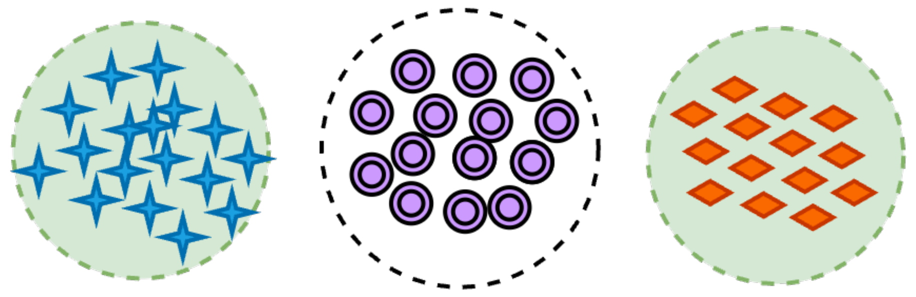
- Free Energy and virtual outlier synthesis methods show outstanding performance for OOD detection[1,2].
- These methods use the training class labels, which might not be available/complete in a real scenario.
- Standard object detectors capability is limited by the object categories in the training set.

We leverage Open-World Object Detection with class-agnostic self-supervised outlier synthesis (SSOS) for object-based anomaly detection!

Virtual Outlier Synthesis

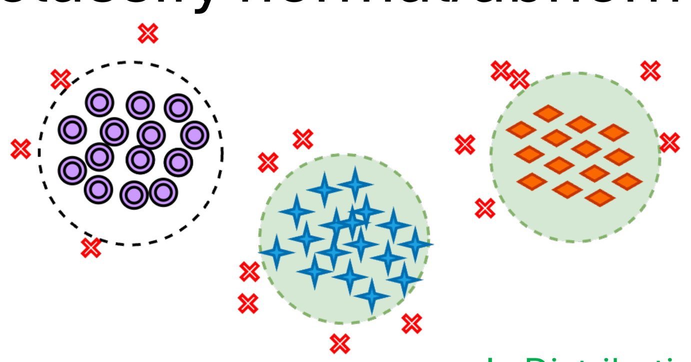
Given object features $\mathbf{v}_i \in \mathbb{R}^d$ and their class label $c_i \in \mathcal{C}, \mathcal{C} = \{1, \dots, C\}$, VOS consists of first learning categorical normal distributions for the k-th class:

$$\boldsymbol{\mu}_k = \frac{1}{N_k} \sum^{N_k} \mathbf{v}_i$$



$$\boldsymbol{\Sigma} = \frac{1}{N} \sum_{k=1}^{C} \sum^{N_k} (\mathbf{v}_i - \boldsymbol{\mu}_k)(\mathbf{v}_i - \boldsymbol{\mu}_k)^\top$$

Then, outliers $\hat{\mathbf{v}}$ are sampled form these distributions and we use the Free Energy E to classify normal/abnormal.



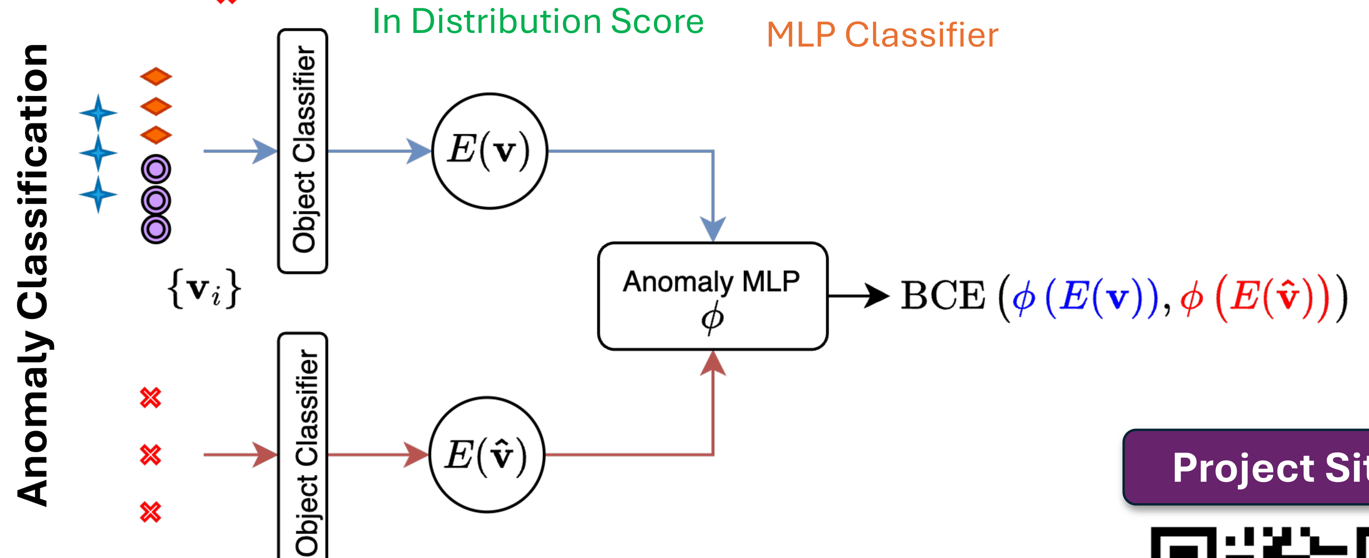
$$E(\mathbf{v}) = -\log \sum_{k=1}^{C} \exp(\boxed{f_k})$$

Class-logit for object **v**

$$\boxed{\lambda} = \boxed{\phi}(E(\mathbf{v}))$$

In Distribution Score

MLP Classifier



Project Site

References

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2. N. Kumar, S. Šegvić, et al. *CVPR*, 2023.
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6. F. Yu, H. Chen, et al. *CVPR, 2020.*
7. S. Akçay, M. Kundegorski, et al. *IEEE Transactions on Information Forensics and Security*, 13(9), 2018.
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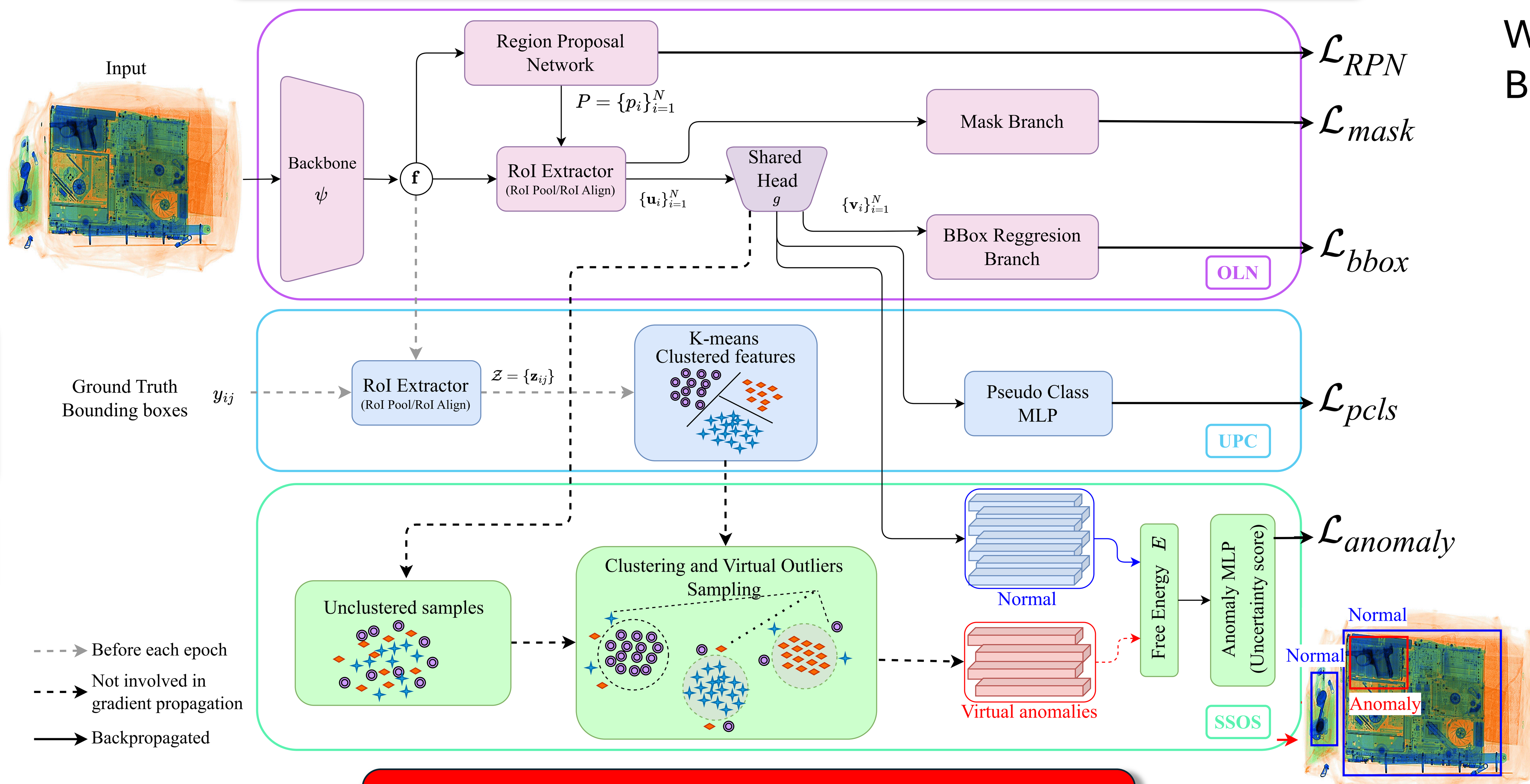
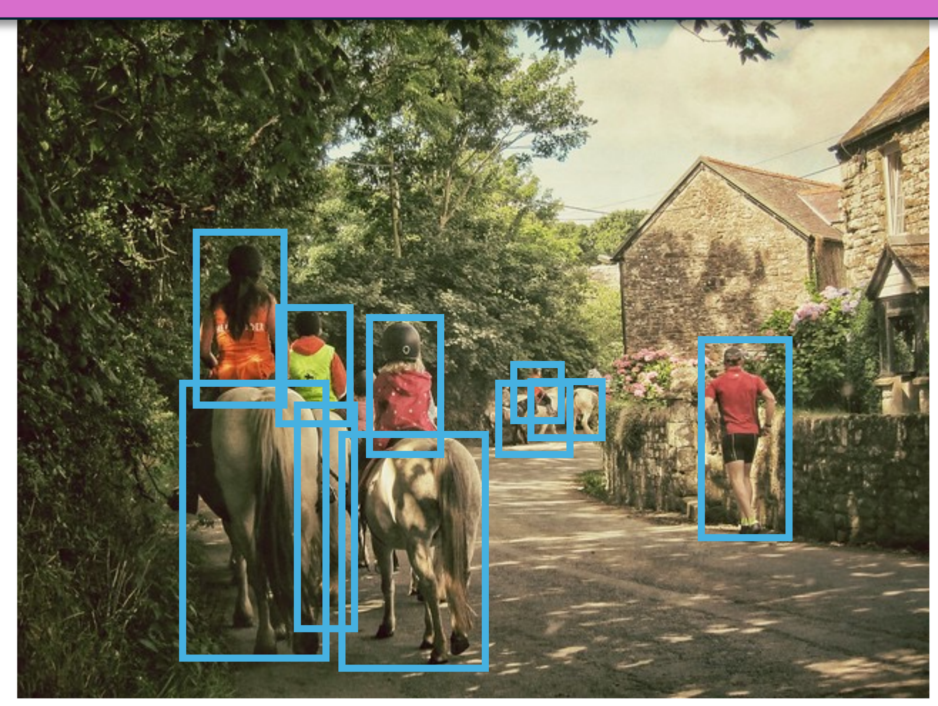
Methodology: OLN-SSOS

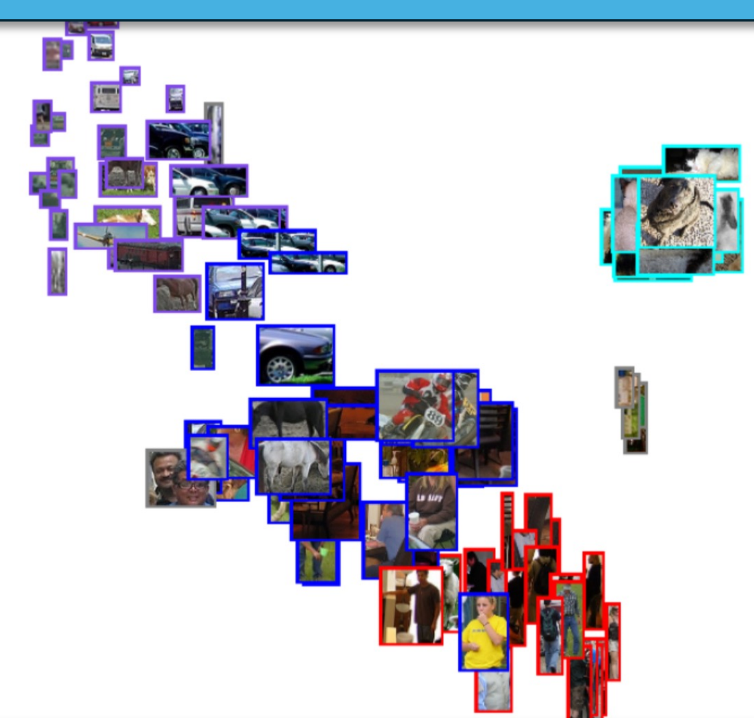


We also test the use of normalising flows (as in FFS[2]), creating the OLN-FFS variant

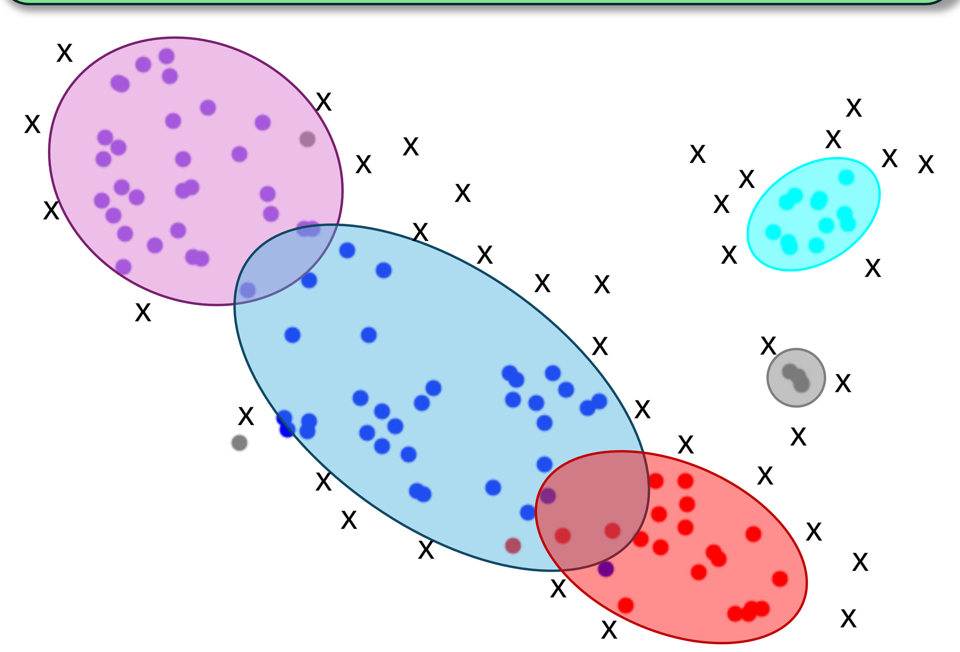
Using an Open-World detector (e.g. OLN[3]) for detecting all objects



Unsupervised Pseudo-Clustering of Object Features



Self-Supervised Outlier Synthesis for training



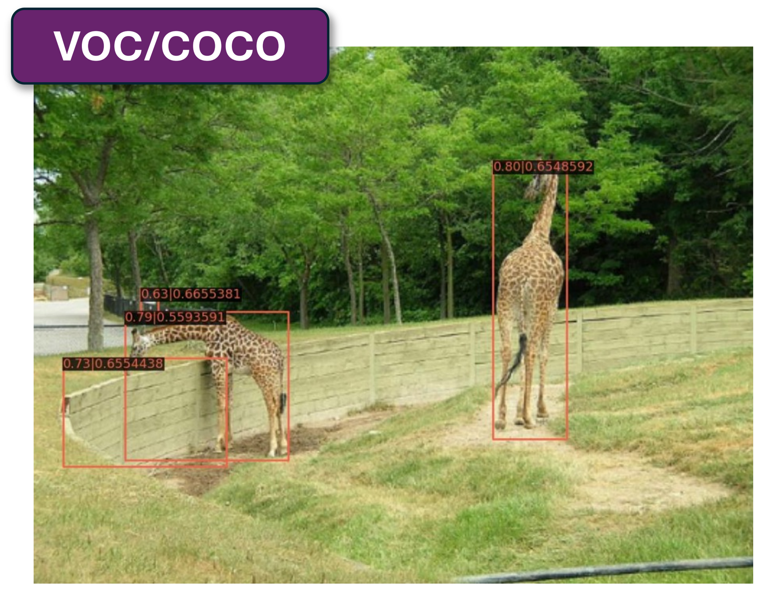
Open World Anomaly Detection

Results

We evaluate recall (0.5 IoU) in 5 datasets: VOC[4]/COCO[5], BDD[6]/COCO[5], DBF6[7], SIXRay10[8] and LTDImaging[9].

	Method	In-Distribution		OOD	
		AR@10	AR@100	AR@10	AR@100
VOC/COCO	VOS[1]	56.3	59.5	**20.0**	**20.6**
	FFS[2]	**58.1**	**60.9**	19.2	19.6
	OLN-SSOS	27.9	45.9	11.1	14.8
	OLN-FFS	49.6	61.3	11.2	17.8
BDD/COCO	VOS[1]	**32.3**	**51.7**	8.6	9.9
	FFS[2]	31.9	51.4	**9.0**	10.3
	OLN-SSOS	27.9	45.9	1.6	3.5
	OLN-FFS	27.0	44.1	6.0	**15.9**
DBF6	VOS[1]	54.3	54.4	32.8	32.8
	FFS[2]	**56.5**	**56.5**	35.4	35.4
	OLN-SSOS	44.2	49.1	**46.1**	**48.8**
	OLN-FFS	45.8	51.5	35.9	46.3
SIXRay10	VOS[1]	63.6	63.6	0.1	0.1
	FFS[2]	**65.4**	**65.4**	0.8	0.8
	OLN-SSOS	49.2	55.2	25.8	35.3
	OLN-FFS	50.4	55.1	**27.3**	**35.6**
LTDImaging	VOS[1]	**34.3**	52.5	0	0
	FFS[2]	34.2	**52.5**	0	0
	OLN-SSOS	15.5	17.8	12.2	18.2
	OLN-FFS	16.8	19.4	**12.3**	**18.3**

VOC/COCO

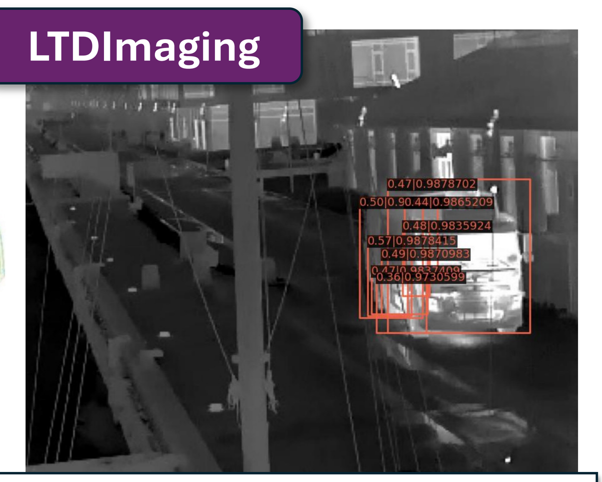


BDD/COCO

DBF6

SIXRay10

LTDImaging



Conclusions

- We introduce OLN-SSOS, an open-world anomaly detector uses self-supervised feature clustering for VOS.
- Our method is competitive with class-supervised methods while no using any categorical information
- We stablish the SOTA for OOD detection in DBF6, SIXRay10 and LTDImaging.