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

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Motivation

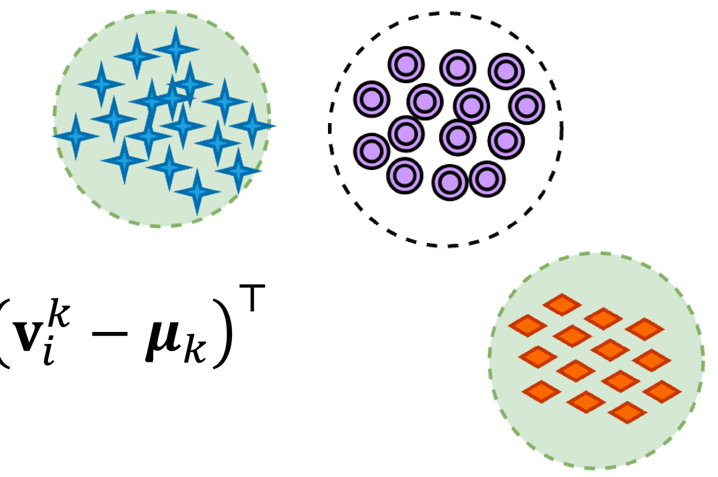
- **Virtual outlier synthesis** shows outstanding performance for **OOD detection**[1,2].
- Ground truth training class labels might not be available/complete in a real scenario.
- Standard object detectors are limited by the object categories in the training set.

Virtual Outlier Synthesis

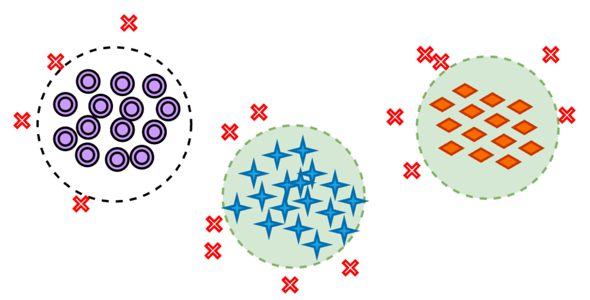
Categorical Gaussian distributions are fit using ground truth object features $\mathbf{v}_i^k$ from the k-th class

$$\boldsymbol{\mu}_k = \frac{1}{N_k}\sum_{i}^{N_k}\mathbf{v}_i^k$$

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



Outliers $\hat{\mathbf{v}}$ are sampled from low-likelihood regions, then using the Energy E for normal/abnormal classification

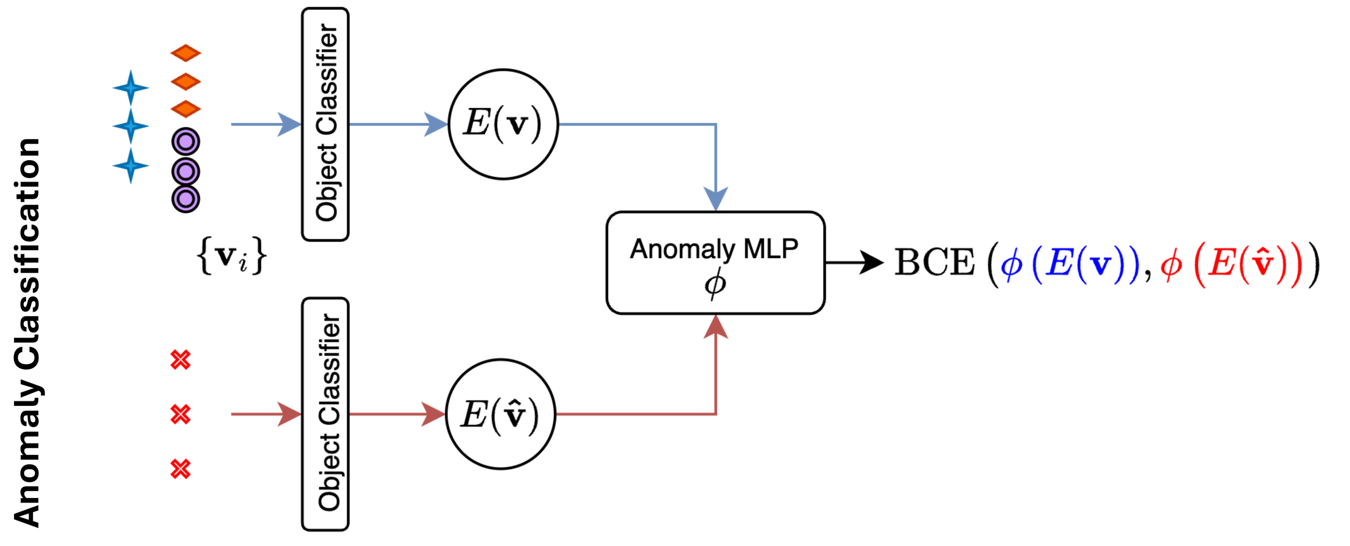


$$E(\mathbf{v}) = -\log\sum_{k=1}^{C}\exp(\boxed{f_k})$$

Class-logit for object v

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

Uncertainty MLP Classifier

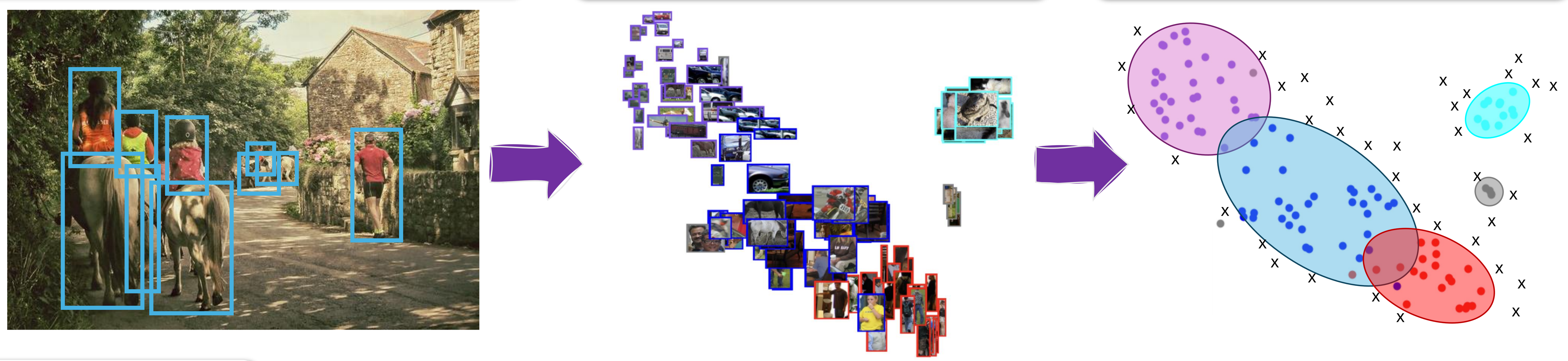


We leverage Open-World Object Detection with class-agnostic Self-Supervised Outlier Synthesis (SSOS) for object-based anomaly detection

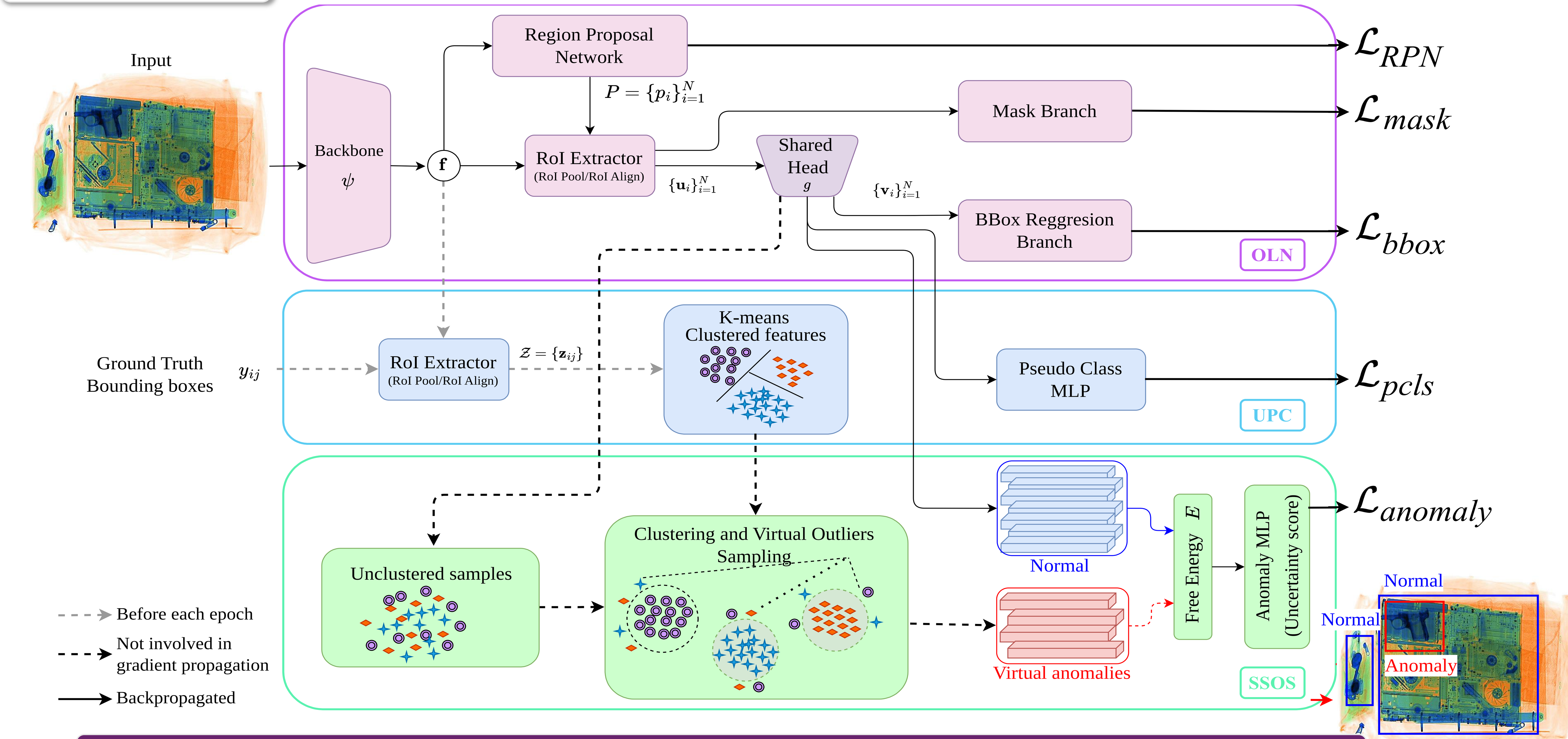
Object Localisation Network (OLN)[3], an Open-World detector for detecting all objects

Unsupervised Pseudo-Clustering of Object Features

Self-Supervised Outlier Synthesis for training



OLN-SSOS



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

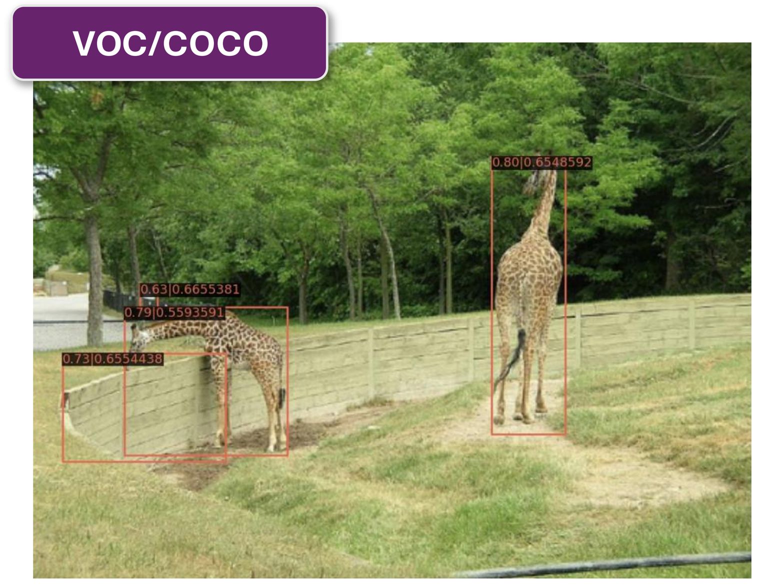
Results

We evaluate our methods, **OLN-SSOS** and **OLN-FFS**, and report 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 AR@10/AR@100	OOD 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**

	Method	In-Distribution AR@10/AR@100	OOD AR@10/AR@100
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	16.819.4	**12.3**/12.8

VOC/COCO

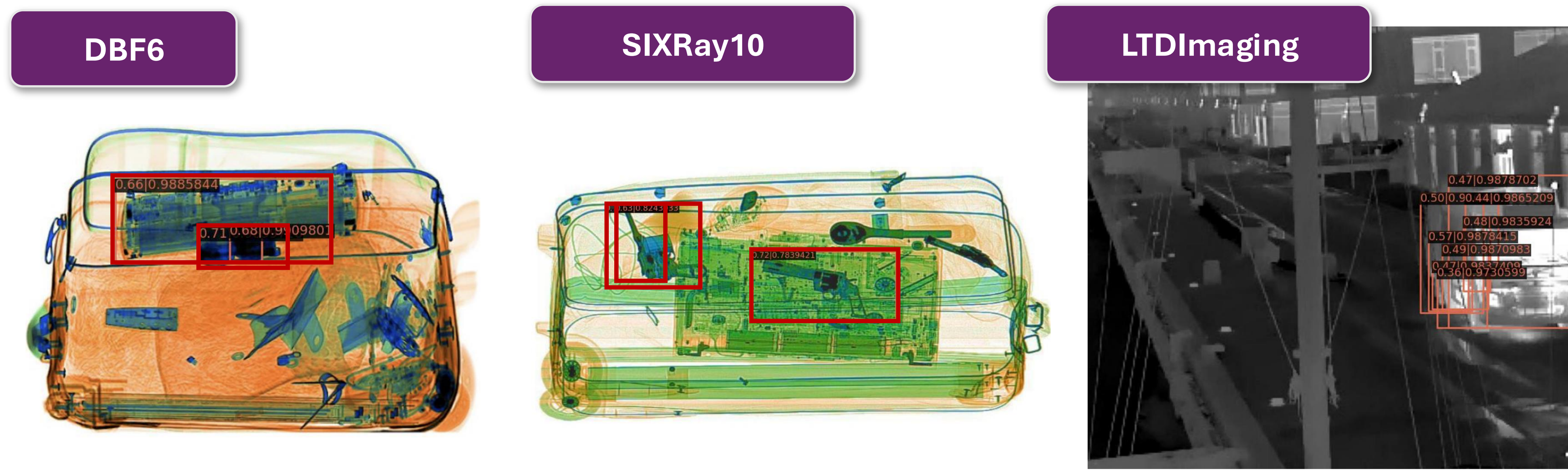


BDD/COCO

DBF6

SIXRay10

LTDImaging



Summary

- We introduce **OLN-SSOS**, an **open-world anomaly detector** that uses **self-supervised feature clustering** for VOS without class-supervision.
- **OLN-SSOS** is competitive with class-supervised methods.
- We establish **SOTA** for **OOD detection** in **DBF6, SIXRay10 and LTDImaging**.

References

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