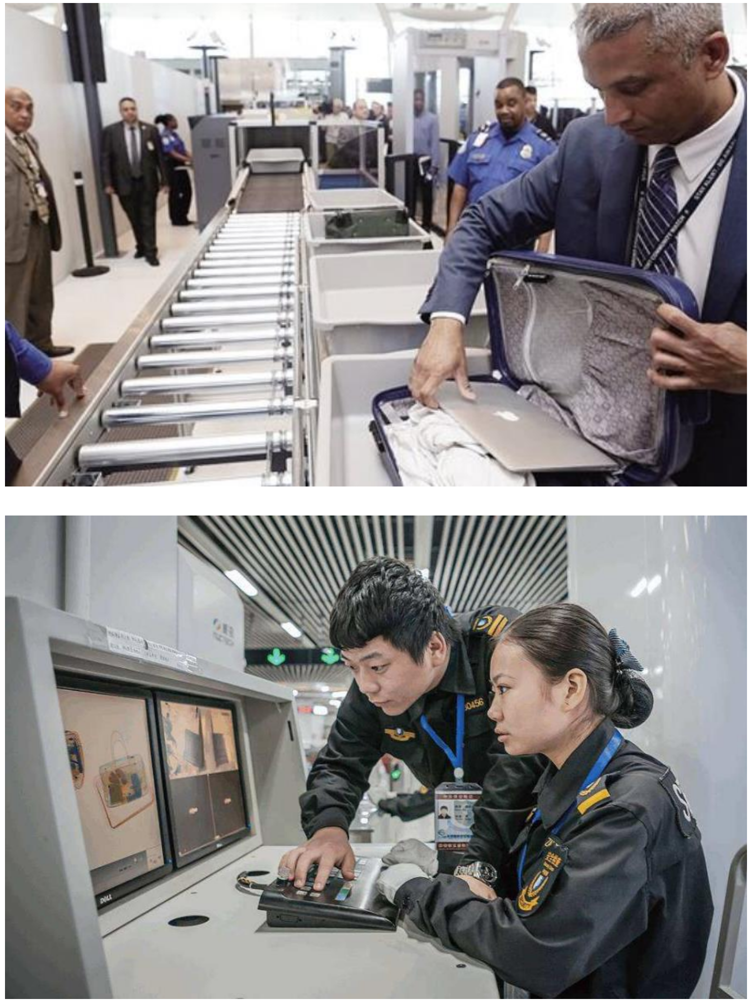
Towards Real-world X-ray Security Inspection: A High-quality Benchmark and Lateral Inhibition Module for Prohibited Items Detection

Renshuai Tao[1,2] Yanlu Wei[1] Xiangjian Jiang[1] Hainan Li[1]
Haotong Qin[1] Jiakai Wang[1] Yuqing Ma[1] Libo Zhang[3] Xianglong Liu[1*]
[1]State Key Laboratory of Software Development Environment, Beihang University
[2]iFLYTEK Research [3]Institute of Software Chinese Academy of Sciences
{rstao, weiyanlu, hainan, qinhaotong, jk_buaa_scse, mayuqing, xlliu}@buaa.edu.cn
silencejiang12138@gmail.com, libo@iscas.ac.cn

陶仁帅
软件开发环境国家重点实验室
北京航空航天大学
科大讯飞AI研究院
个人主页：rstao95.github.io

Background

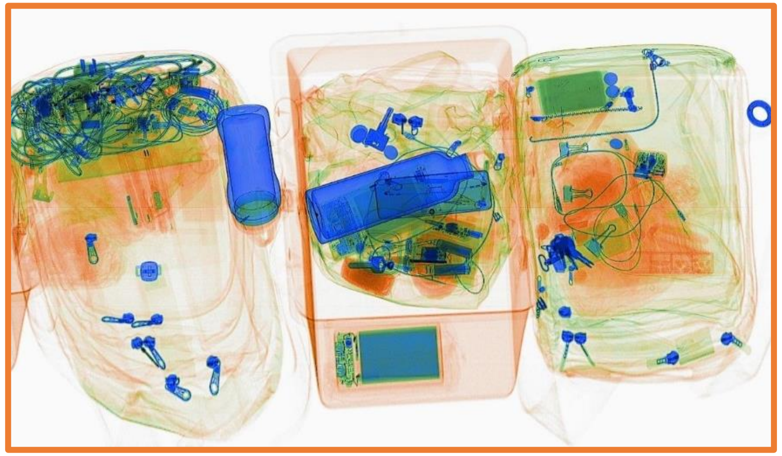
Deep learning applications



AI Security Inspection ?

Difficulties and Related Works

Difficulties:
(1) Various
(2) Small
(3) Randomly stacked
(4) Heavily overlapped



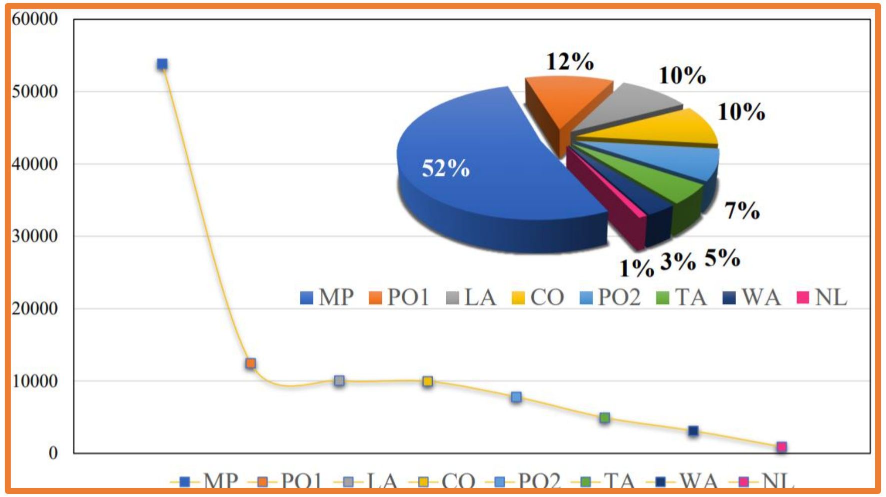
Related Works:

Dataset	Year	Category	N_p	Annotation			Color	Task	Data Source
				Bounding Box	Number	Professional			
GDXray [23]	2015	3	8,150	✓	8,150	✗	Gray-scale	Detection	Unknown
SIXray [25]	2019	6	8,929	✗	✗	✗	RGB	Classification	Subway Station
OPIXray [40]	2020	5	8,885	✓	8,885	✓	RGB	Detection	Artificial Synthesis
HiXray	**2021**	**8**	**45,364**	✓	**102,928**	✓	RGB	Detection	Airport

High-quality X-ray (**HiXray**) security inspection image dataset

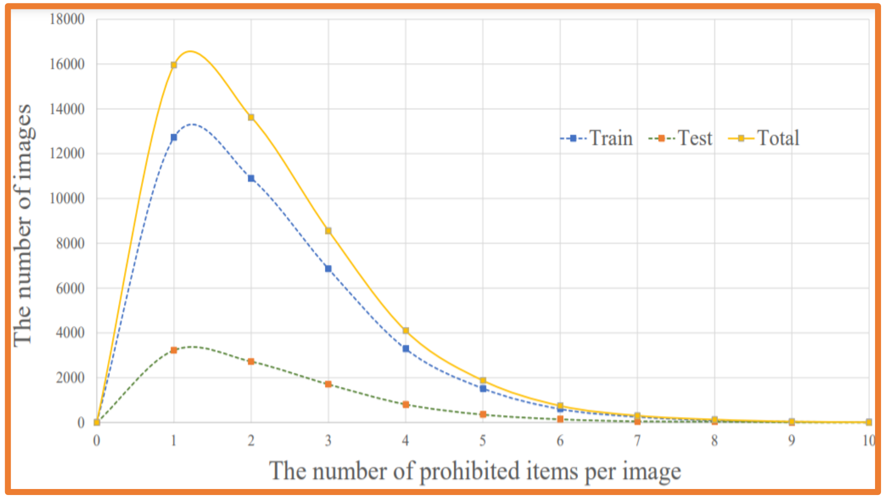
Category	PO1	PO2	WA	LA	MP	TA	CO	NL	Total
Training	9,919	6,216	2,471	8,046	43,204	3,921	7,969	706	82,452
Testing	2,502	1,572	621	1,996	10,631	997	1,980	177	20,476
Total	12,421	7,788	3,092	10,042	53,835	4,918	9,949	883	102,928

The distribution of instances per category.



N_i	1	2	3	4	5	6	7	8	9	10
Training	12,726	10,905	6,860	3,286	1,521	602	254	91	35	11
Testing	3,227	2,722	1,705	810	354	145	54	41	8	2
Total	15,953	13,627	8,565	4,096	1,875	747	308	132	43	13

The distribution of instances per image.



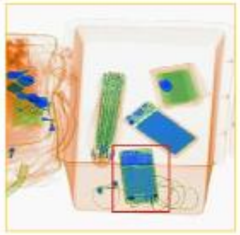
Potential Tasks

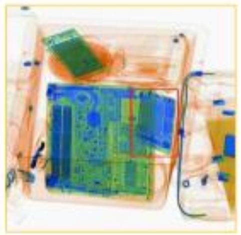
Small object detection

Category	Total	Large	Medium	Small
PO2	2,502	587	986	929
MP	10,631	3,547	4,248	2,836

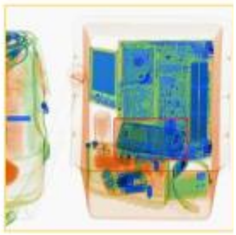
Table 5. The category distribution of “Portable Charger 2” and “Mobile Phone” (PO2 and MB for short) when the two thresholds are set as 0.1% and 0.2%.

Occluded object detection





OL 1
(no or slight occlusion)



OL 2
(partial occlusion)

OL 3
(severe or full occlusion)

Few shot Detection

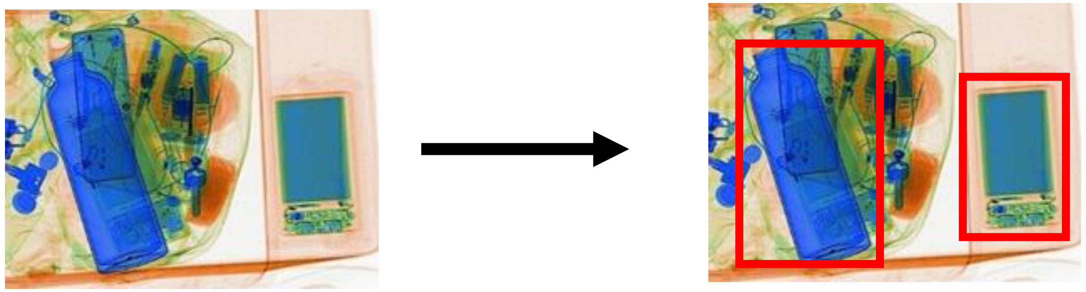
Category	PO1	PO2	WA	LA	MP	TA	CO	NL	Total
Training	9,919	6,216	2,471	8,046	43,204	3,921	7,969	706	82,452
Testing	2,502	1,572	621	1,996	10,631	997	1,980	177	20,476
Total	12,421	7,788	3,092	10,042	53,835	4,918	9,949	883	102,928

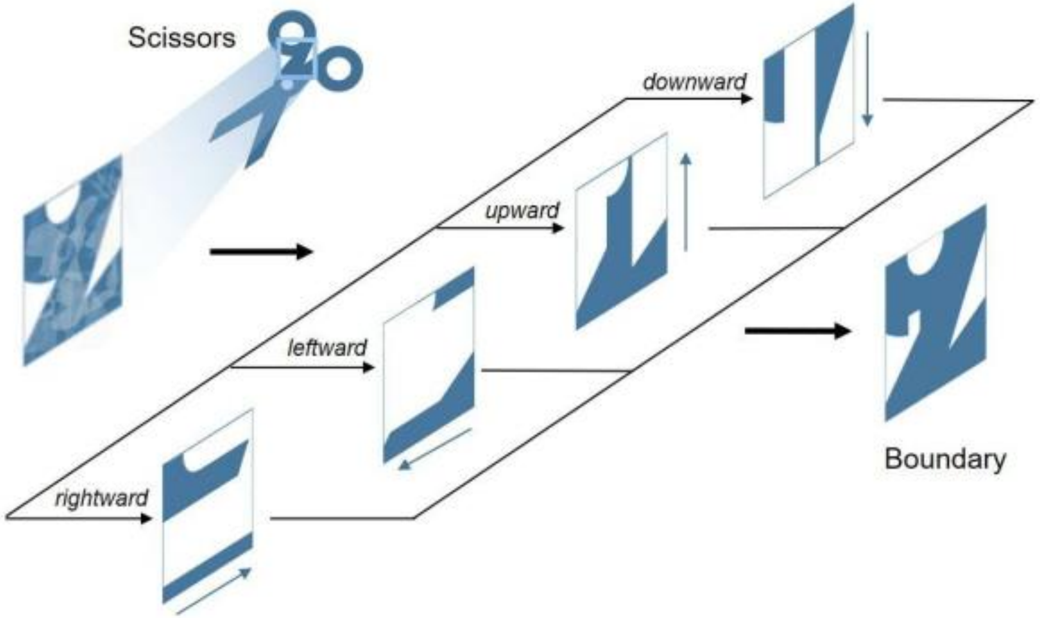
Dataset Access

https://github.com/HiXray-author/HiXray

rstao@buaa.edu.cn

LIM Model

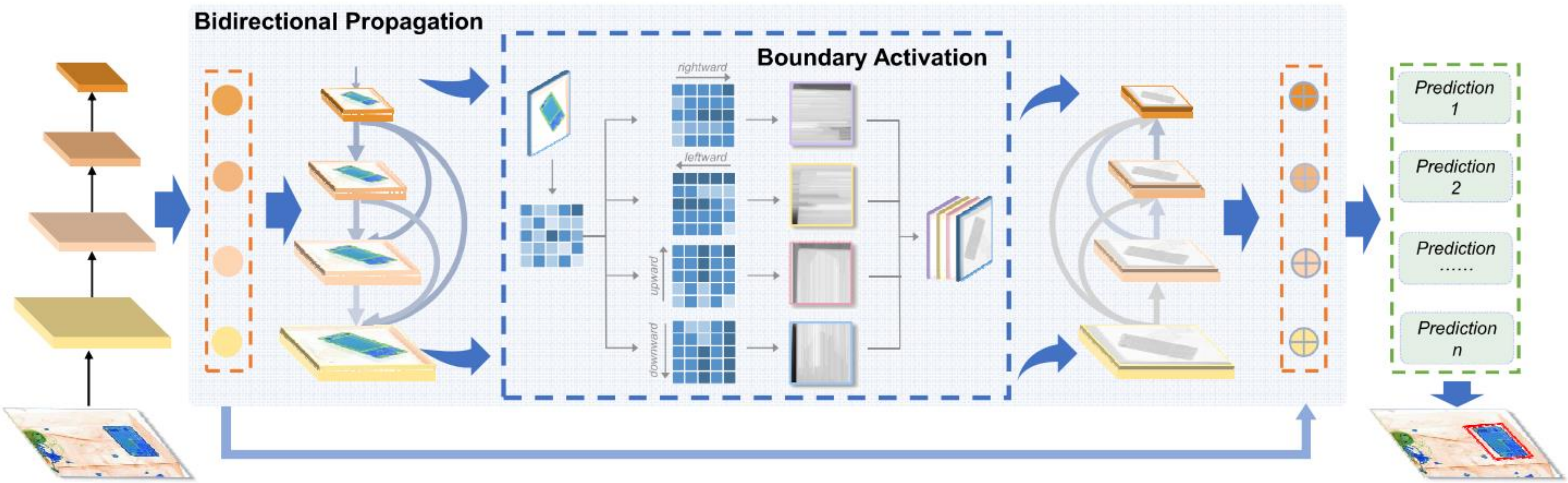




出发点：

1. 我们认为，X光成像下，最大程度地保留了物体的形状特征，而这种形状特征通过边缘的形式最大化地进行了体现。因此，我们想到在卷积神经网络中强化边缘的操作。
2. X光成像过程中，待检测物体周围有很多噪音，我们要赋予网络更多的特征学习的能力，最大程度筛选掉这些噪音信息。

LIM Model



双向传播的左侧： $$\mathbf{A}^l = \mathcal{V}\left(\mathcal{F}^l(\mathbf{x})\right) + \sum_{m=1}^{L-l} \mathcal{U}^m\left(\mathbf{A}^{l+m}\right), \tag{1}$$

双向传播的右侧： $$\mathbf{C}_{\mathrm{t}}^l = \mathcal{V}\left(\mathbf{B}^l\right) + \sum_{m=1}^{l-1} \mathcal{D}^m\left(\mathbf{C}_{\mathrm{t}}^{l-m}\right), \tag{2}$$

左右聚合： $$\mathbf{C}^l = \mathbf{C}_{\mathrm{t}}^l + \mathcal{F}^l(\mathbf{x}), \tag{3}$$

边界激活操作： $$\mathbf{B}_{ijc}^l = \begin{cases} \mathbf{A}_{iWc}^l & \text{if } j = W, \\ \max\left\{\mathbf{A}_{ijc}^l, \mathbf{A}_{i(j+1)c}^l, \ldots, \mathbf{A}_{iWc}^l\right\} & \text{otherwise}, \end{cases} \tag{4}$$

Experiments

Comparing with detection methods:

Method	HiXray Dataset (**Ours**)									OPIXray Dataset [40]					
	AVG	PO1	PO2	WA	LA	MP	TA	CO	NL	**AVG**	FO	ST	SC	UT	MU
SSD [20]	71.4	87.3	81.0	83.0	97.6	93.5	92.2	36.1	0.01	70.9	76.9	35.0	93.4	65.9	83.3
SSD+DOAM [40]	72.1	88.6	82.9	83.6	97.5	94.1	92.1	38.2	0.01	74.0	81.4	41.5	95.1	68.2	**83.8**
SSD+LIM	**73.1**	**89.1**	**84.3**	**84.0**	**97.7**	**94.5**	**92.4**	**42.3**	**0.1**	**74.6**	**81.4**	**42.4**	**95.9**	**71.2**	82.1
FCOS [35]	75.7	88.6	86.4	86.8	89.9	88.9	88.9	63.0	13.3	82.0	86.4	68.5	90.2	78.4	86.6
FCOS+DOAM [40]	76.2	88.6	87.5	87.8	89.9	89.7	88.8	63.5	12.7	82.4	86.5	68.6	90.2	78.8	**87.7**
FCOS+LIM	**77.3**	**88.9**	**88.2**	**88.3**	**90.0**	**89.8**	**89.2**	**69.8**	**14.4**	**83.1**	**86.6**	**71.9**	**90.3**	**79.9**	86.8
YOLOv5 [14]	81.7	95.5	94.5	92.8	97.9	98.0	94.9	63.7	16.3	87.8	93.4	67.9	98.1	85.4	94.1
YOLOv5+DOAM [40]	82.2	95.9	94.7	93.7	98.1	98.1	95.8	65.0	16.1	88.0	93.3	69.3	97.9	84.4	**95.0**
YOLOv5+LIM	**83.2**	**96.1**	**95.1**	**93.9**	**98.2**	**98.3**	**96.4**	**65.8**	**21.3**	**90.6**	**94.8**	**77.6**	**98.2**	**88.9**	93.8

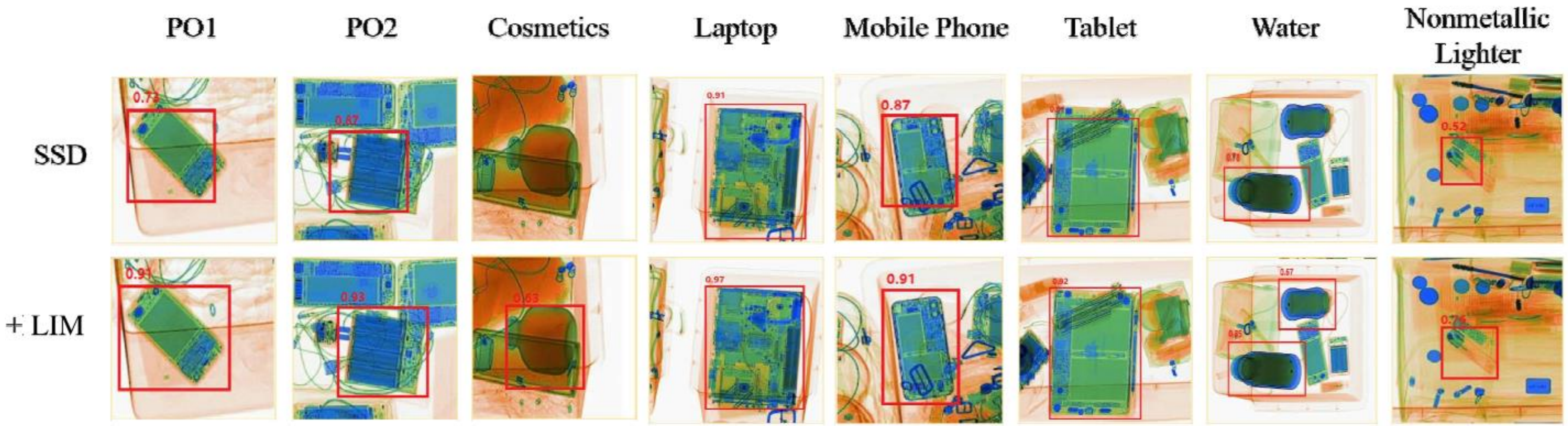
Comparing with Pyramid Networks:

Method	**AVG**	PO1	PO2	WA	LA	MP	TA	CO	NL
SSD [20]	71.4	87.3	81.0	83.0	97.6	93.5	92.2	36.1	0.01
+FPN [17]	72.0	87.4	81.5	83.2	97.9	93.9	92.2	40.3	0.02
+PANet [39]	72.0	88.3	83.2	82.8	**97.9**	93.8	**92.6**	37.3	0.01
+LIM	**73.1**	**89.1**	**84.3**	**84.0**	97.7	**94.5**	92.4	**42.3**	**0.1**

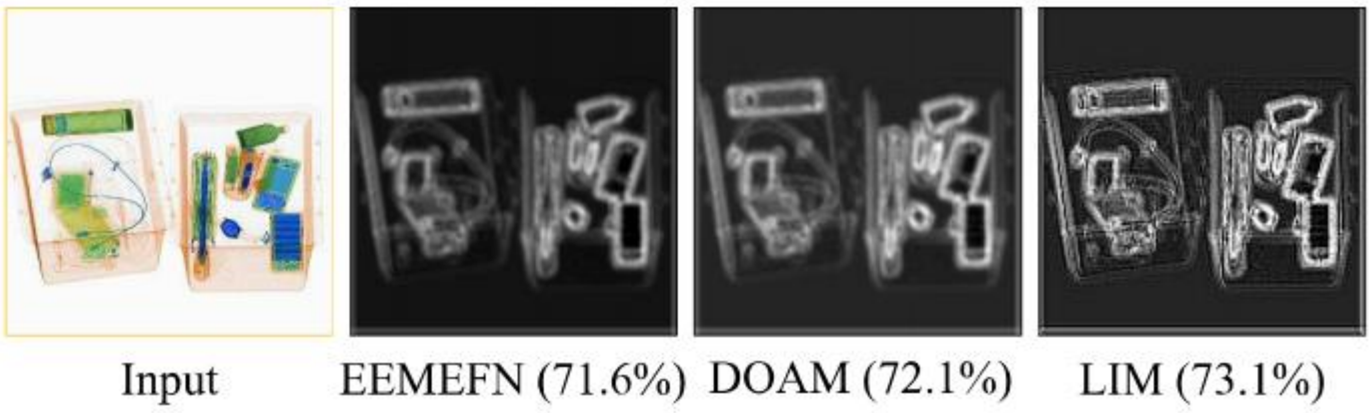
Ablation Studies:

Method	**AVG**	PO1	PO2	WA	LA	MP	TA	CO	NL
SSD [20]	71.4	87.3	81.0	83.0	97.6	93.5	92.2	36.1	0.01
+SP	72.1	87.9	82.3	83.8	97.9	92.4	92.6	38.8	0.63
+BP	72.6	88.1	83.4	83.9	**97.8**	93.8	**92.8**	40.3	0.03
+BP+BA	**73.1**	**89.1**	**84.3**	**84.1**	97.7	**94.5**	92.4	**42.3**	**0.1**

Visualization



Visualization of SSD and SSD+LIM



Visualization of the boundary aggregation

一、课题组其他相关X光工作：

1. 遮挡X光目标检测（ACM MM 2020）

研究内容：我们研究不同遮挡程度对检测性能的影响，构建了OPIXray遮挡分级数据集，并提出DOAM模块，通过特定的注意力机制来提高模型在遮挡情境下的性能。

2. 不同X光机上模型迁移检测（研究中）

研究内容：由于不同X光机成像差异，导致模型在不同X光机间的迁移性能很差。在没有大量目标机器图片标注的情况下，如何提升模型跨域检测的性能？

3. X光对抗攻防（研究中）

研究内容：在X光安检场景下，通过打印贴片放进行李箱的方式，是否使违禁品逃脱检测模型的识别？

二、联合工业界探讨：人工智能时代下，AI安检离我们还有多远？

PRCV 2021 专题论坛之

X 光安检场景下的违禁品检测

万方，中国科学院大学；陶仁帅，北京航空航天大学；

王伯英，中国科学院大学；金博伟，科大讯飞股份有限公司

Thank you for listening!

陶仁帅
软件开发环境国家重点实验室 博士生
北京航空航天大学
个人主页：rstao95.github.io

刘祥龙
教授、博士生导师、国家优青获得者
北京航空航天大学
个人主页：sites.nlsde.buaa.edu.cn/~xlliu

For more information, welcome to click on our home page!