Improving Few-Shot and Cross-Domain Object Detection on Aerial Images with a Diffusion-Based Detector.

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2024 IEEE International Geoscience and Remote Sensing Symposium
July 11, 2024

Overview of the presentation

1. Principle of Object Detection and Few-Shot Object Detection
2. Related Work
3. Application on Remote Sensing Images
4. Proposed Approaches
5. Perspectives
6. Conclusion

1.1 Object Detection

Regular Object Detection

Given a set of classes $\mathcal{C}$, find all occurences of objects belonging to any class $c \in \mathcal{C}$ in an image I. Each object is reprented as (x_1, y_1, x_2, y_2, c).

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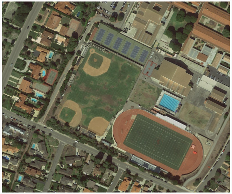

Input image I

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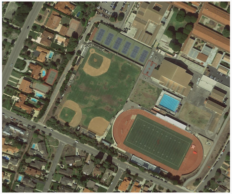

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$$\mathcal{C} = \{\text{Baseball-diamond, Swimming-pool, Ground-track-field}\}$$

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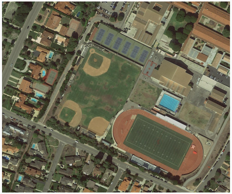

Input image I

$\longrightarrow$ Detection model

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Input image I — Detection results

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n-way k-shot object detection

Given support examples $\{(x_1, a_1), \ldots, (x_{nk}, a_{nk})\}$ it consists in detecting all occurrences of classes in $\mathcal{C}$ ($|\mathcal{C}| = n$) in a query image x_q.

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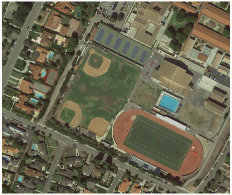

Query image

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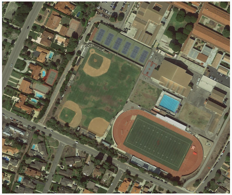

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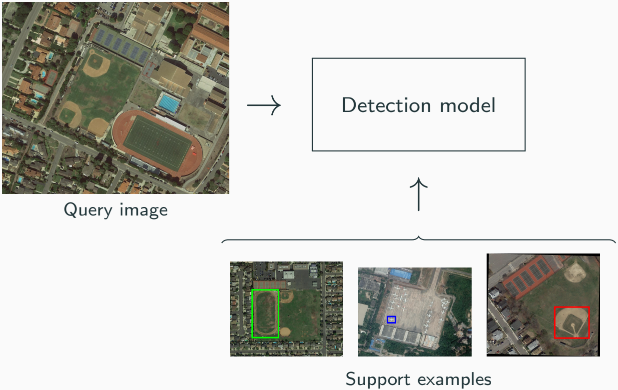

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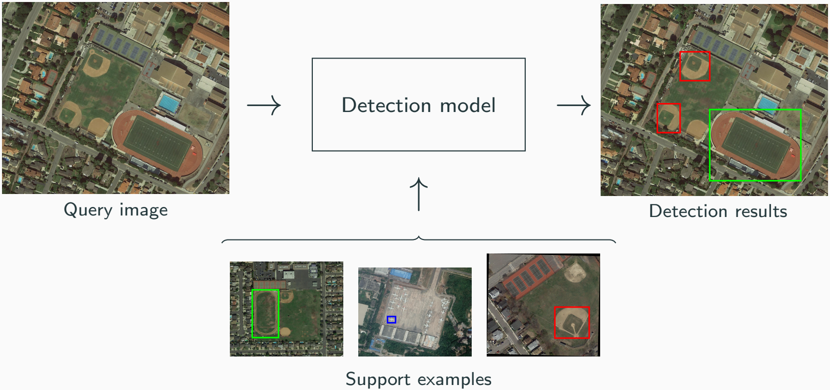

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Cross-Domain Few-Shot Object Detection

In Cross-Domain Few-Shot Object Detection (CD-FSOD), two distinct datasets are used during base training and fine-tuning. CD-FSOD is more challenging as the model must not only adapt to new classes but also to new images.

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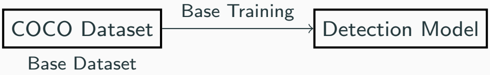

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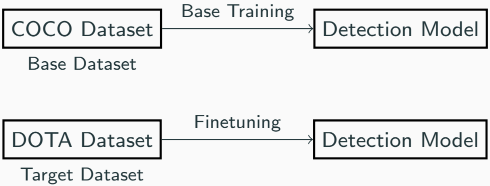

2.1 Few-Shot Object Detection

Plenty of methods introduced for FSOD, based on **Fine-tuning**, **Metric-learning** and **Attention**.

- **Fine-tuning**: train carefully on the few available examples to avoid overfitting or catastrophic forgetting.
- **Metric learning**: compute prototypes from support examples and classify boxes by comparison with the prototypes.
- **Attention**: combine query and support information and separately detect objects for each class.

2.1 Few-Shot Object Detection

Approach	Name	Framework	Episodic Training	Datasets
Attention	FRW (Kang et al. 2019)	YOLO (no FPN)	Yes	Pascal / COCO
	RSI (X. Li, Deng, and Fang 2021)	YOLO	Yes	DIOR / NWPU VHR
	MRCNN (Yan et al. 2019a)	Faster R-CNN (no FPN)	Yes	Pascal / COCO
	ARMRD (Q. Fan et al. 2020)	Faster R-CNN	No	COCO
	VEOW (Y. Xiao and Marlet 2020)	Faster R-CNN	No	Pascal / COCO
	SAA (Z. Xiao et al. 2021)	Faster R-CNN	No	RSOD / NWPU VHR
	CACE (Hsieh et al. 2019)	Faster R-CNN	No	Pascal / COCO
	KT (Kim, Jung, and S.-W. Lee 2020)	Faster R-CNN	No	Pascal
	IFSOD (Ganea, Boom, and Poppe 2021)	Center Ne (no FPN)	Yes	Pascal / COCO / Deepfashion
	WOFT (X. Li, L. Zhang, et al. 2020)	FCOS	Yes	Pascal / COCO
	FPDI (Gao et al. 2021)	Faster R-CNN	No	DOTA / NWPU VHR
	MFRCN (Yan et al. 2019b)	Faster R-CNN	No	Pascal / COCO
	MDETR (G. Zhang, Luo, et al. 2022)	DETR (no FPN)	No	Pascal / COCO
	DRL (W. Liu et al. 2021)	Faster R-CNN	Yes	Pascal / COCO
	DANA (T.-I. Chen et al. 2021)	Faster R-CNN and RetinaNet	Yes	Pascal / COCO
	SP (H. Xu et al. 2021)	Faster R-CNN	No	Pascal / COCO
	JCACR (Chu et al. 2021)	YOLO	No	Pascal / COCO
	TI (A. Li and Z. Li 2021)	Faster R-CNN	Yes	Pascal / COCO
	FCT (G. Han et al. 2022)	Faster R-CNN	No	Pascal / COCO
Attention/ Metric	PNPDet(G. Zhang, Cui, et al. 2021)	Center Net (no FPN)	No	Pascal / COCO
	UPE (A. Wu, Y. Han, et al. 2021)	Faster R-CNN	No	Pascal / COCO
	GD (L. Liu et al. 2021)	FCOS	Yes	Pascal / COCO
Metric Learning	RM (Karlinsky et al. 2019)	Faster R-CNN	No	Pascal / ImageNet Loc
	RNI (Yang et al. 2020)	Faster R-CNN	No	Pascal / ImageNet Loc
	FSCE (Sun et al. 2021)	Faster R-CNN	No	Pascal / COCO
	PFRCN (Jeune et al. 2021)	Faster R-CNN	Yes	DOTA / DIOR
	AD (Cao et al. 2021)	Faster R-CNN	No	Pascal / COCO
	GDSVD (A. Wu, Zhao, et al. 2021)	Faster R-CNN	No	Pascal / COCO
Fine-tuning	LSTD (H. Chen et al. 2018)	Faster R-CNN	No	Pascal / COCO
	WOFG (Z. Fan et al. 2021)	Faster R-CNN	No	Pascal / COCO
	TFA (X. Wang et al. 2020)	Faster R-CNN	No	Pascal / COCO
	MSPSR (Jiaxi Wu et al. 2020)	Faster R-CNN	No	Pascal / COCO
	DETRG (Bar et al. 2022)	Faster R-CNN	No	COCO
	HFSOD (W. Zhang and Y.-X. Wang 2021)	Faster R-CNN	No	Pascal / COCO
	DHP (Wolf et al. 2021)	Faster R-CNN	No	iSAID / NWPU VHR
	SAM (Huang et al. 2021)	Faster R-CNN	No	DIOR / NWPU VHR
	SIMPL (Y. Xu et al. 2021)	Faster R-CNN (no FPN)	No	xView (plane only)

Table 1: Comparison of the FSOD methods from an attention perspective. All frameworks are working with multiscale features except for the one with the mention no FPN.

3.1 Difference Between Natural and Aerial Images

Most methods are evaluated on natural images: Pascal VOC and MS COCO datasets.
$\Rightarrow$ this does not guarantee good performance on aerial images.

Objects' sizes are extremely different between aerial and natural images.

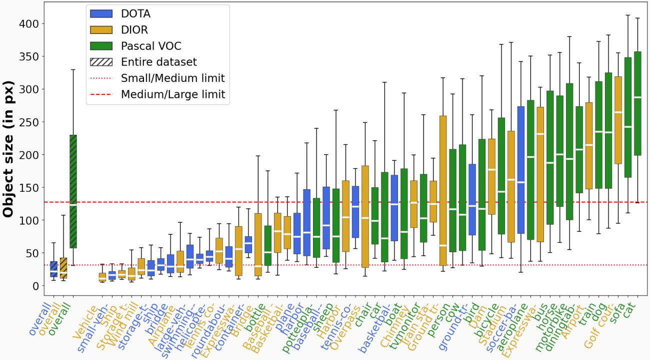

Figure 1: Boxplot of objects' size in DOTA (Xia et al. 2018), DIOR (K. Li et al. 2020) and Pascal VOC (Everingham et al. 2010); per class **(right)** and overall **(left)**.

3.2 Performance Analysis

Impossible to compare performance on different datasets. However, it is possible to compare FSOD performance against non few-shot baseline and compare this across several datasets.

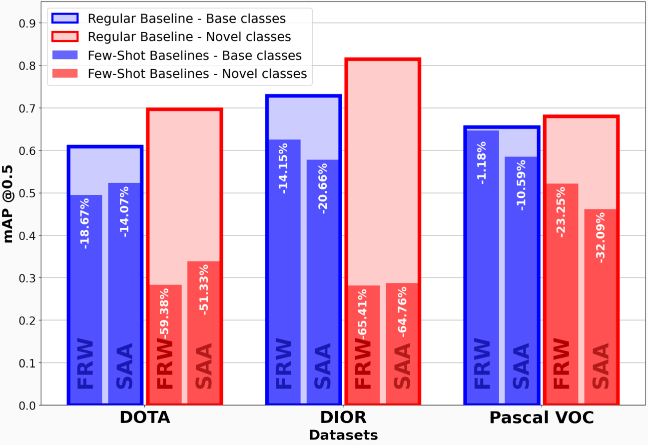

Figure 2: FSOD performance compared on DOTA, DIOR and Pascal VOC. (Le Jeune and Mokraoui 2022)

Large size discrepencies between average class size suggests analyzing performance per class. Clear correlation between average class size and performance compared to baseline.

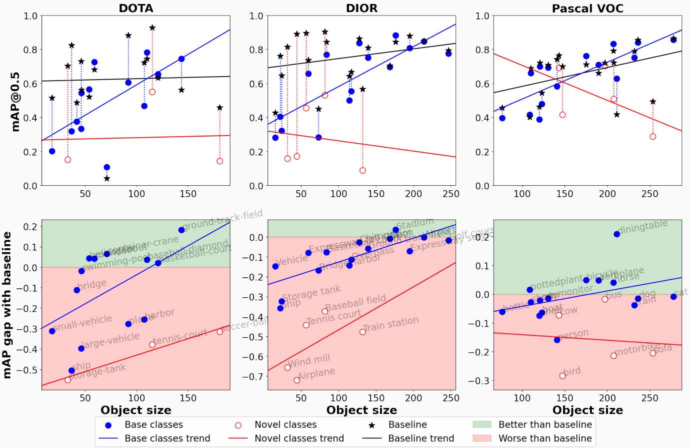

Figure 3: Per class performance analysis and comparison with non few-shot baseline on DOTA, DIOR and Pascal VOC. (Le Jeune and Mokraoui 2022)

4.1 Diffusion Based Models

The main idea of DiffusionDet is to apply the diffusion principle to box generation.

Random boxes are first sampled, and a model is trained to refine iteratively the size and position of the boxes so that they localize the objects in the input image.

Specifically, the boxes are iteratively denoised by the model.

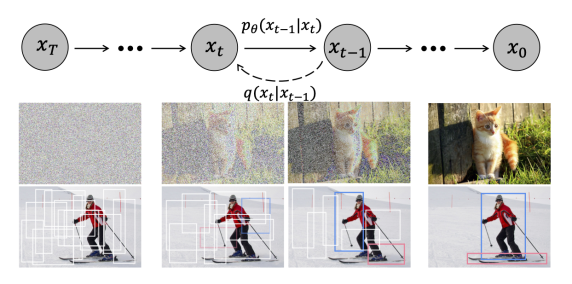

Figure 4: Diffusion model for object detection. In the first line a diffusion model where q is the diffusion process and p_θ is the reverse process. Then a diffusion model for image generation task. And in the last one we propose to formulate object detection as a denoising diffusion process from noisy boxes to object boxes.
taken from DiffusionDet paper Shoufa Chen et al. 2022

4.1 Diffusion Based Models

The denoising part of DiffusionDet is a lightweight hybrid network, it consists of a self-attention layer (transformer-like) followed by a dynamic layer (called an Instance Interaction layer). The detection head processes object features independently, but the Instance Interaction layer enables interactions between instances. The detection head is applied iteratively to refine the bounding boxes

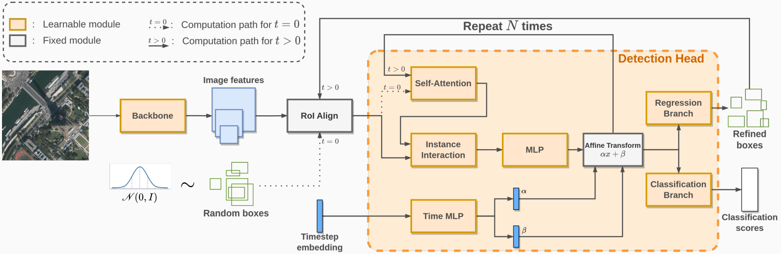

Figure 5: DiffusionDet architecture and detailed detection head design.

4.2 Few-Shot DiffusionDet

Let us introduce some notations.

We denote by $\mathcal{F}_c$ and $\mathcal{F}_r$ the sub-models responsible for classification and regression respectively:

$$\mathcal{F}_c = f_c \circ f, \tag{1}$$

$$\mathcal{F}_r = f_r \circ f, \tag{2}$$

$$\text{with } f = f^{L-1} \circ f^{L-2} \circ \cdots \circ f^{1}. \tag{3}$$

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To leverage DiffusionDet in the few-shot regime, we propose to adopt a Transfer Learning approach. Once, the model is base-trained, it is prepared for fine-tuning.

A large part of the model is frozen. The crucial part is that we can finely control the amount of frozen layers with a hyperparameter γ.

Denoting frozen layers with a bar ($\overline{f^1}$), the frozen detection model is expressed as

$$f = f^L \circ \cdots \circ f^{\gamma+1} \circ \overline{f^\gamma} \circ \cdots \circ \overline{f^1}. \tag{4}$$

4.3 Freezing Sweet-Spot

Determining how much of the model should be fine-tuned is a complex task in FSOD. Here, we investigate this choice with thorough experiments on four datasets.

Freezing point	Plasticity	DOTA	DIOR	Pascal VOC	COCO
FT whole	100.00 %	60.09	52.17	43.10	17.15
Bias only	35.98 %	**60.45**	55.12	49.90	20.19
BatchNorm only	35.97 %	59.35	55.63	51.96	19.70
Up to stage 1	99.98 %	58.85	53.37	43.81	17.72
Up to stage 4	99.47 %	57.41	53.21	41.23	17.73
Up to stage 3	96.57 %	59.88	54.36	47.57	19.49
Up to stage 4	79.66 %	56.13	**57.51**	**53.72**	**21.88**
FT head only	35.97 %	51.82	55.70	51.72	19.96
FT last layer only	0.03 %	0.05	0.11	0.53	0.01

Table 2: Influence of the freezing point on the FS performance on DOTA, DIOR, Pascal VOC, and COCO. mAP is reported with a 0.5 IoU threshold and $k = 10$ shots.

4.4 Cross-Domain Senarios

The great results of FSDD on aerial images suggest trying the more complex scenario of CD-FSOD almost untouched in the literature.

-1st Senario: COCO $\rightarrow$ X,

k **Shots**	**DIOR**	**DOTA**	**DeepFruits**	**SIXRay**	**VisDrone**
1	11.10	4.03	38.47	4.80	2.83
5	30.42	14.45	55.58	13.25	5.74
10	38.73	25.02	68.37	21.26	7.50
20	48.23	33.31	73.95	30.06	9.14
50	56.97	43.23	76.65	41.93	11.47

Table 3: Cross-domain performance results on 5 scenarios COCO $\rightarrow$ DIOR / DOTA / DeepFruits (K. Lee et al. 2022) / SIXRay (Miao et al. 2019) / VisDrone (Zhu et al. 2021).

4.4 Cross-Domain Senarios

-2nd Senario: DOTA $\rightarrow$ DIOR and DIOR $\rightarrow$ DOTA,

	DOTA $\rightarrow$ DIOR		**DIOR $\rightarrow$ DOTA**	
***k* shots**	**FT head only**	**FT whole**	**FT head only**	**FT whole**
1	**20.18**	9.40	**5.41**	5.09
5	**34.43**	29.57	**25.88**	24.90
10	**41.48**	38.44	31.99	**33.30**
20	**49.00**	45.36	38.77	**41.30**
50	**54.07**	53.51	44.07	**49.22**

Table 4: FSDiffusionDet Cross-Domain (CD-FSOD) results on the scenarios DOTA $\rightarrow$ DIOR and DIOR $\rightarrow$ DOTA. Performance is reported with $mAP_{0.5}$ values.

This analysis of the freezing point is a first in the FSOD domain and should be extended as future work.

- Here it is a **hyperparameter**, we can expect to find a criteria to find it **automatically** according to datasets and model.
- This idea could be expanded to **cross-domain** tasks by identifying the base dataset that yields the best results for our target dataset.

6.0 Conclusion

To summarize, our contributions are:

- A **novel FSOD model** and a training strategy with greater versatility than existing approaches,
- Extensive experiments to showcase the superiority of **FSDD** over existing **FSOD** methods on **aerial images**, and
- A demonstration of promising results in the challenging **CD-FSOD** scenarios.

Thank you for your attention

Any questions ?

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