

# Foggy-DOTA: An Adverse weather Dataset for Object detection in Aerial images

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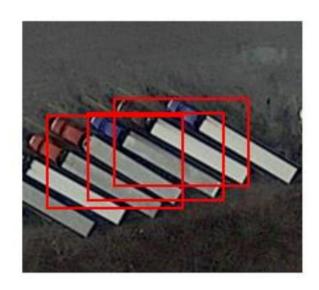
- 1. Introduction.
- 2. Foggy-DOTA dataset.
- 3. Computational models.
- 4. Evaluation and Discussion.
- 5. Conclusion and Future work.



## **INTRODUCTION**







(a) Horizontal object detector

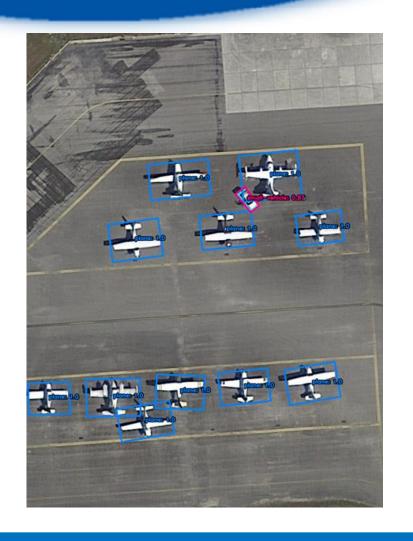


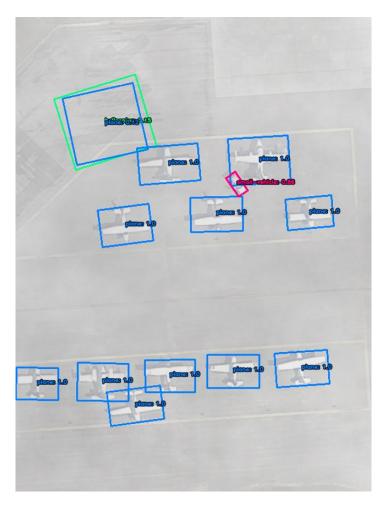
(b) Oriented object detector

## Introduction









## Contributions



- 1. Introducing a well-designed Foggy-DOTA dataset.
- 2. Re-implementing three SOTA (S2ANet, ReDet, Rol Transformer) methods to give an in-depth analysis of this methods and dataset's challenge.



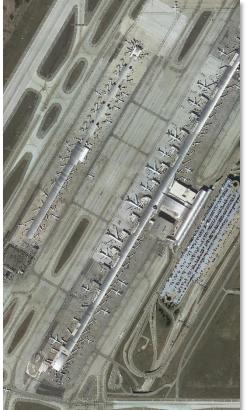
### **FOGGY-DOTA DATASET**

## Foggy-DOTA dataset WNUHCM





- DOTA is a large-scale aerial object detection dataset proposed in 2018.
  - + **2,806** images
  - + 15 classes: plane, baseballdiamond, bridge, ground-trackfield, small-vehicle, large-vehicle, ship, tennis court, basketball court, storage tank, soccer-ballfield, roundabout, harbor, swimming pool, and helicopter.





# Foggy-DOTA dataset WNUHCM







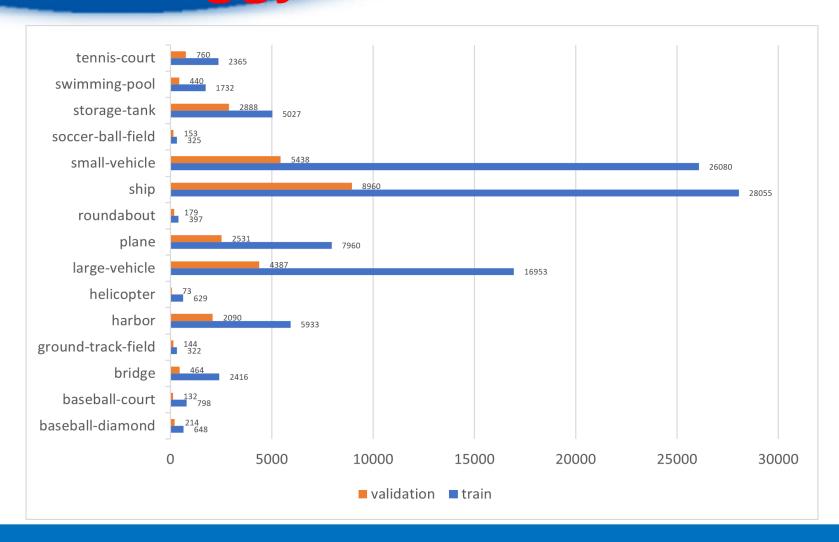
**Imagaug** 



## Foggy-DOTA dataset WNUHCM







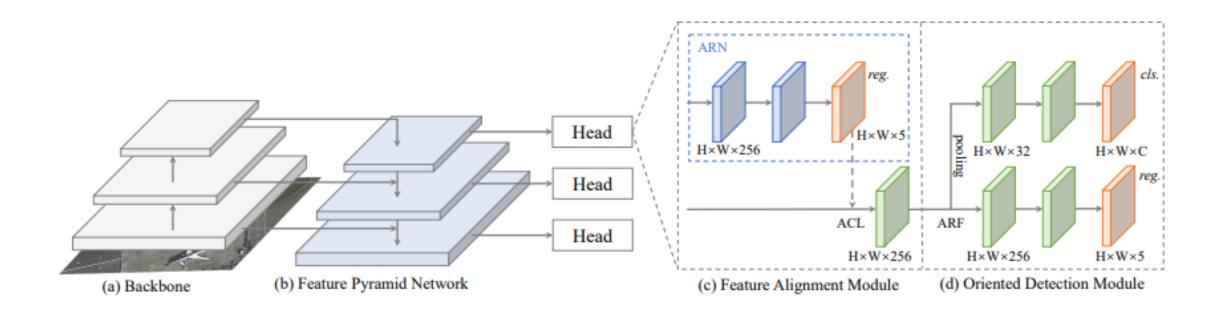


#### **COMPUTATIONAL MODELS**

## Computational models VNUHCM



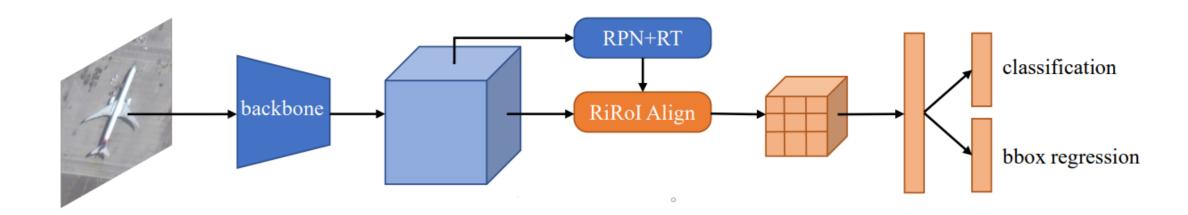
#### 1. S2ANet







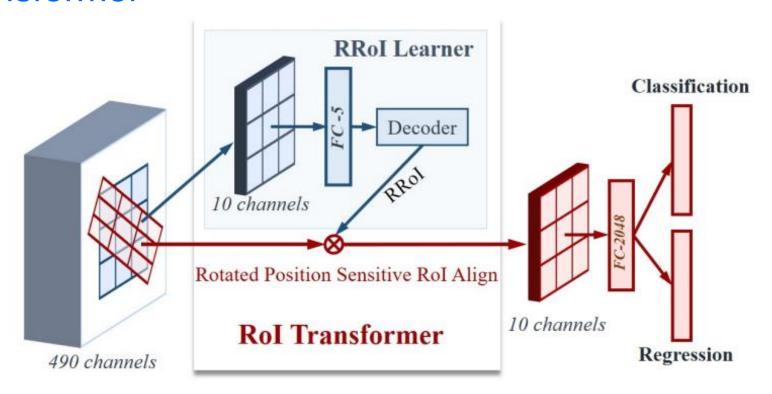
#### 2. ReDet







#### 3. Rol Transformer





### **EVALUATION AND DISCUSSION**

## **Evaluation Metrics**



— Intersection over Union (IoU):

$$loU = \frac{Area \ of \ Overlap}{Area \ of \ Union}$$

Mean Average Precision (mAP) – MS COCO

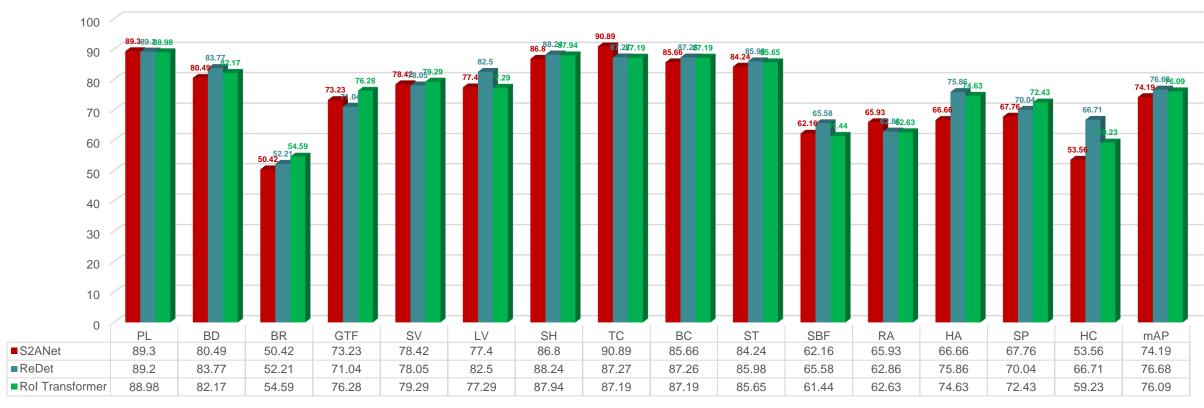
$$mAP@\alpha = \frac{1}{n} \sum_{i=1}^{n} AP_i$$
 for n classes

+ mAP: AP at IoU = .50:.05:.95





#### EXPERIMENTAL RESULTS ON MODELS TRAINED AND TESTED ON THE ORIGINAL DOTA DATASET

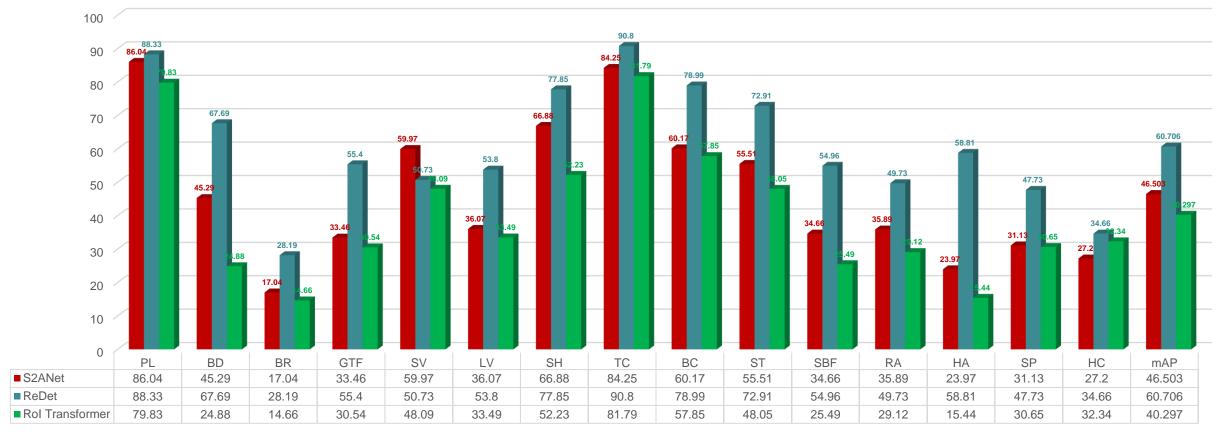


■S2ANet ■ReDet ■Rol Transformer



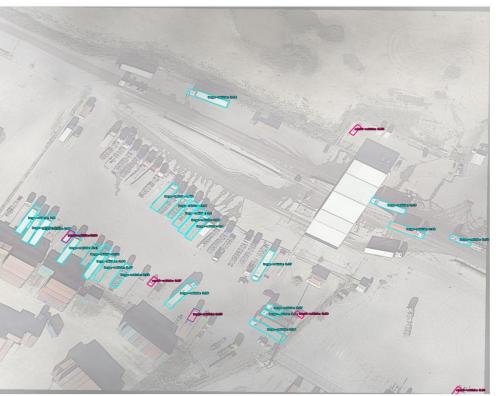


#### EXPERIMENTAL RESULTS ON MODELS TRAINED ON THE ORIGINAL DOTA AND TESTED ON THE FOGGY-DOTA









ReDet trained on the original DOTA

Left: test on original DOTA. Right: test on Foggy-DOTA





#### EXPERIMENTAL RESULTS ON MODELS TRAINED AND TESTED ON THE FOGGY-DOTA DATASET







ReDet trained and test on Foggy-DOTA





#### TABLE I

#### EXPERIMENTAL RESULTS ON MODELS TRAINED AND TESTED ON THE ORIGINAL DOTA DATASET

Computational Models	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	mAP
S2ANet	89.3	80.49	50.42	73.23	78.42	77.4	86.8	90.89	85.66	84.24	62.16	65.93	66.66	67.76	53.56	74.19
ReDet	89.2	83.77	52.21	71.04	78.05	82.5	88.24	90.86	87.26	85.98	65.58	62.86	75.86	70.04	66.71	76.68
RoI Transformer	88.98	82.17	54.59	76.28	79.29	77.96	87.94	90.91	87.19	85.65	61.44	62.63	74.63	72.43	59.23	76.09

#### TABLE II

#### EXPERIMENTAL RESULTS ON MODELS TRAINED ON THE ORIGINAL DOTA AND TESTED ON THE FOGGY-DOTA DATASET

Computational Models	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	mAP
S2ANet	86.04	45.29	17.04	33.46	59.97	36.07	66.88	84.25	60.17	55.51	34.66	35.89	23.97	31.13	27.20	46.503
ReDet	88.33	67.69	28.19	55.4	50.73	53.80	77.85	90.80	78.99	72.91	54.96	49.73	58.81	47.73	34.66	60.706
RoI Transformer	79.83	24.88	14.66	30.54	48.09	33.49	52.23	81.79	57.85	48.05	25.49	29.12	15.44	30.65	32.34	40.297

#### **TABLE III**

#### EXPERIMENTAL RESULTS ON MODELS TRAINED AND TESTED ON THE FOGGY-DOTA DATASET

Computational Models	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	mAP
S2ANet	89.08	72.01	45.92	69.44	79.07	75.14	85.9	90.88	80.34	84.26	57.81	61.85	65.24	67.12	50.38	71.629
ReDet	89.46	75.67	50.80	69.46	79.14	77.65	88.25	90.88	85.84	84.78	60.53	57.68	74.87	67.28	60.61	74.194
RoI Transformer	89.05	75.37	47.23	70.37	79.03	76.96	87.65	90.91	82.97	84.95	57.00	58.02	68.59	71.04	61.58	73.381



## **CONCLUSION AND FUTURE WORK**

### Conclusion



- 1. We introduced the fine Foggy-DOTA dataset for adverse weather oriented/horizontal object detection in aerial images.
- 2. We experiment extensively with many oriented object detection methods to provide an in-depth analysis of dataset challenges and model structures.

### **Future** work



1. In the future, we're opening our scope more to aerial image object detection as well as image adaptive for adverse weather conditions.

#### References



[1] Han, J., Ding, J., Xue, N., & Xia, G. S. (2021). Redet: A rotation-equivariant detector for aerial object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2786-2795).

[2] Ding, J., Xue, N., Long, Y., Xia, G. S., & Lu, Q. (2019). Learning Rol transformer for oriented object detection in aerial images. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2849-2858).

#### References



[3] Han, J., Ding, J., Li, J., & Xia, G. S. (2021). Align deep features for oriented object detection. IEEE Transactions on Geoscience and Remote Sensing, 60, 1-11.



#### THANK YOU FOR YOUR ATTENTION!

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