

# Bottle Detection in the Wild Using Low-Altitude Unmanned Aerial Vehicles

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# Outline

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1. Introduction
2. UAV-Bottle Dataset
3. Baselines and Methods
4. Conclusion and Future Work



# Introduction

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# Motivation

It's very **dangerous** for the sanitation workers who pick up rubbish on the mountain. Can we help them? Yes!

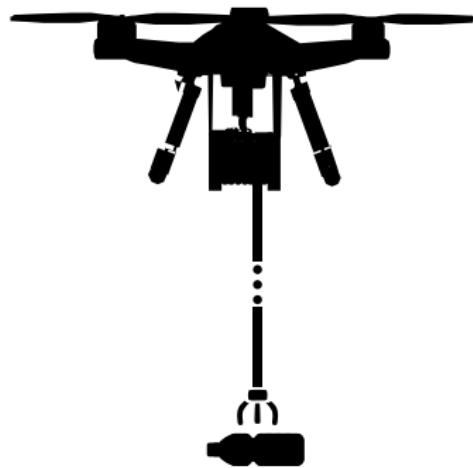


The sanitation workers on the Huashan Mountain.



# Motivation

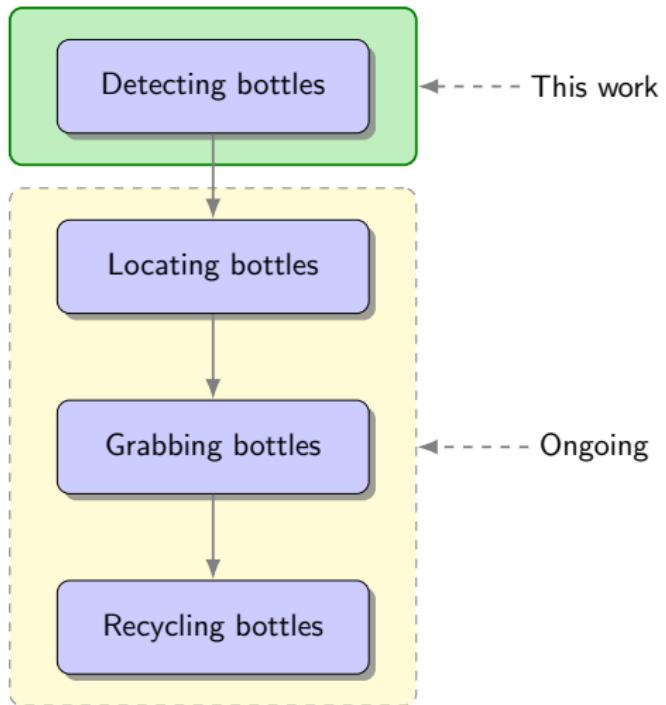
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UAVs can help them!

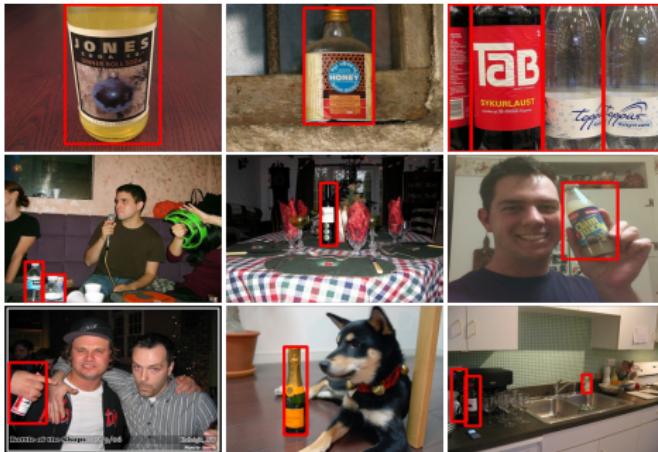


# Pipeline



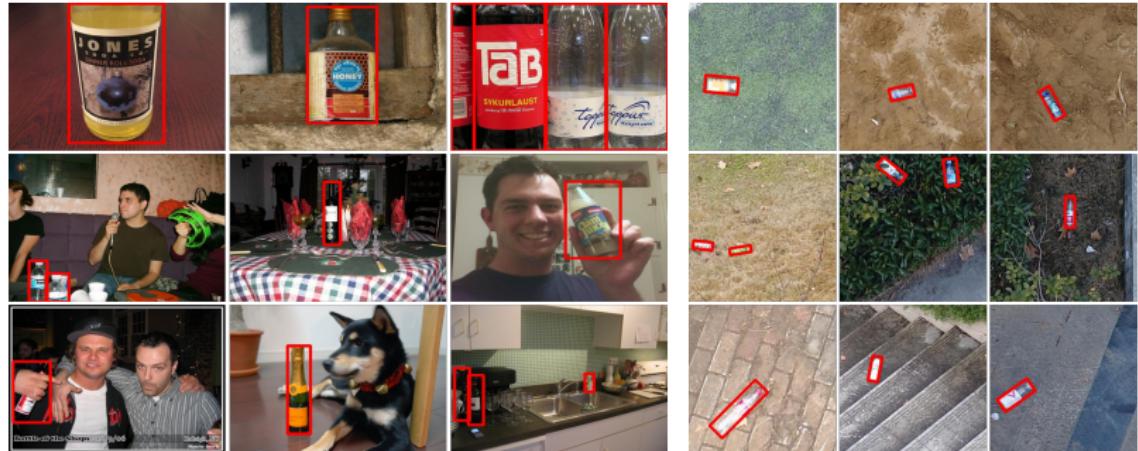
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- ① The size is very small, generally less than  $50 \times 50$  pixels.
- ② Backgrounds are very complex.
- ③ Arbitrary orientations.
- ④ Plastic bottles are often transport, increasing the difficulty of detection.

# UAV-Bottle Dataset

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# Dataset

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To build a baseline for bottle detection in UAV images, we establish a large scale bottle detection dataset, we call **UAV-Bottle Dataset(UAV-BD)** and benchmark.



# Dataset Collection

We used **DJI Phantom 4 Pro** to collect images. The resolution of the captured images are **5472×3078 pixels**. At the same time, we follow four key suggestions:



- ◎ Wide range of scale and aspect ratios.



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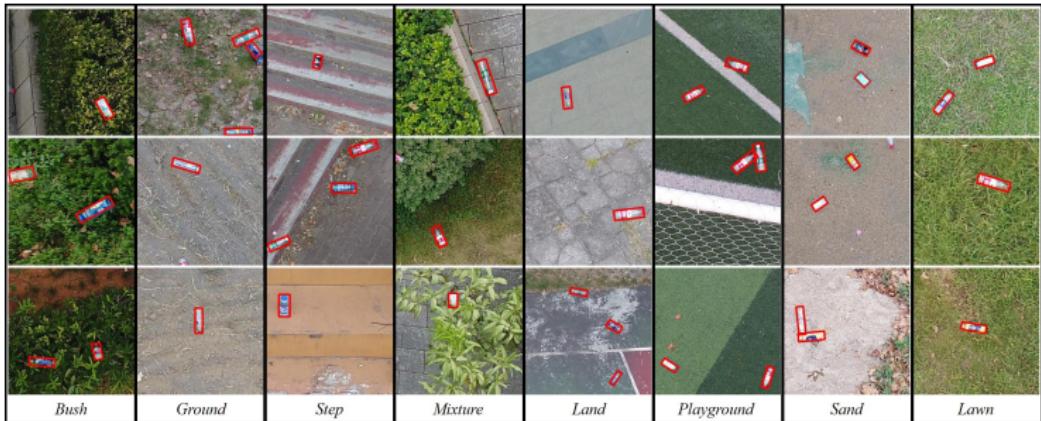
- ◎ Wide range of scale and aspect ratios.
- ◎ Different backgrounds.
- ◎ Different orientation.
- ◎ As many types of bottles as possible.



# Dataset Collection

8 background scenes are chosen and annotated in our UAV-BD:

- Bushforest land
- Waste land
- Step
- Forest land
- Flat land
- Plastic stadium
- Sand land
- Grassland



# Annotation Method

A common description of horizontal bounding boxes is  $(c_x, c_y, h, w)$ , where  $(c_x, c_y)$  is the center location,  $h, w$  are the height and width.



However, horizontal bounding box cannot accurately or compactly outline oriented instances such as the bottles in UAV images. So we use  $(c_x, c_y, h, w, \theta)$  to describe bounding boxes, where  $\theta$  is the angle from the horizontal direction of the horizontal bounding box.



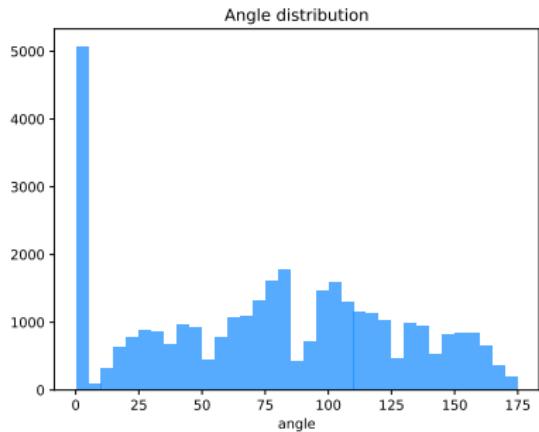
# Dataset Statistics

The size of original image(OI) in UAV-BD is  $5472 \times 3078$  pixels, they are too large to be trained for CNN-based algorithms. So we segment each OI into 144 small subimages(SIs), and the size of SIs is  $342 \times 342$  pixels. Images and instances number in UAV-BD are shown in the table below.

Scenes	OI	SI	Instances in OI	Instances in SI
Bushforest land	230	4134	1812	3047
Wasteland	379	7598	4355	5800
Step	135	2691	1325	2106
Forest land	285	5724	3702	4891
Flat land	134	2803	1538	2142
Plastic stadium	336	6807	4180	4998
Sand land	249	5570	2704	4008
Grassland	456	9029	5778	7787
<b>Total</b>	<b>2204</b>	<b>44356</b>	<b>25394</b>	<b>34779</b>



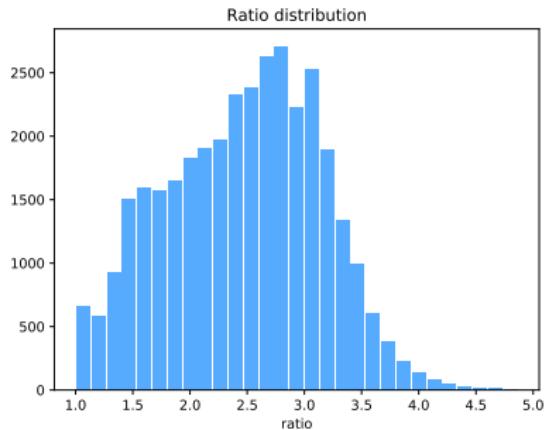
# Dataset Statistics



Angle distribution of UAV-BD.  
The angle ranges from 0 to  $180^\circ$ .



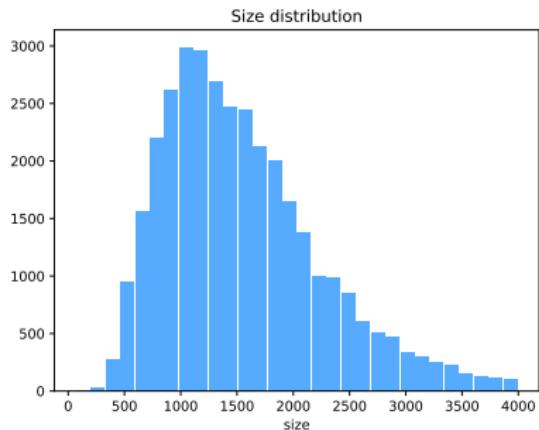
# Dataset Statistics



Ratio distribution of UAV-BD.  
The ratio ranges from 1.0 to 5.0.



# Dataset Statistics



Size distribution of UAV-BD. The size ranges from 0 to 4000.



## Baselines and Methods

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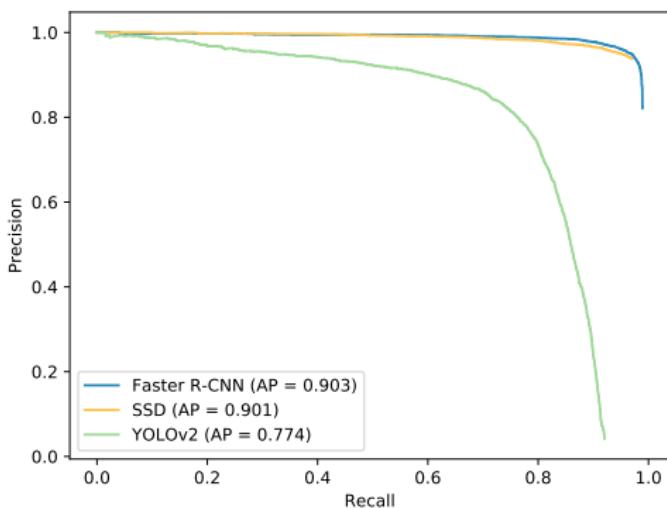
# Dataset Split

We randomly select 64%, 16% and 20% of the UAV-BD as the **training**, **validation** and **testing** data. So the whole UAV-BD contains 16,258 images with 22,211 instances for training, 4,055 images with 5,624 instances for validation and 5,081 images with 6,944 instances for testing.



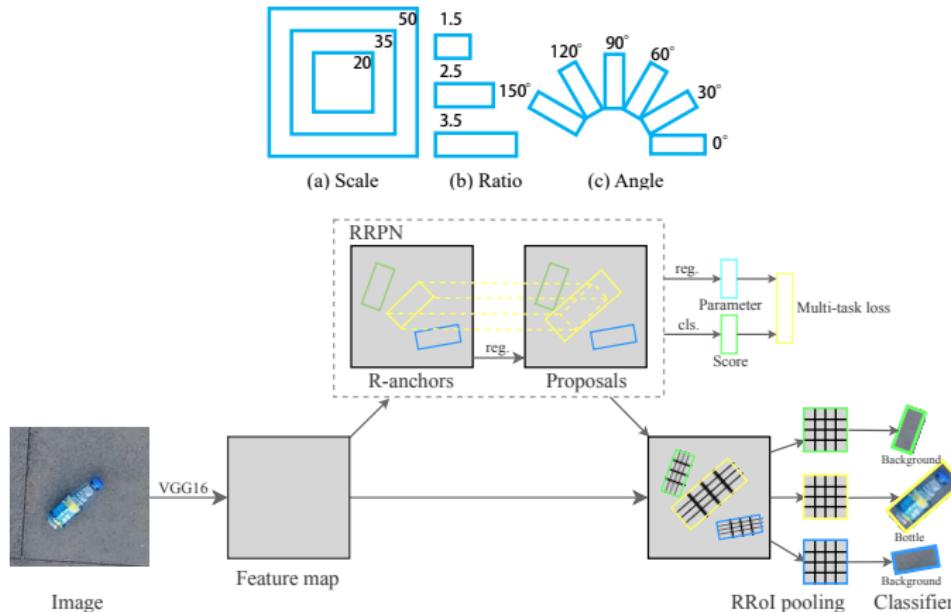
# Baselines with Horizontal Bounding Boxes(HBB)

We select **Faster R-CNN**, **SSD**, **YOLOv2** as our baseline for horizontal object detection. The experimental results of HBB prediction are shown in figure below.



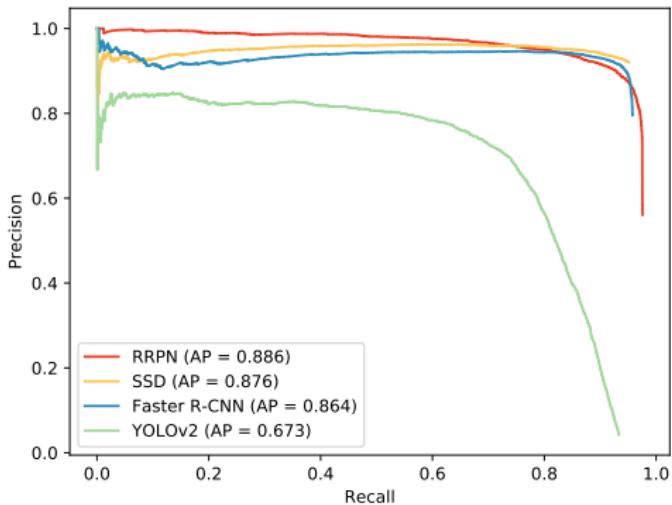
# Baseline with Oriented Bounding Boxes(OBB)

For oriented object detection, we modify the original [Rotation Region Proposal Network\(RRPN\)](#) algorithm to predict properly oriented bounding boxes. RRPN's network structure is shown in figure below.

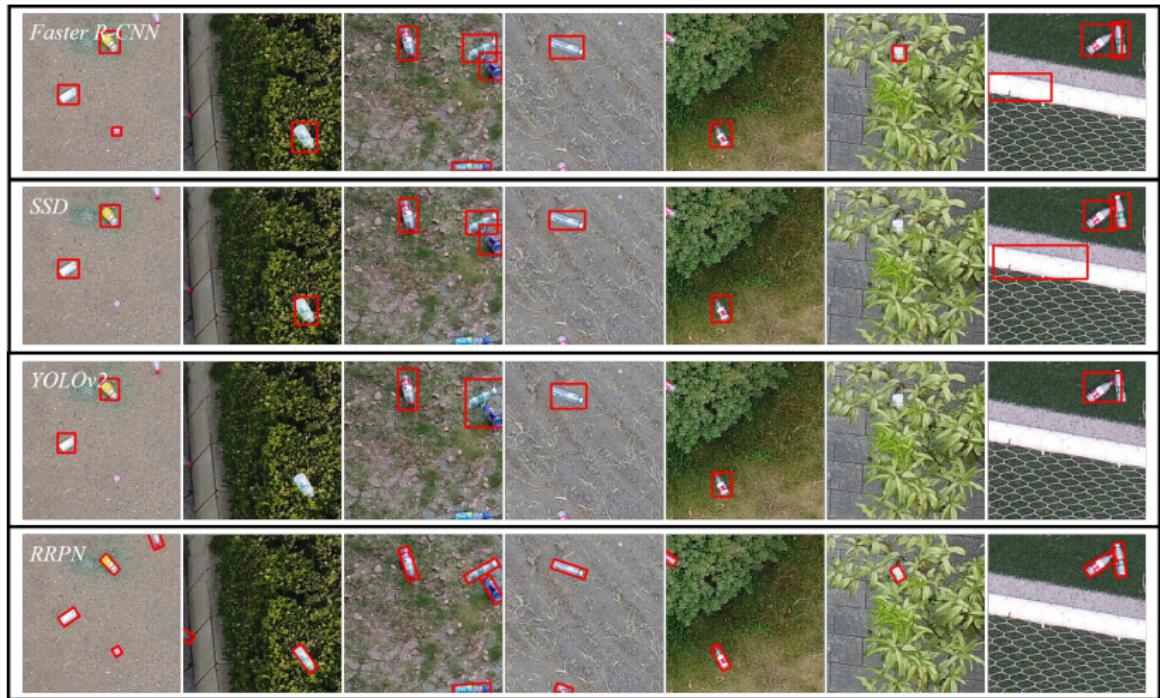


# Baseline with Oriented Bounding Boxes(OBB)

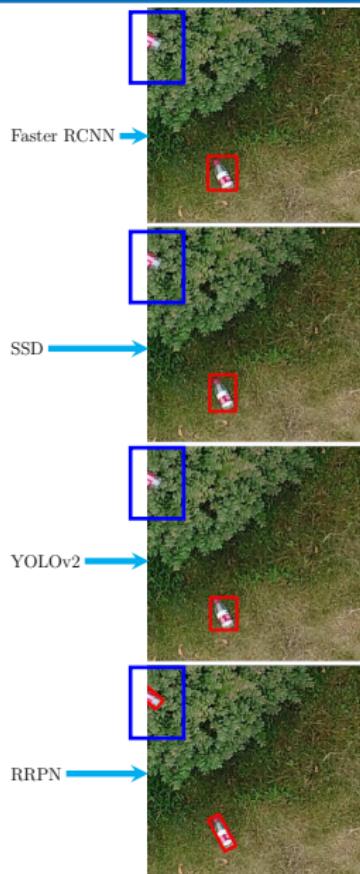
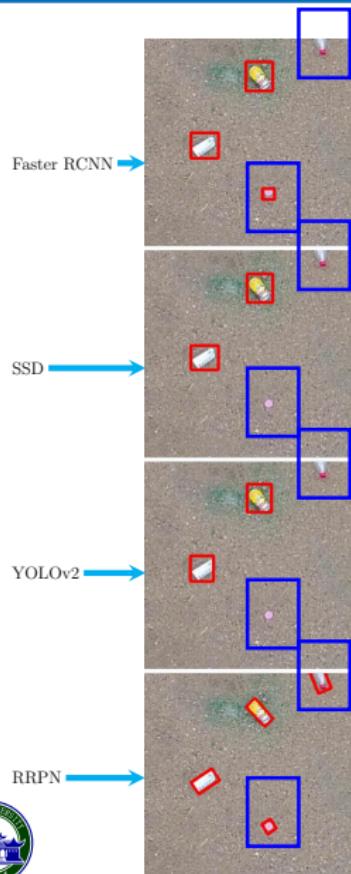
The experimental results of OBB prediction are shown in figure below.



# Experimental Analysis



# Some Details



## Conclusion and Future Work

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## Contribution

- ⑤ Built a large-scale dataset for bottle detection in UAV images named UAV-BD.

## Future Work



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- ◎ Annotated a huge number of well-distributed bottles with oriented bounding boxes.

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## Contribution

- ◎ Built a large-scale dataset for bottle detection in UAV images named UAV-BD.
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## Future Work

- ◎ We will focus on locating and recycling bottles in the real-world using UAV.



# Get UAV-Bottle Dataset

UAV-Bottle Dataset and Development Kit can be downloaded on Google Drive and Github.

UAV-Bottle Dataset

<https://jwwangchn.github.io/UAV-BD/>

Development Kit

<https://github.com/jwwangchn/UAV-BD.git>



# References

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Thanks!