Swimming Pools Detection from Aerial Imagery

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OVERVIEW

- ➢ **Complexity with Aerial imagery**: detect the objects with different variations, scale and representations.
- ➢ **Many civil applications**: geographic information system mapping, agriculture, traffic planning, and navigation…

- ➢ **Swimming pool detection: important for property tax assessment** because they impact the value of the property.

For companies to help redirect their marketing efforts

For Public health and mosquito control agencies

- ➢ Previous works often use **single stage detector like Yolo, SSD or Double stage detector (RCNN)**
- ➢ Previous works use **common benchmark like COCO to detect multiples objects in images.**

- ➢ Goal: show the efficiency of cutting-edge models for detecting swimming pools with satellites images. We will show that CornerNet and DynamicHead are better.

DATA

Dataset available on Kaggle:

- ➢ Original size is 25,000 x 25,000 pixels
- ➢ Patches of 512x512 pixels and 1224 patches
- ➢ 3,197 annotated pools with different shapes and hues
- ➢ We use Cross-validation with k=5folds

References

[1] Law and J. Deng. Cornernet: Detecting objects as paired keypoints. CoRR, abs/1808.01244, 2018.
[2] Law, Y. Teng, O. Russakovsky, and J. Deng. Cornernet-lite: Efficient keypoint based object detection. CoRR, abs/1904.08900, 2020.
[3] Dai, Y. Chen, B. Xiao, D. Chen, M. Liu, L. Yuan, and L. Zhang. Dynamic head: Unifying object detection heads with attentions, 2021.

APPROACH

CornerNet: one-stage approach. Detects an object bounding box as a pair of keypoints without using anchor boxes.
->**Corner pooling** that helps the network to better localize corners.
=predict heatmaps and embedding vector

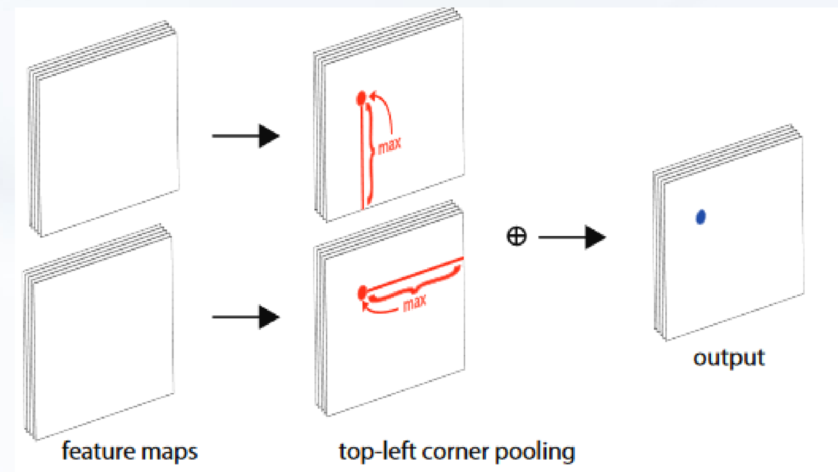
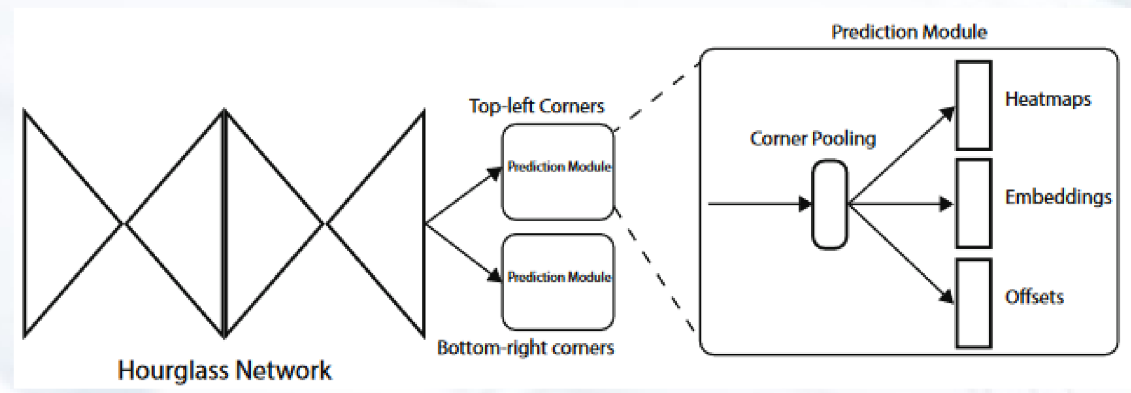
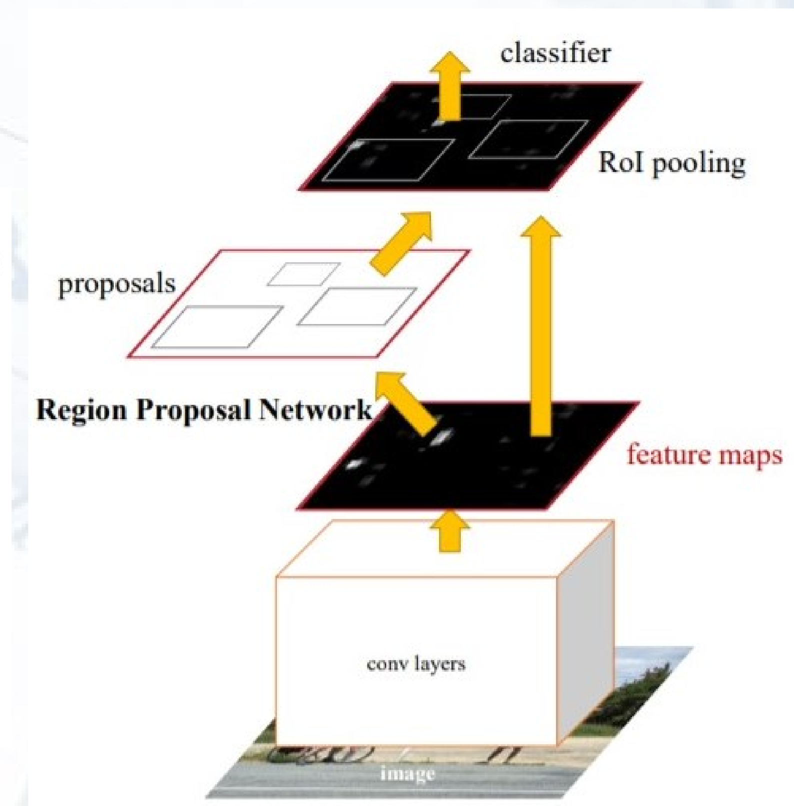


Figure 1: Corner pooling and CornerNet model



FasterRCNN model: 2 stage detectors. It constructs a Region Proposal Network .
=Simultaneously regress region bounds and objectness scores
= predict multiple region proposals called anchors.
= combines two loss: for the regression and for the classifier

Figure 2: FasterRCNN model



DynamicHead: unify object detection heads with attentions by combining multiple self-attention mechanisms between feature of 3 levels. Scale-aware, spatial-aware, task-aware.

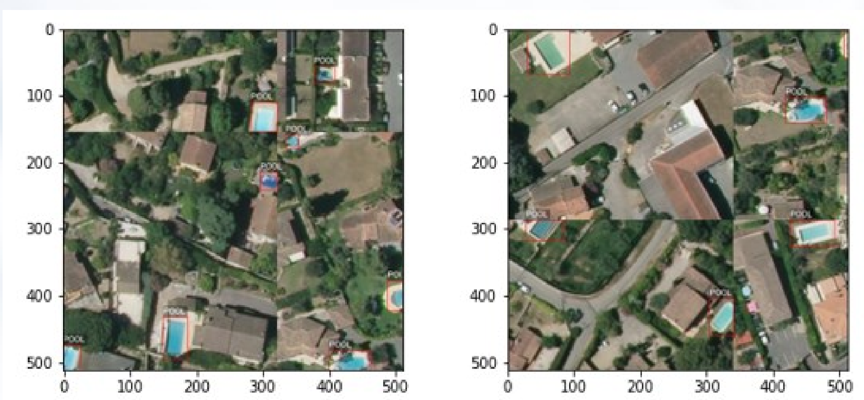


Figure 4: Cutmix data augmentation

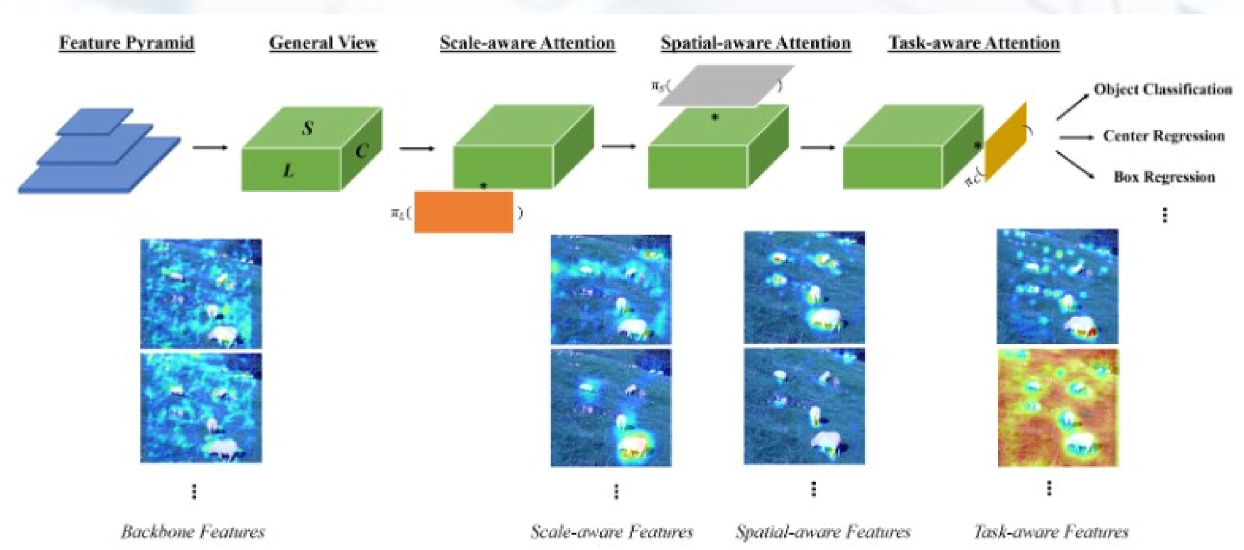


Figure 3: DynamicHead model

RESULTS

Method	Precision	Recall	F1 score
Faster R-CNN	0.88	0.95	0.90
CornerNet	0.92	0.92	0.92
Dynamic Head	0.95	0.93	0.94

Table 1. Performance of models.

Fig 7: Example of input

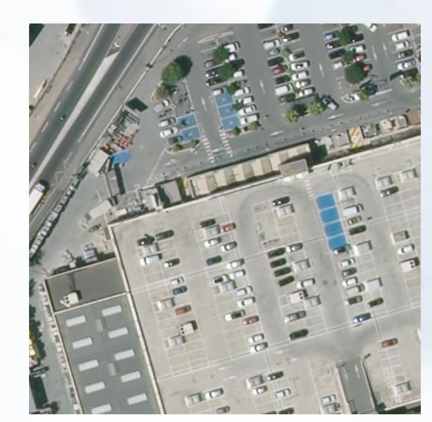


Fig 5: Example of bias correctly predicted

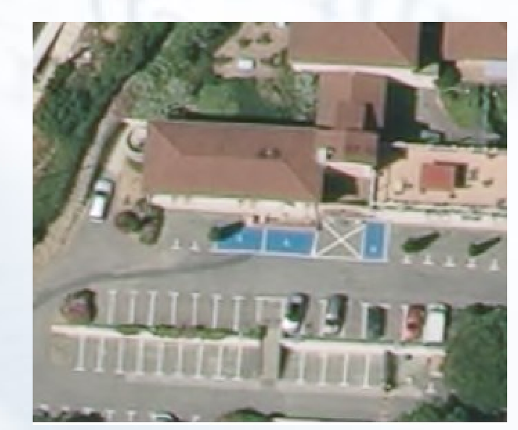


Fig 6: Example of wrong prediction

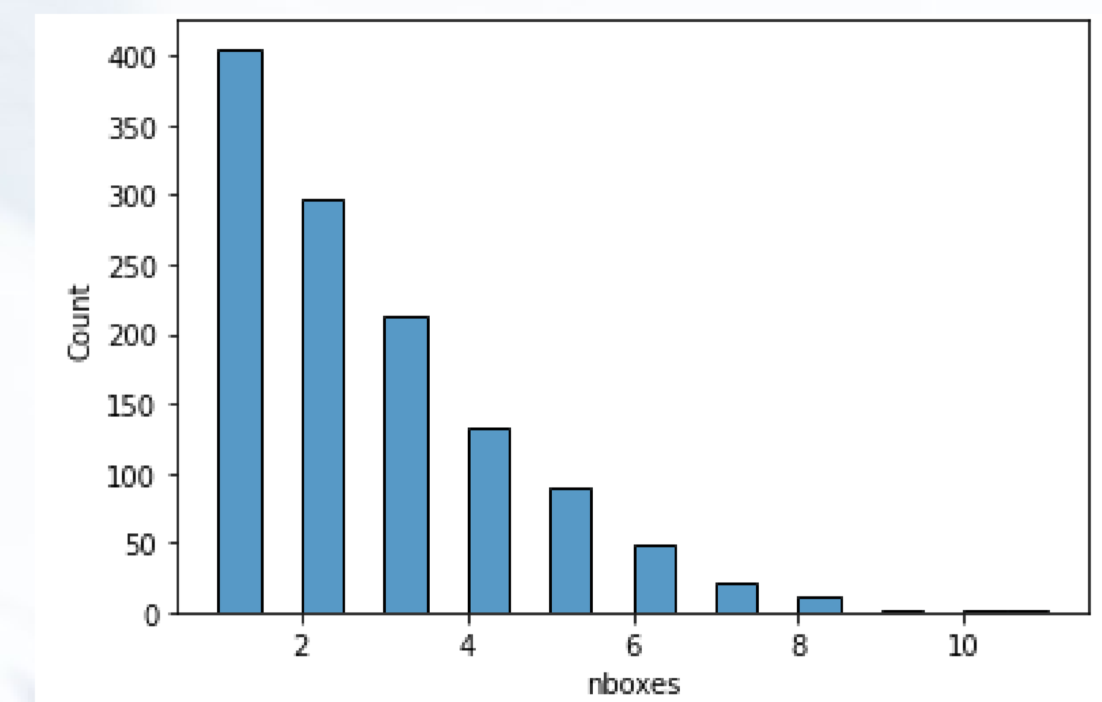
- All implemented models are efficient on this task
- FasterRCNN is weaker with many variations, contrast in images.
- Wrong prediction of swimming pool (using background)

- Bias or exceptional situation in image
- Error of dataset or data augmentation
- CornerNet and DynamicHead achieves higher scores

METHODS

- ➢ **Metrics**: We used **Precision, Recall and F1 score** for the detection task.
- ➢ **Models**: We used **a FasterRCNN, CornerNet and DynamicHead with pretrained weights.**
- ➢ **Data augmentation:** HueSaturationValue,RandomBrightnessContrast, Horizon and vertical flips,random rotate, transpose, compression, resize and cutmix.

Figure: Number of images per boxes



CONCLUSION

- ❖ All models are efficient on this swimming pool detection task.
- ❖ CornerNet and DynamicHead are much efficient even when there are many variations and different scale, representations of objects.
- ❖ **Future work: Try to improve models by using their variants, change backbones or use Dynamic-Head as plugin block to any other model.**