CSCI 677: Advanced Computer Vision, HW2

Matin Barekatain 1385073716

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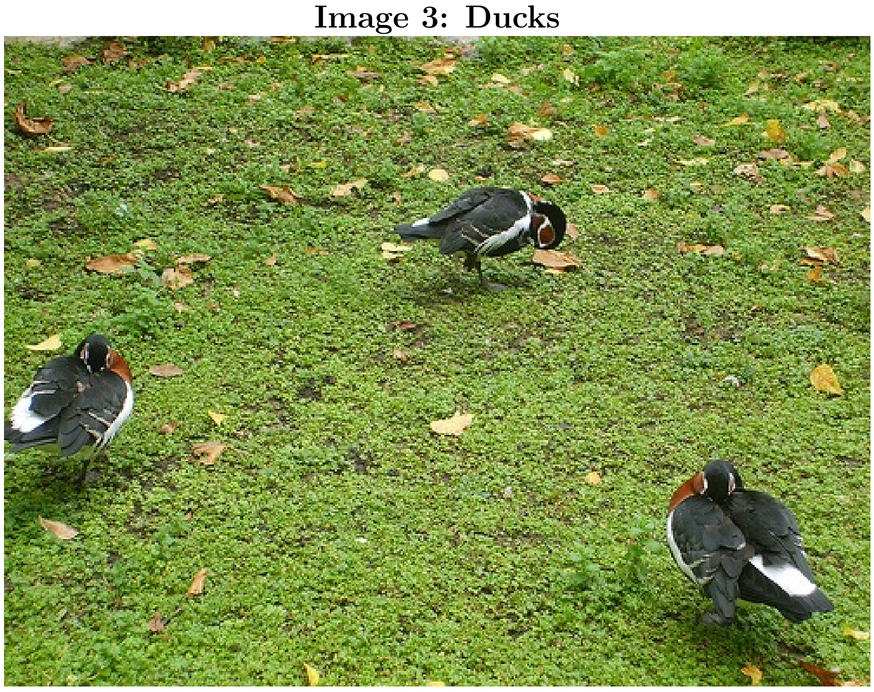
There are 3 images shown below that we analyze in this report.

Image 1: Buffaloes

Image 2: People

Image 3: Ducks



In this Program, we benefit from the Selective Search algorithm based on Graph Segmentation.

Structuring Algorithms

```
ss = cv2.ximgproc.segmentation.createSelectiveSearchSegmentation()
gs = cv2.ximgproc.segmentation.createGraphSegmentation()
```

Then we set the required parameters for the graph segmentation method.

Setting Parameters

```
gs.setK(200)
gs.setSigma(0.75)
```

We add the image, and the graph segmentation object to the selective search algorithm.

Setting Parameters

```
ss.addImage(img)
ss.addGraphSegmentation(gs)
```

We receive the strategy as the input. There are two valid inputs as strategies which are 'color' and 'all'. The latter includes 'color', 'fill', 'texture', and 'size'.

Applying Strategies (e.g. Color)

```
curr_strategy = cv2.ximgproc.segmentation.
        createSelectiveSearchSegmentationStrategyColor()
ss.addStrategy(curr_strategy)
```

Finally we run the process to achieve the proposal rectangular boxes.

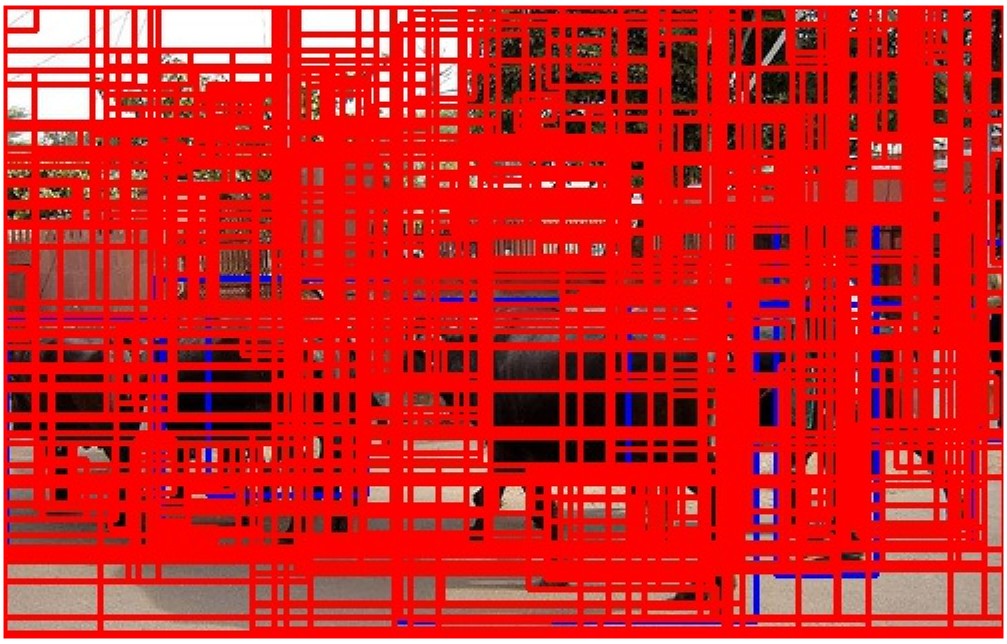
Process

```
bboxes = ss.process()
```

Without considering the intersection over union (IoU) factor, the number of proposals are more than a hundred for each photo through each of the 2 strategies. In what follows, all proposal rectangles (in red) have been shown together with the ground truth boxes (in blue). The number of proposals, and the strategy used for each sample have been mentioned at the bottom of each image.

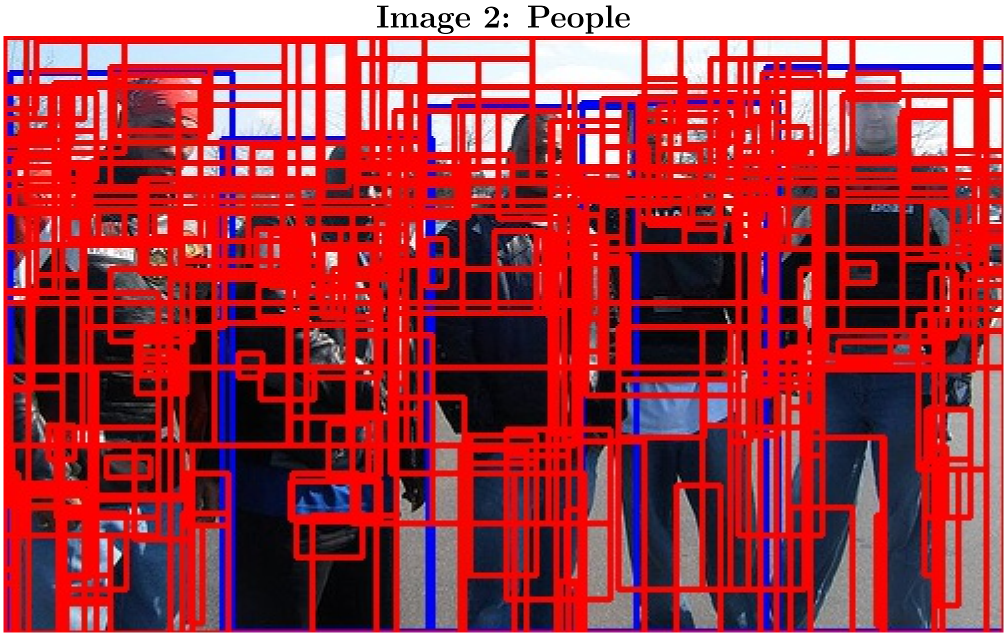
Image 1: Buffaloes

Number of Proposals with Color Strategy: 360



Number of Proposals with All Strategies: 783

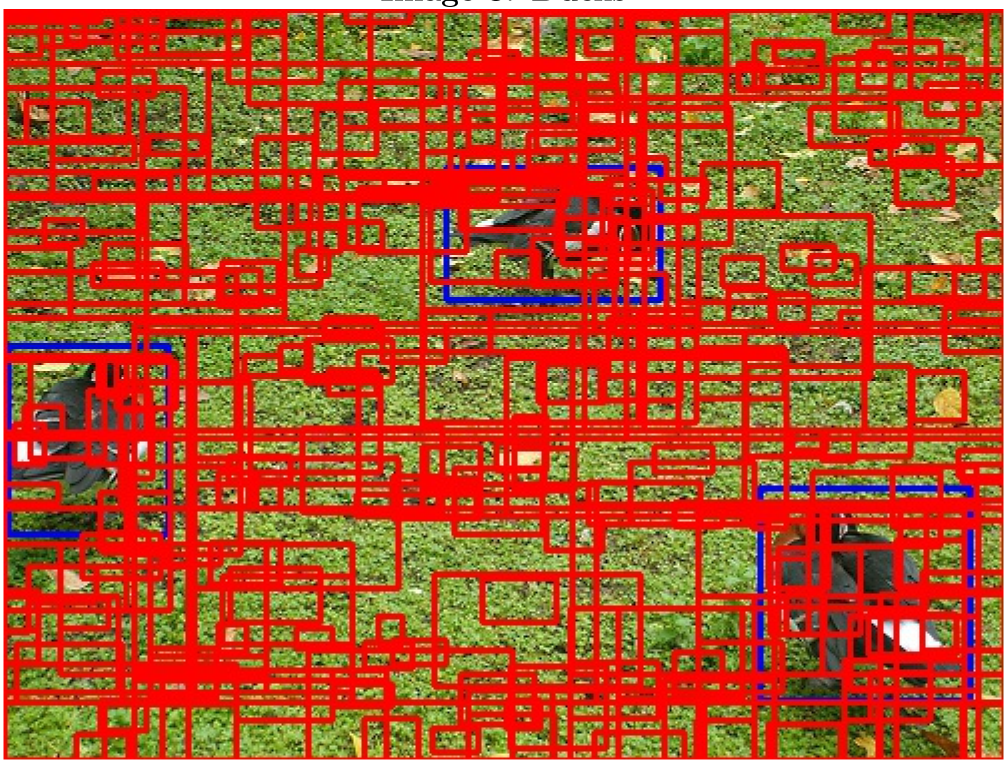
Image 2: People



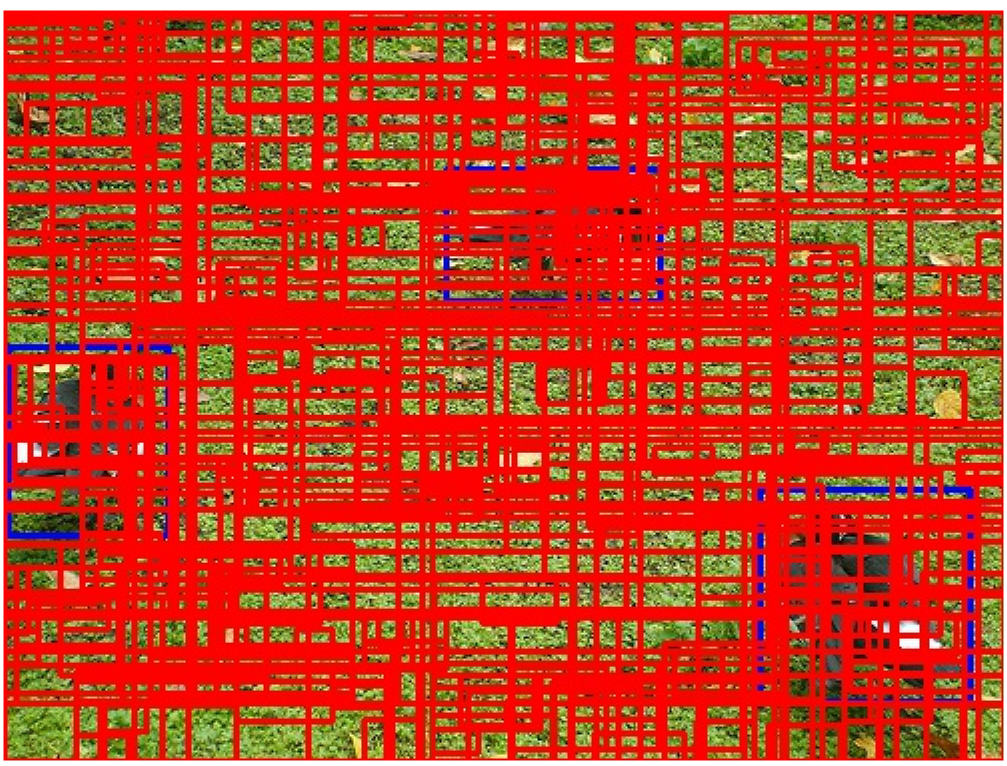
Number of Proposals with Color Strategy: 291

Number of Proposals with All Strategies: 615

Image 3: Ducks



Number of Proposals with Color Strategy: 266



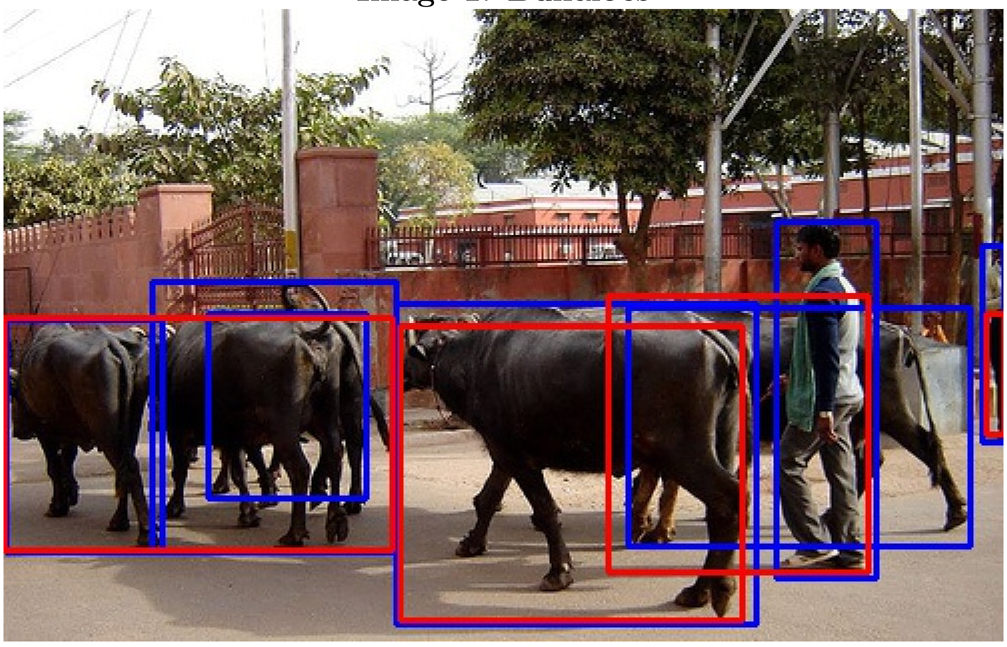
Number of Proposals with All Strategies: 556

In order to find the proposals with the highest accuracy while benefiting from the ground-truth coordinates, we calculate IoU between each proposed and ground-truth boxes.

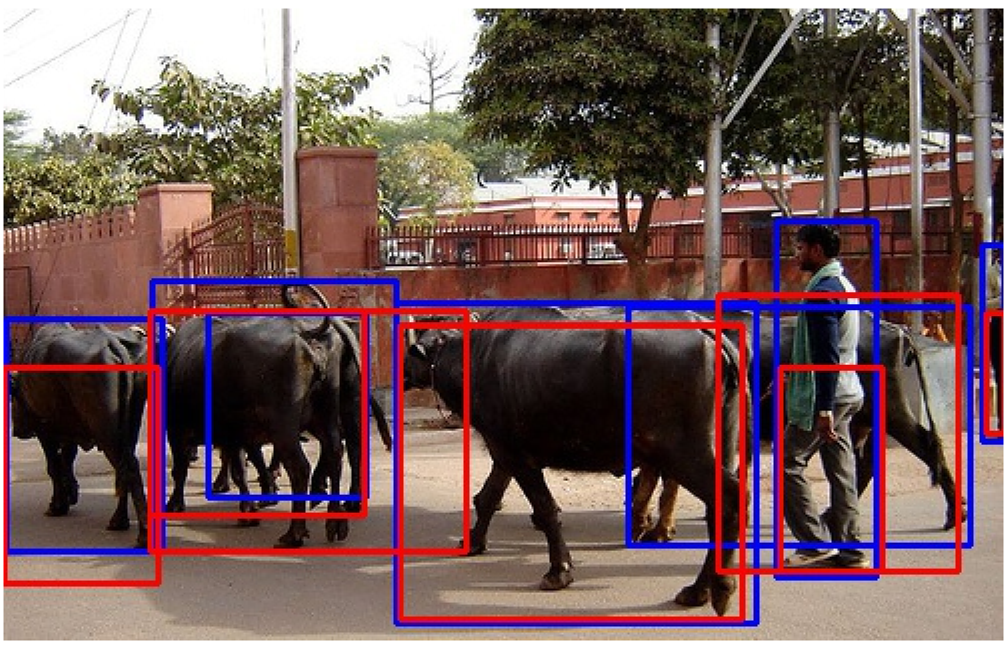
```
x0_intersect= max(boxA[0],boxB[0])
y0_intersect= max(boxA[1],boxB[1])

x1_intersect= min(boxA[2],boxB[2])
y1_intersect= min(boxA[3],boxB[3])

if x0_intersect >= x1_intersect or y0_intersect >= y1_intersect:
    iou = 0.0
else:
    S_intersect= (y1_intersect-y0_intersect)*(x1_intersect-x0_intersect)
    S_union = (boxA[2]-boxA[0])*(boxA[3]-boxA[1])
            +(boxB[2]-boxB[0])*(boxB[3]-boxB[1])-S_intersect

    iou = S_intersect/S_union
```

The remaining boxes with a $IoU \geq 0.5$ have been shown in the following together with the computed recall values. We returned the intersection areas through the IoU function to calculate the value of recall.

Image 1: Buffaloes

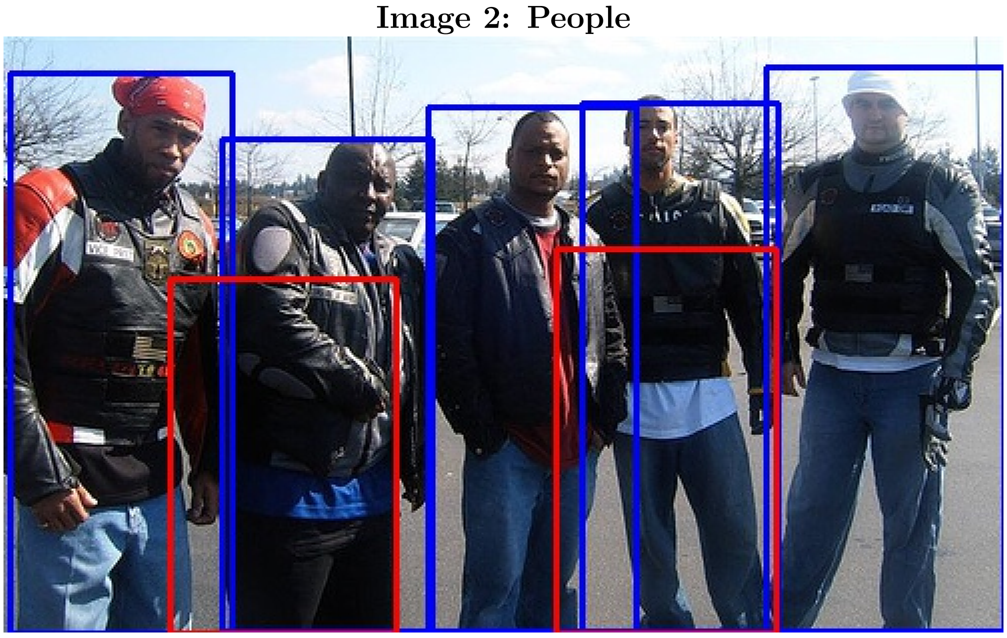


Number of Boxes with Color Strategy: 4, Recall: 0.5862

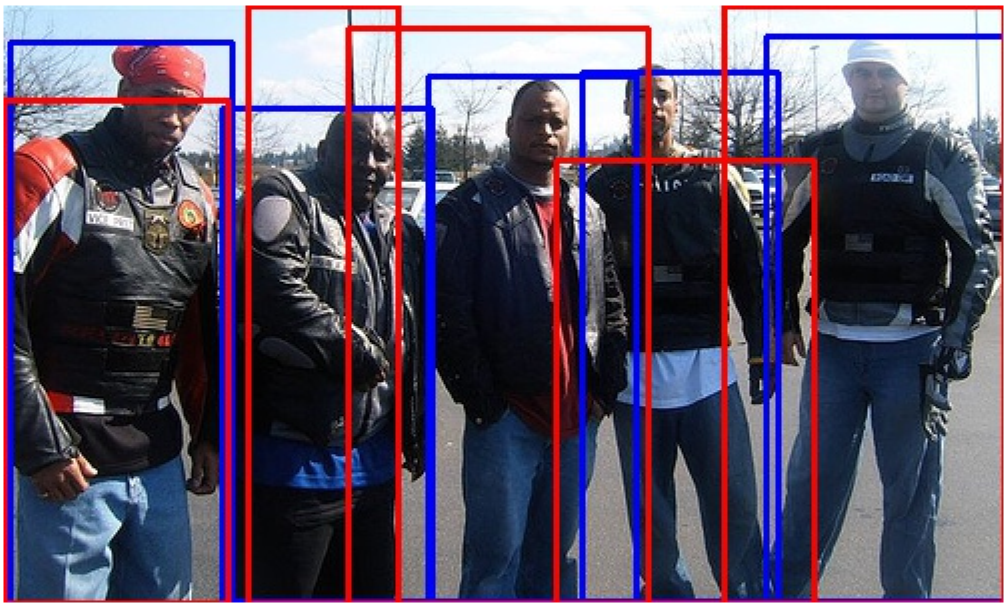


Number of Boxes with All Strategies: 7, Recall: 0.8014

Image 2: People

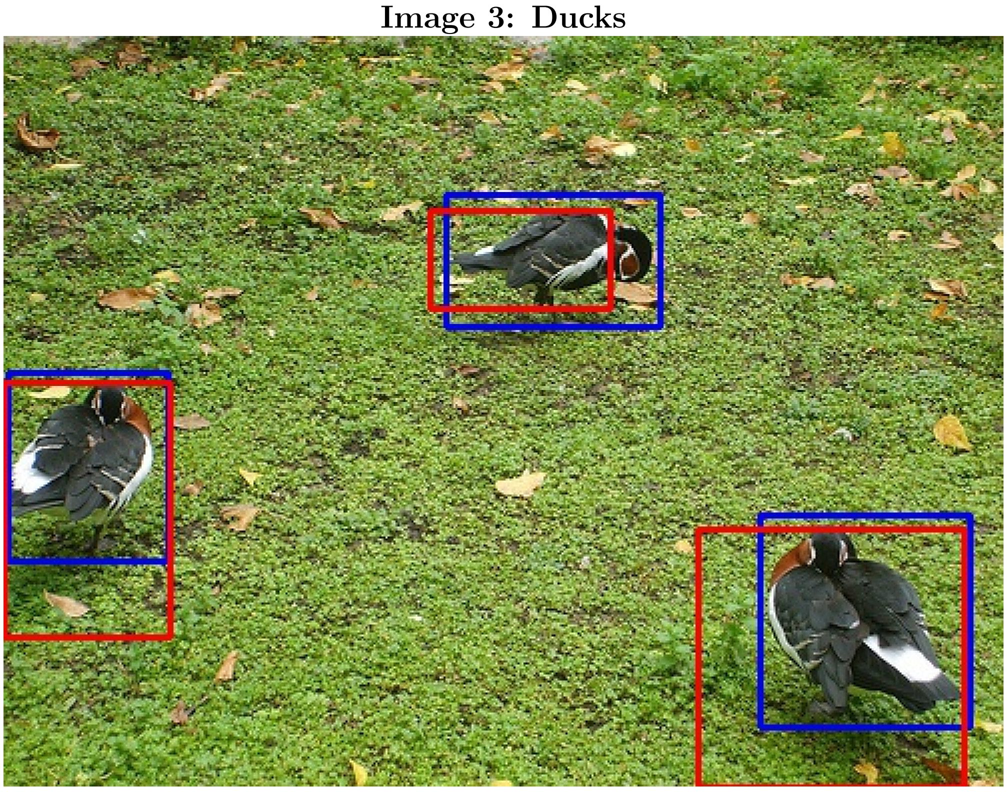


Number of Boxes with Color Strategy: 2, Recall: 0.2357

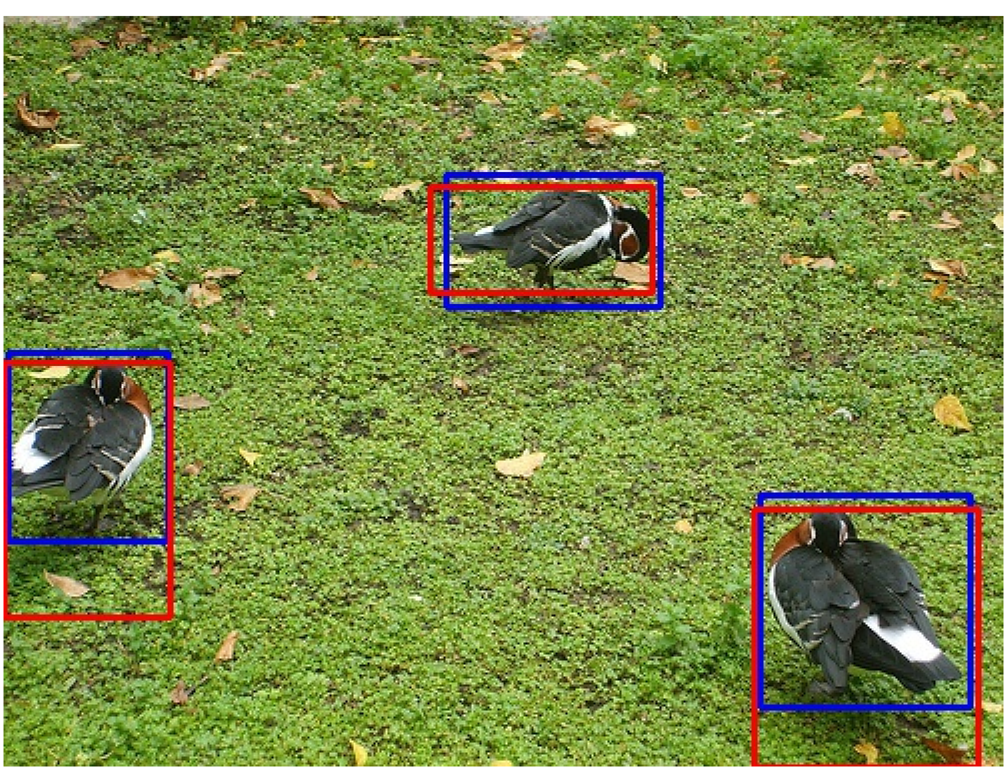


Number of Boxes with All Strategies: 5, Recall: 0.8927

Image 3: Ducks



Number of Boxes with Color Strategy: 3, Recall: 0.8259



Number of Boxes with All Strategies: 3, Recall: 0.8935

Analysis

• The number of proposal boxes increase when we add multiple strategies on top of each other. This is due to finding more reasonable patterns between the regions through various strategies.

• For image 3 that has a wider spectrum of colors, the accuracy of the selected proposal boxes based on IoU is higher compared to that of images 1 and 2. For image 2, we were able to only have 2 boxes with $IoU \geq 0.5$ by applying only the color strategy and for image 1, we missed 3 blocks. That is why the recall value of these 2 samples for the color strategy alone is very low (0.5862 and 0.2357). However, by including the texture, size, and fill strategies to the same algorithm, helped finding all potential blocks for these images.

• It seems the patterns are identified better toward the center areas of each image compared to edges. For instance, in the ducks image, the proposed box for the duck located more toward the center than the edge (the top one) has a much higher IoU compared to the lowest duck. This might be due to the graph segmentation technique we applied. Finding the optimized cut and correlations with the cropped pixels after the edge is impossible, so we usually observe that the proposed boxes at the edge of the image are more over-extended.

• Considering the color alone, we observe that when multiple objects of the same type (e.g., cows) do not have a different object (with a far different color) in between them, it is difficult to distinguish between them. This justifies why in the first image, after applying the color strategy alone, the 2 cows located at the left are considered as one object.

• Decreasing sigma would relax the constraints on selecting proposed boxes. For instance, when sigma is reduced to 0.4, the number of proposal boxes for image 3 becomes 1,700 applying all strategies.

• Decreasing K would most of the time result in smaller final boxes, more proposed boxes, and less recall values. For instance, with $K = 100$, the boxes shrunk for image 3 and the recall value became 0.7 which is much less than the previously obtained value.

• Considering other strategies one by one, we would figure out which strategy is more helpful for each of these images. For instance, for image 2, texture finds much better proposed boxes with higher IoU with GT boxes compared to color. This is matched to our expectations because the color variance in image 2 is not noticeable enough. On the other hand, the texture has a more identifiable pattern for this image. In contrast, for image 3, the color strategy works perfectly fine.

• Instead of using IoU as the main factor for selecting final proposal boxes, we could use intersection over summation of areas which is:

$$\frac{2 \times (S_{proposal} \cap S_{GT})}{S_{Proposal} + S_{GT}}$$

Note that the factor 2 normalizes the obtained values. This metric works very similar to IoU, however, the obtained values are normally higher than IoU.