## Machine Learning Project

Instance Segmentation using YOLOv8 on Repair Dataset

### Step 1

• Goal: We want to see how reducing the number of classes in the Repair dataset affects the model's accuracy

Tuning Yolov8 hyper-parameters [1]

- Learning Rate: 0.1
- Momentum: 0.937
- weight\_decay: 0.0005
- hsv\_h= 0.015
- hsv\_s= 0.7
- hsv\_v= 0.4

[1] https://docs.ultralytics.com/modes/train/#train-settings

# Step 1: Training 14 class model Training

Pre-trained Model: yolov81-seg

• Image Size: 800 \* 800 pixels

• Batch Size: 16

• Epochs: 250

• Device: L4[2]

[2] GPU: 22.5 GB Memory

Training Results

Table 3. YOLOv8 achieves the best results regarding the motif segmentation ( $PA_{motifs}$  includes all classes without background), while UNET wins when including the background in the evaluation ( $PA_{avg}$  refer to all classes including background, same for IoU).

| Architecture   | $IoU_{motifs}$ | $IoU_{avg}$ | $PA_{motifs}$ | $PA_{avg}$ |
|----------------|----------------|-------------|---------------|------------|
| YOLOv8         | 0.582          | 0.538       | 0.634         | 0.797      |
| Original U-NET | 0.416          | 0.606       | 0.452         | 0.630      |
| Modified U-NET | 0.345          | 0.569       | 0.392         | 0.600      |

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| Matrica  | Bounding Box |        |        | Segmentation |        |        |
|----------|--------------|--------|--------|--------------|--------|--------|
| Metrics  | Precision    | Recall | mAP@50 | Precision    | Recall | mAP@50 |
| 14 Class | 0.7866       | 0.8659 | 0.8439 | 0.8961       | 0.8113 | 0.9025 |

[3] Semantic Motif Segmentation of Archaeological Fresco Fragments

Training Results

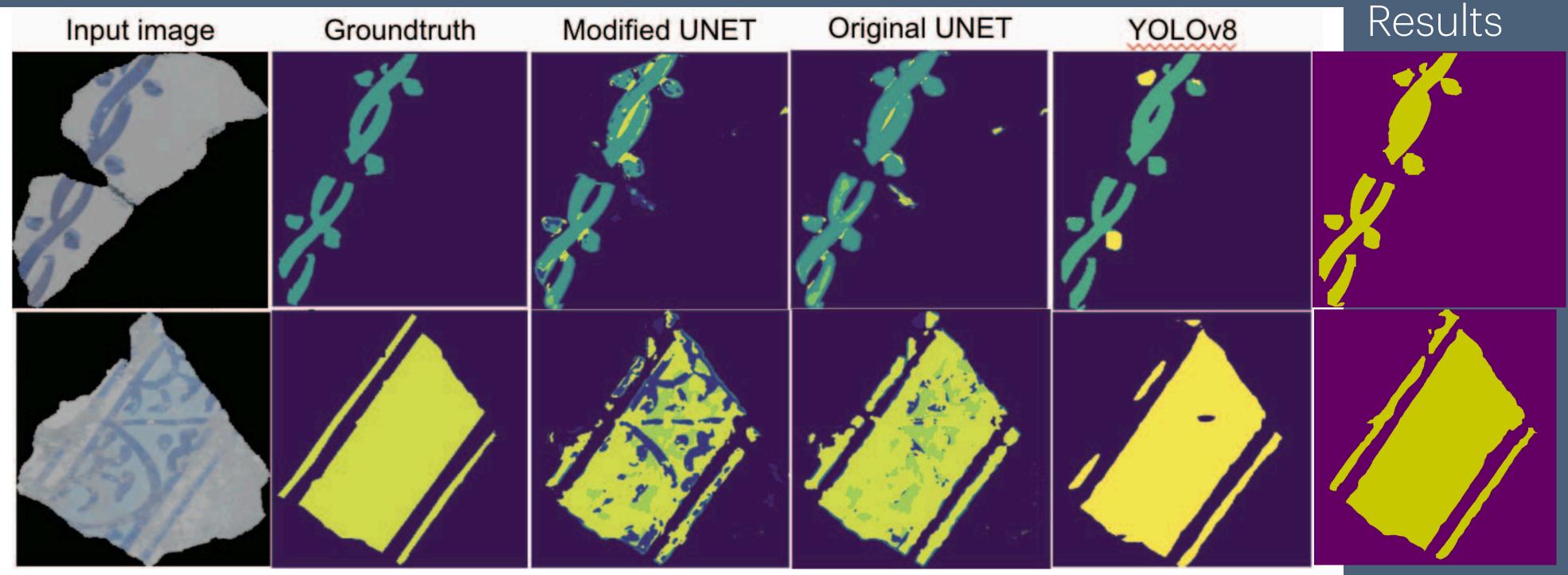
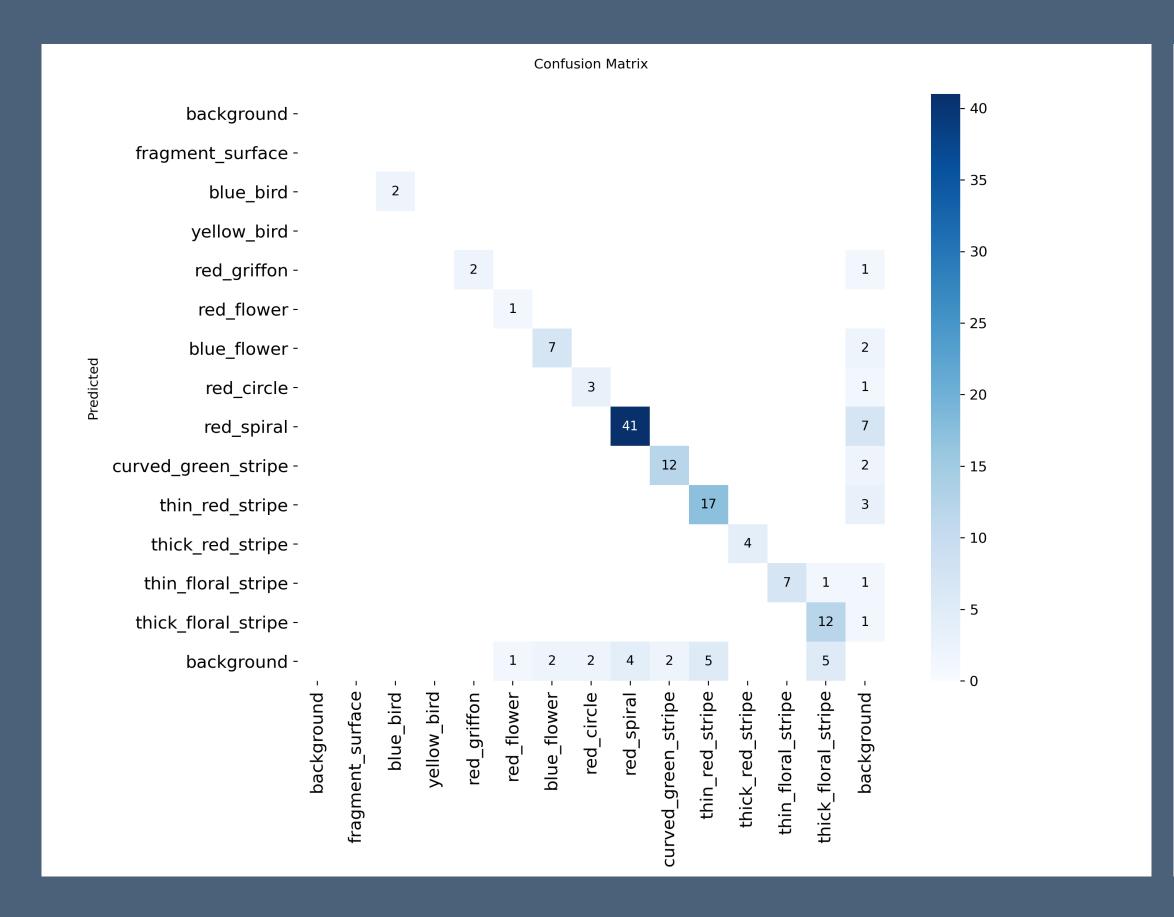
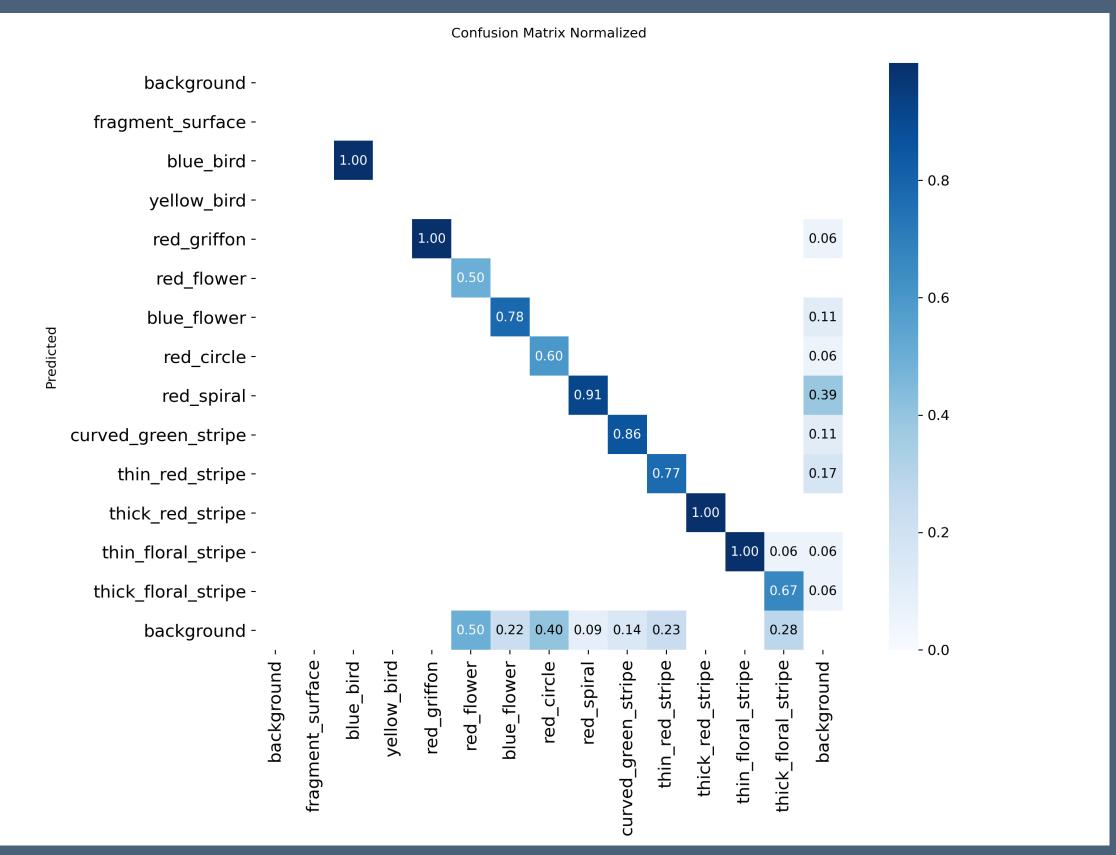


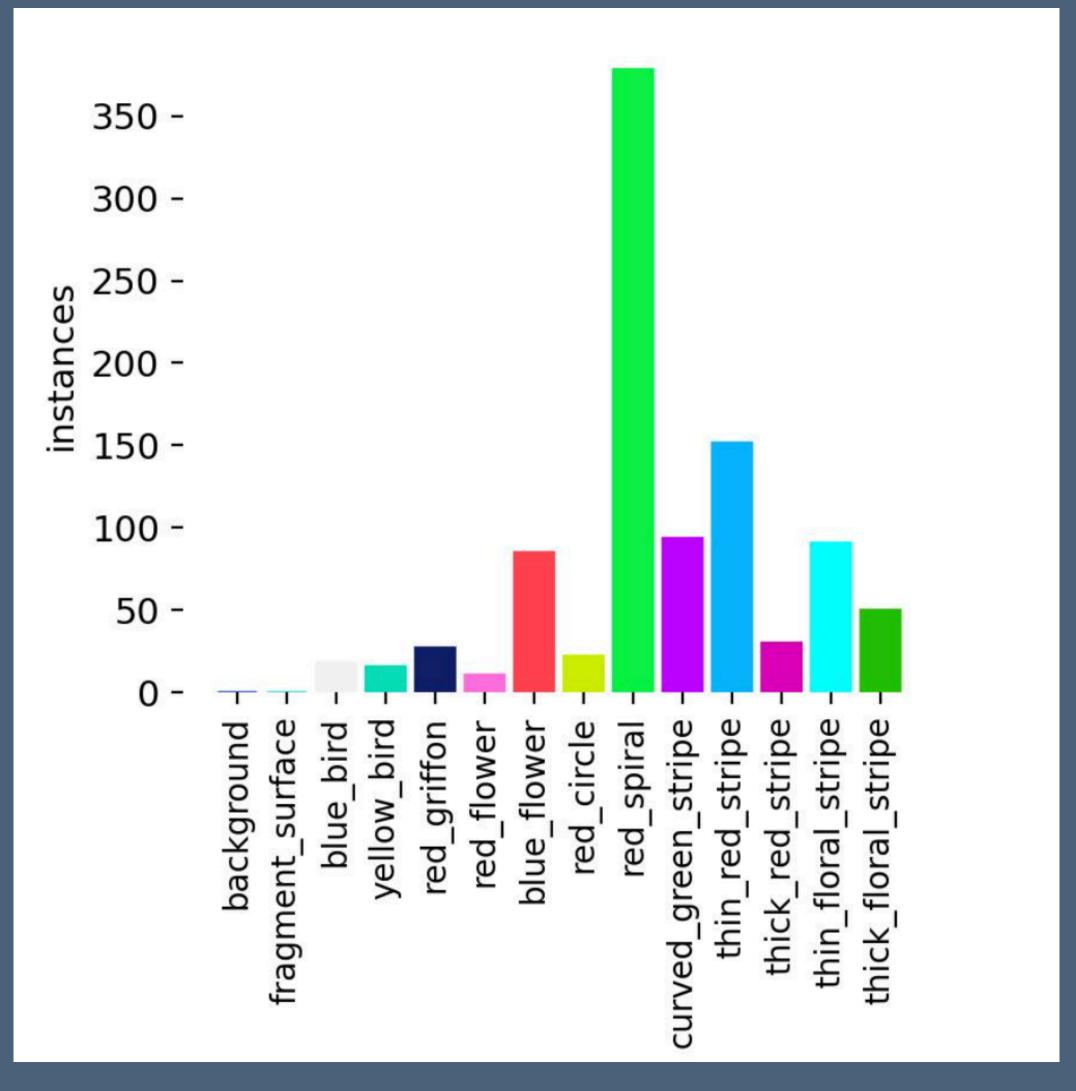
Figure 10. Semantic motif segmentation results of different architectures for Scenario 2.

Training More Results



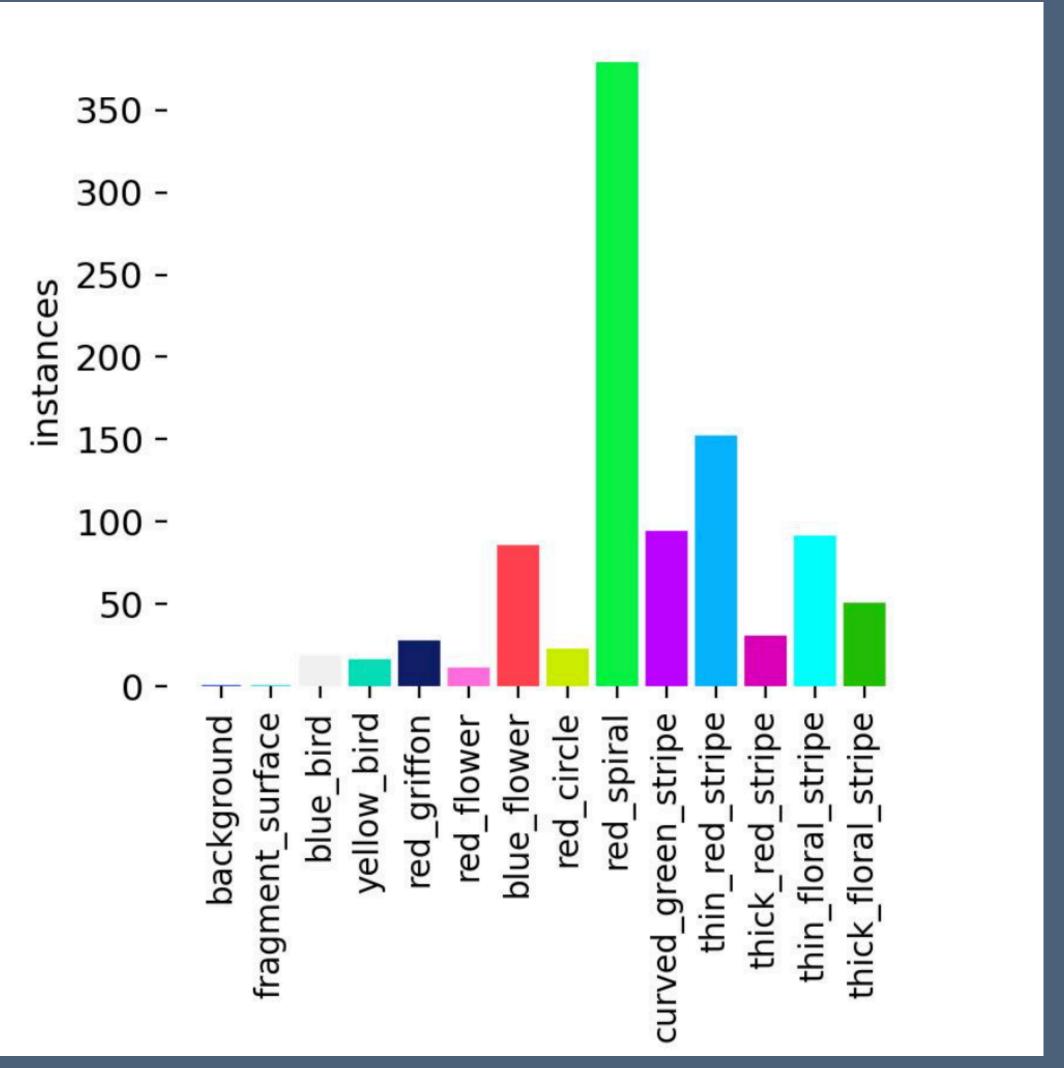


Training



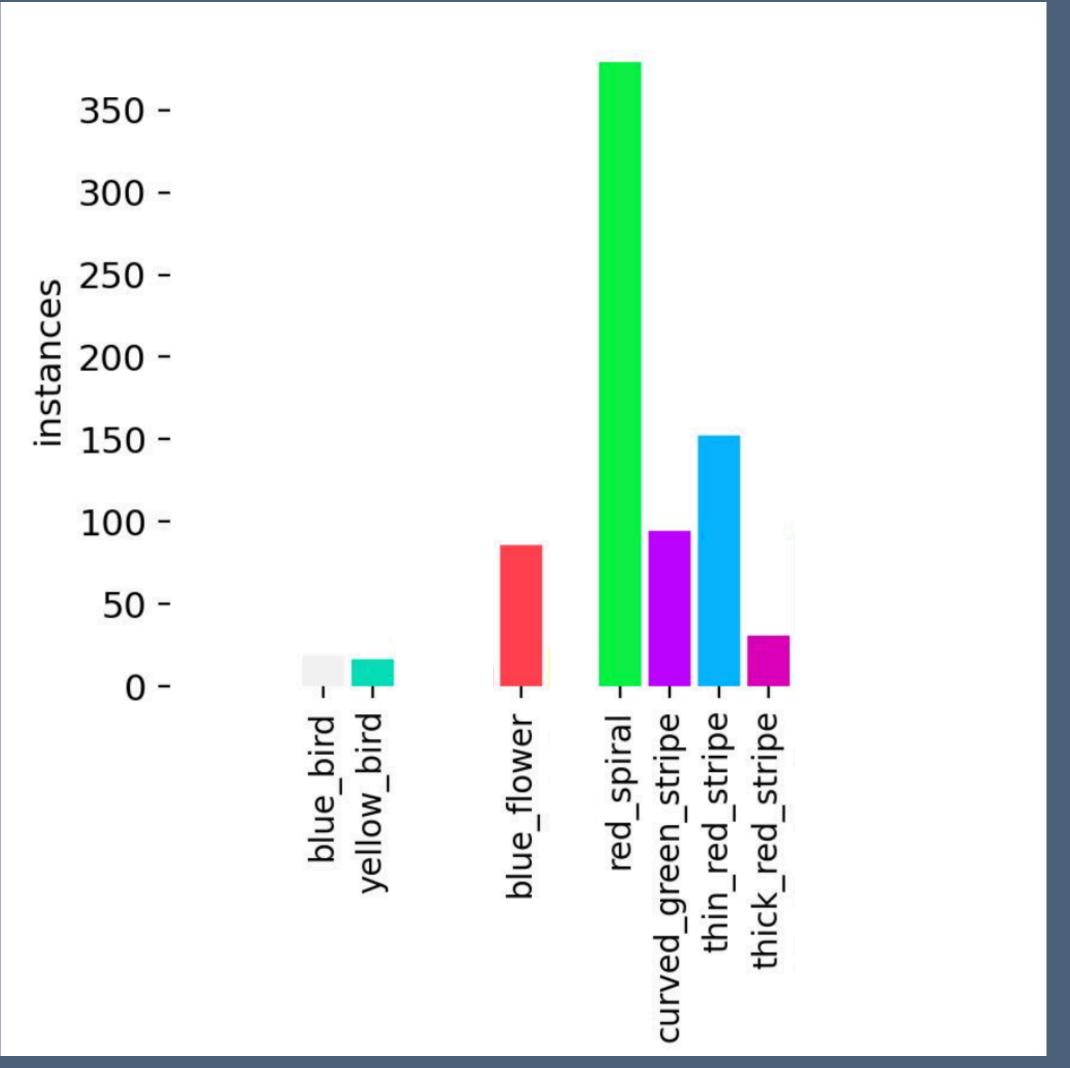
#### Training

• Step 1: I think a good first step would be to train a model which accurately recognizes these.



#### Training

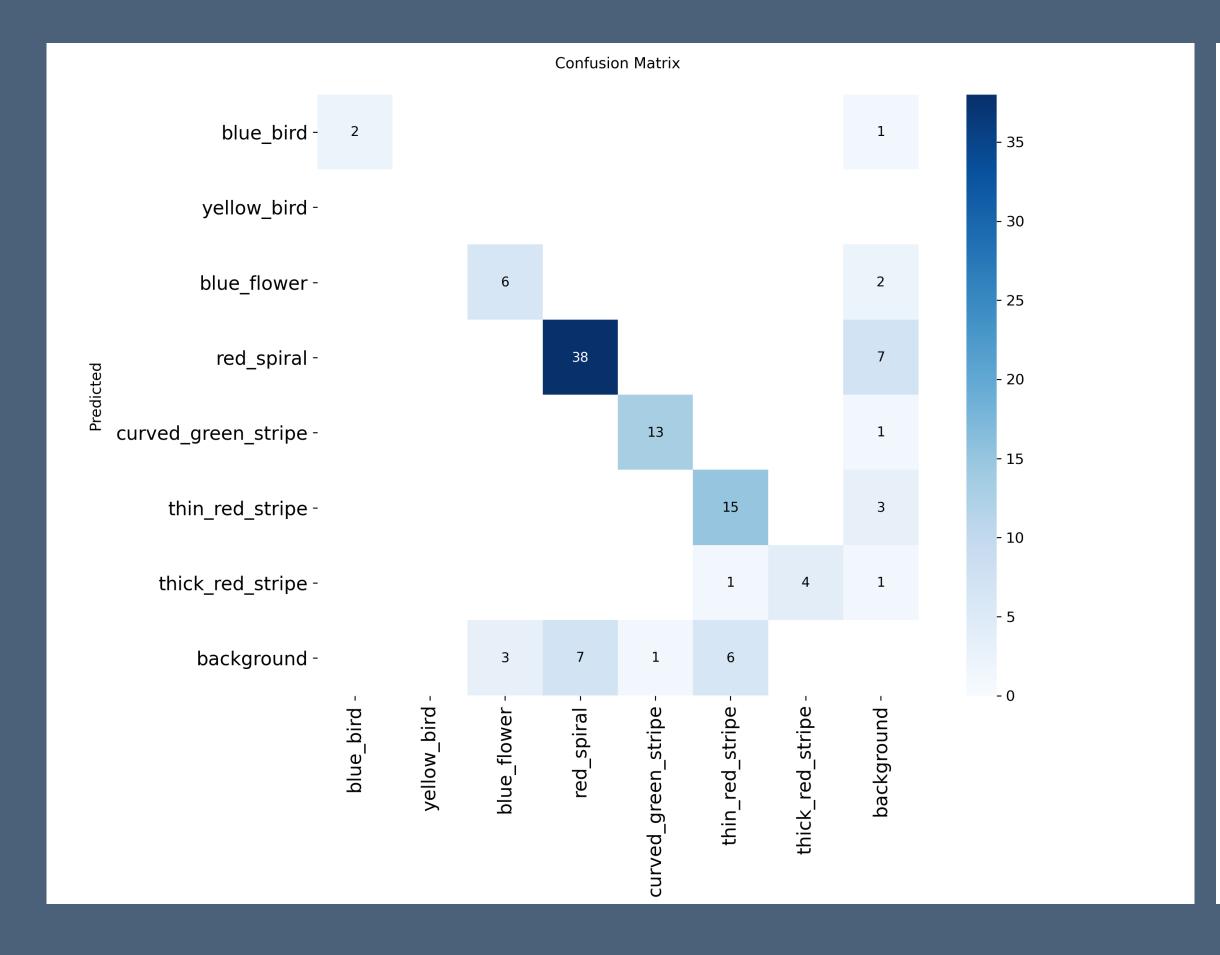
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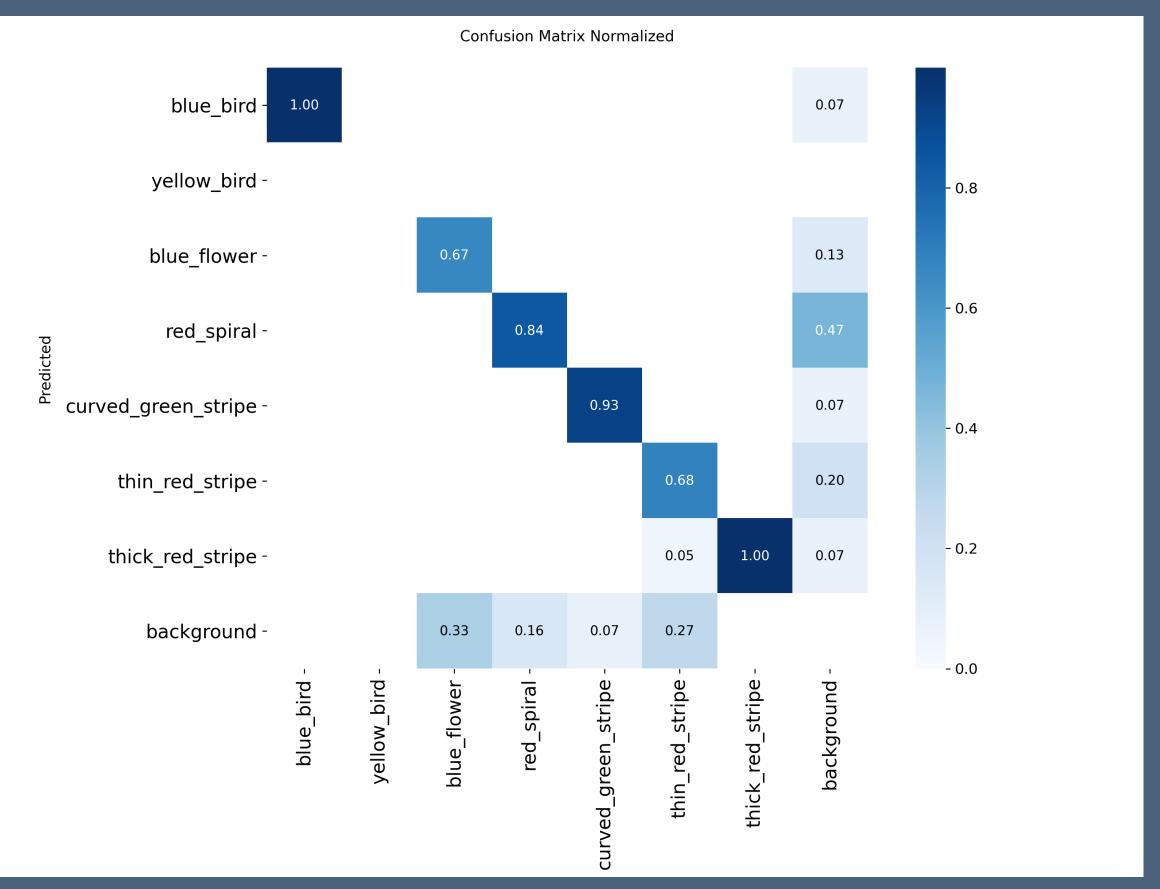


Training Results

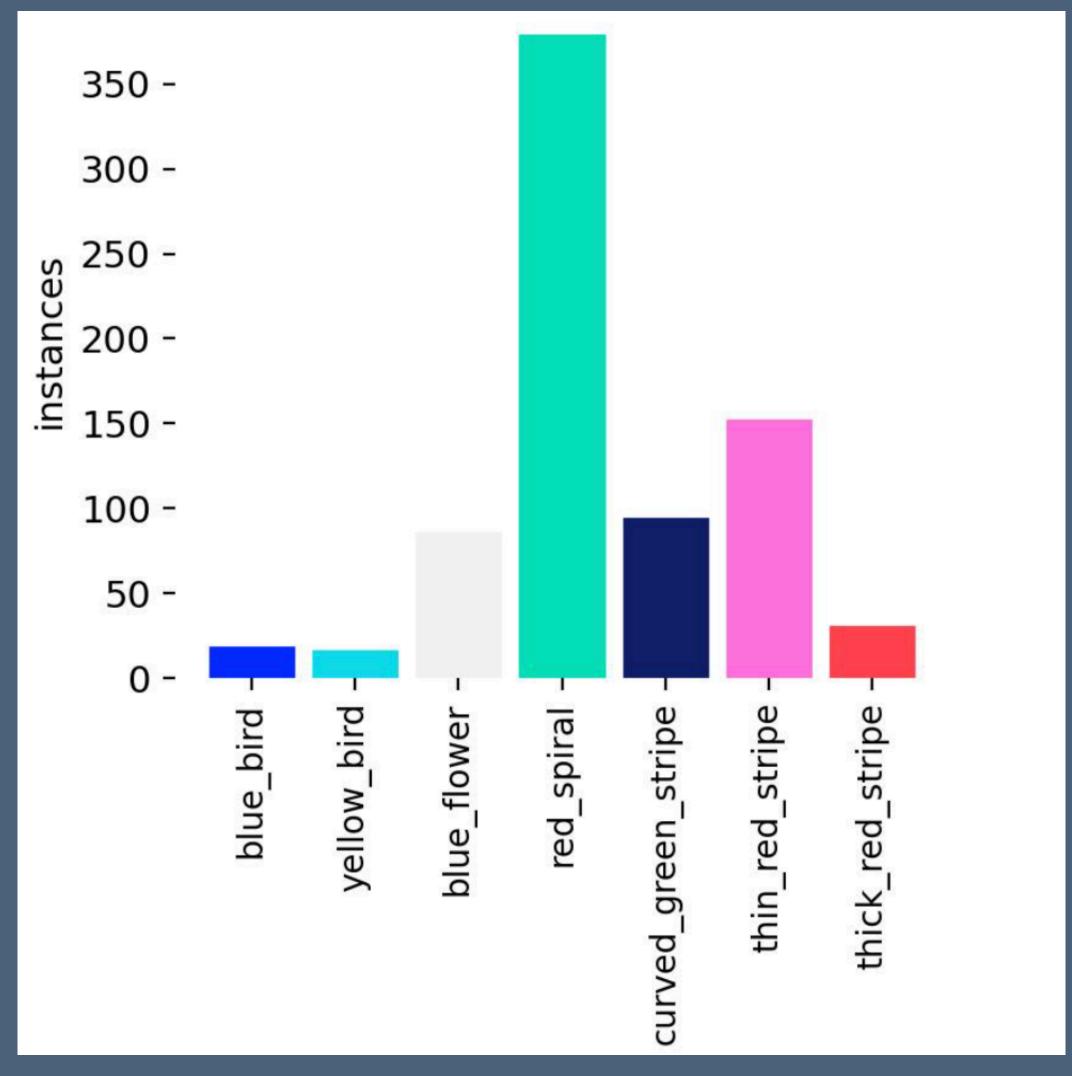
| Matrica  | Bounding Box |        |        | Segmentation |        |        |
|----------|--------------|--------|--------|--------------|--------|--------|
| Metrics  | Precision    | Recall | mAP@50 | Precision    | Recall | mAP@50 |
| 14 Class | 0.7866       | 0.8659 | 0.8439 | 0.8961       | 0.8113 | 0.9025 |
| 7 Class  | 0.8241       | 0.8577 | 0.9203 | 0.8241       | 0.8577 | 0.9203 |

#### Training More Results

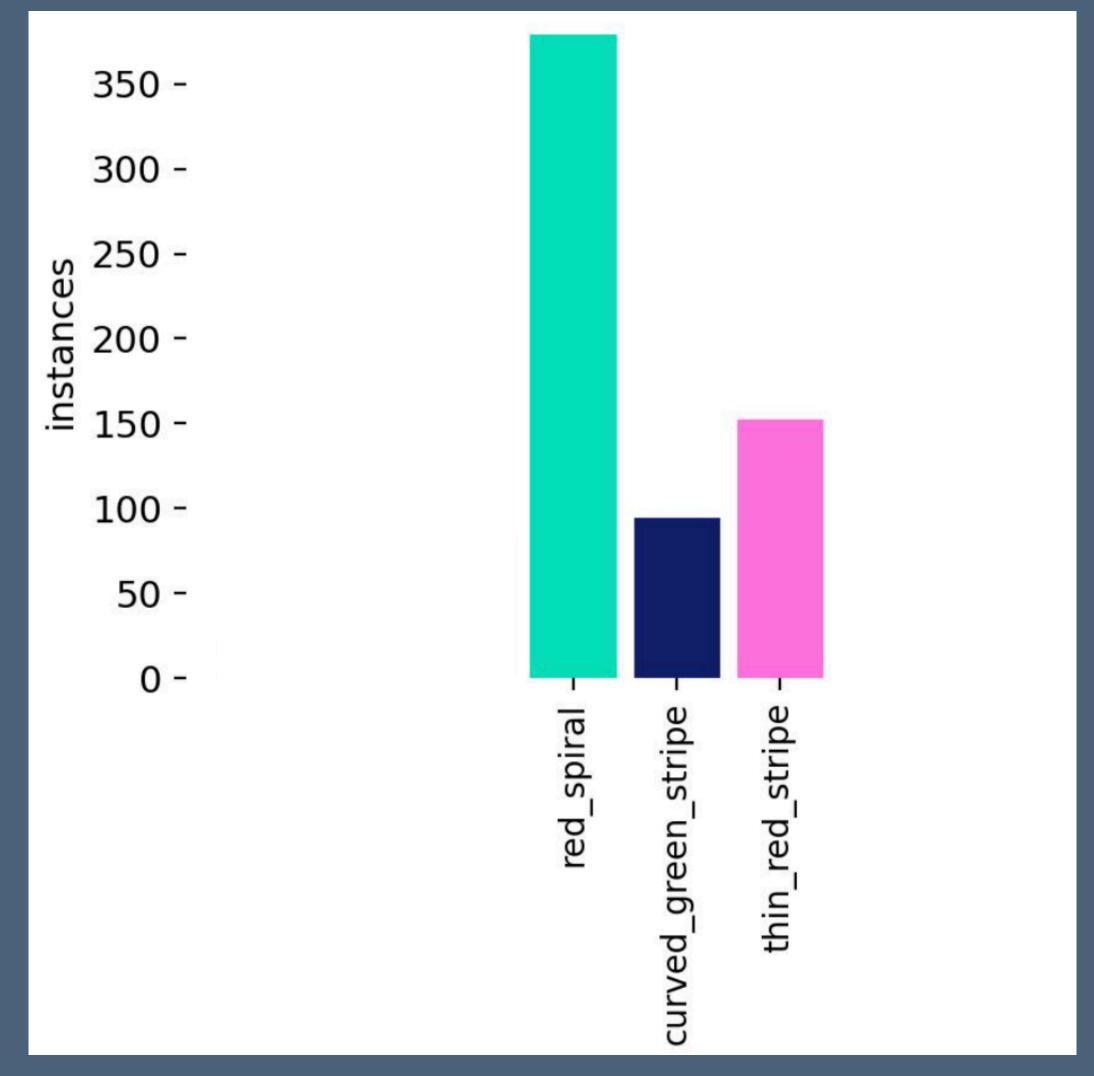




Training



Training



Training Results

| Metrics  | Bounding Box |        |        | Segmentation |        |        |
|----------|--------------|--------|--------|--------------|--------|--------|
|          | Precision    | Recall | mAP@50 | Precision    | Recall | mAP@50 |
| 14 Class | 0.7866       | 0.8659 | 0.8439 | 0.8961       | 0.8113 | 0.9025 |
| 7 Class  | 0.8241       | 0.8577 | 0.9203 | 0.8241       | 0.8577 | 0.9203 |
| 3 Class  | 0.8112       | 0.8953 | 0.8977 | 0.8112       | 0.8953 | 0.8977 |

### Step 1: Compare Models

Class Precision

