

CSE 472

Machine
Learning
Sessional

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PROBLEM

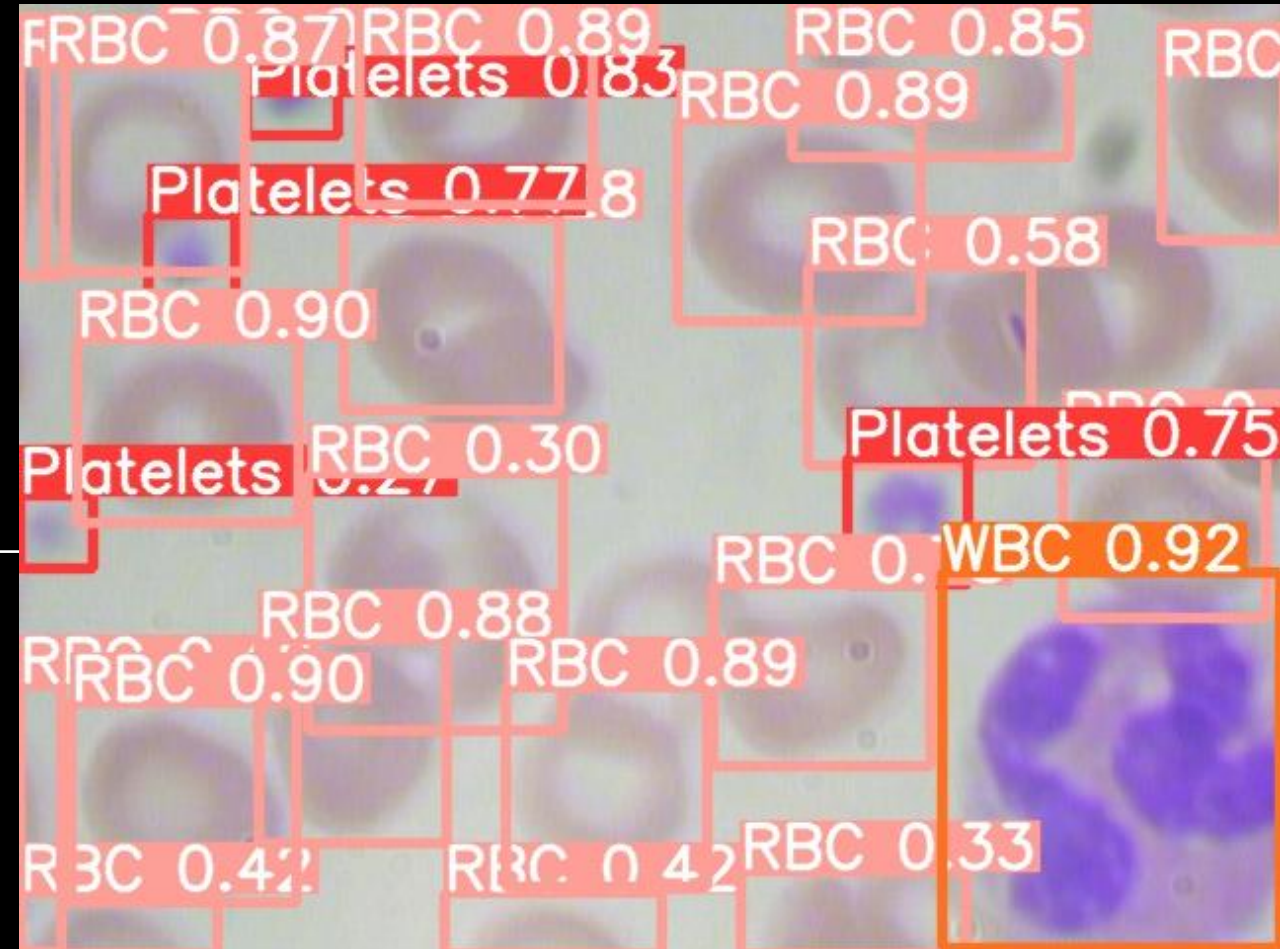
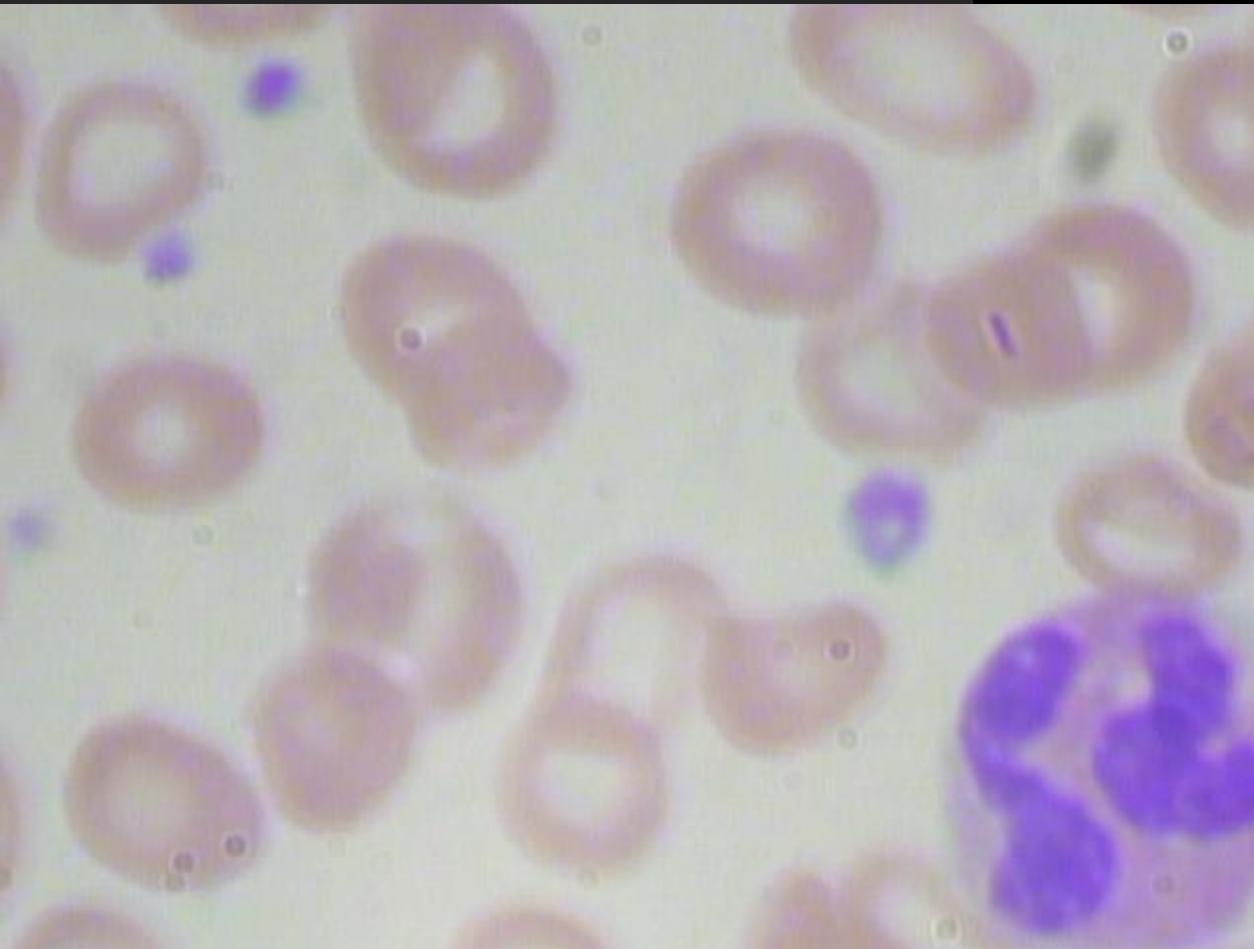
Given images of microscopic views of blood components, we need to detect basic blood cell types **RBC**, WBC, **Platelet** & their *counts* from that image

TYPE:

Image-based, Object Detection, Computer Vision

PROBLEM

Given images of microscopic views of blood components, we need to detect basic blood cell types **RBC**, WBC, **Platelet** & their **counts** from that image



MODEL

YOLO (You Only Look Once) v5:

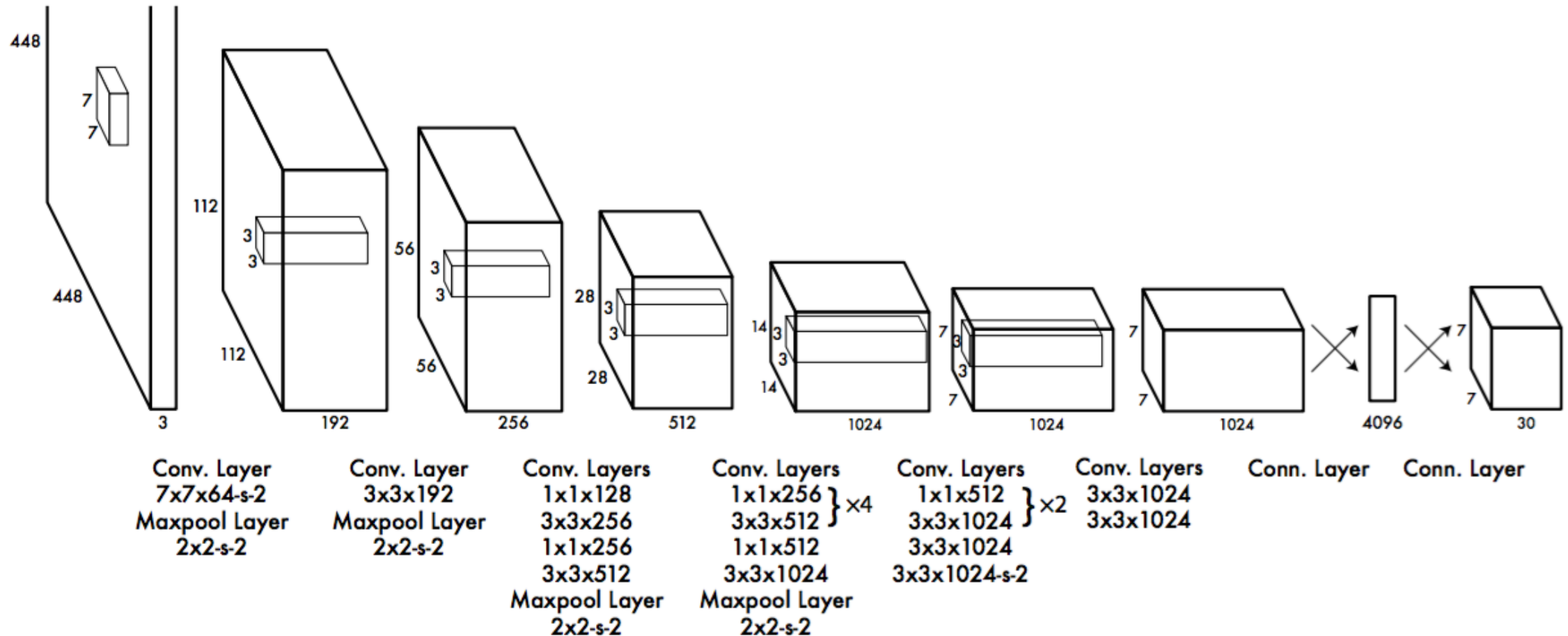
- ❖ Extremely fast (45 frames per second) ([Real Time Demo](#))
- ❖ Reasons globally on the entire image
- ❖ Learn **generalizable** representations (to new domains, like **art**)



YOLO ARCHITECTURE

Model Summary:

- 270 layers (original 24)
- 702720 parameters
- 702720 gradients
- 15.9 GFLOPs



YOLO ARCHITECTURE

	from	n	params	module	arguments
0	-1	1	3520	models.common.Conv	[3, 32, 6, 2, 2]
1	-1	1	18560	models.common.Conv	[32, 64, 3, 2]
2	-1	1	18816	models.common.C3	[64, 64, 1]
3	-1	1	73984	models.common.Conv	[64, 128, 3, 2]
4	-1	2	115712	models.common.C3	[128, 128, 2]
5	-1	1	295424	models.common.Conv	[128, 256, 3, 2]
6	-1	3	625152	models.common.C3	[256, 256, 3]
7	-1	1	1180672	models.common.Conv	[256, 512, 3, 2]
8	-1	1	1182720	models.common.C3	[512, 512, 1]
9	-1	1	656896	models.common.SPPF	[512, 512, 5]
10	-1	1	131584	models.common.Conv	[512, 256, 1, 1]
11	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
12	[-1, 6]	1	0	models.common.Concat	[1]
13	-1	1	361984	models.common.C3	[512, 256, 1, False]
14	-1	1	33024	models.common.Conv	[256, 128, 1, 1]
15	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
16	[-1, 4]	1	0	models.common.Concat	[1]
17	-1	1	90880	models.common.C3	[256, 128, 1, False]
18	-1	1	147712	models.common.Conv	[128, 128, 3, 2]
19	[-1, 14]	1	0	models.common.Concat	[1]
20	-1	1	296448	models.common.C3	[256, 256, 1, False]
21	-1	1	590336	models.common.Conv	[256, 256, 3, 2]
22	[-1, 10]	1	0	models.common.Concat	[1]
23	-1	1	1182720	models.common.C3	[512, 512, 1, False]
24	[17, 20, 23]	1	21576	models.yolo.Detect	[3, [[10, 13, 16, 30, 33,

Model Summary: 270 layers, 7027720 parameters, 7027720 gradients, 15.9 GFLOPs

```

12 # YOLOv5 v6.0 backbone
13 backbone:
14   # [from, number, module, args]
15   [[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
16    [-1, 1, Conv, [128, 3, 2]], # 1-P2/4
17    [-1, 3, C3, [128]],
18    [-1, 1, Conv, [256, 3, 2]], # 3-P3/8
19    [-1, 6, C3, [256]],
20    [-1, 1, Conv, [512, 3, 2]], # 5-P4/16
21    [-1, 9, C3, [512]],
22    [-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
23    [-1, 3, C3, [1024]],
24    [-1, 1, SPPF, [1024, 5]], # 9
25   ]
26
27 # YOLOv5 v6.0 head
28 head:
29   [[-1, 1, Conv, [512, 1, 1]],
30    [-1, 1, nn.Upsample, [None, 2, 'nearest']],
31    [[-1, 6], 1, Concat, [1]], # cat backbone P4
32    [-1, 3, C3, [512, False]], # 13
33
34    [-1, 1, Conv, [256, 1, 1]],
35    [-1, 1, nn.Upsample, [None, 2, 'nearest']],
36    [[-1, 4], 1, Concat, [1]], # cat backbone P3
37    [-1, 3, C3, [256, False]], # 17 (P3/8-small)
38
39    [-1, 1, Conv, [256, 3, 2]],
40    [[-1, 14], 1, Concat, [1]], # cat head P4
41    [-1, 3, C3, [512, False]], # 20 (P4/16-medium)
42
43    [-1, 1, Conv, [512, 3, 2]],
44    [[-1, 10], 1, Concat, [1]], # cat head P5
45    [-1, 3, C3, [1024, False]], # 23 (P5/32-large)
46
47    [[17, 20, 23], 1, Detect, [nc, anchors]], # Detect(P3, P4, P5)
48   ]

```

YOLO

ARCHITECTURE

Activation Function:

- Leaky ReLU in middle / hidden layers
- Sigmoid in the final detection layer

Optimization Function:

- SGD (Stochastic Gradient Descent)
- Adam

In YOLO v5, default optimization function for training is SGD.

Loss Function:

- Binary Cross-Entropy with Logits Loss (default)
- Focal Loss

YOLO ARCHITECTURE

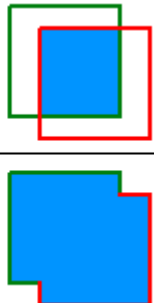
Loss Function

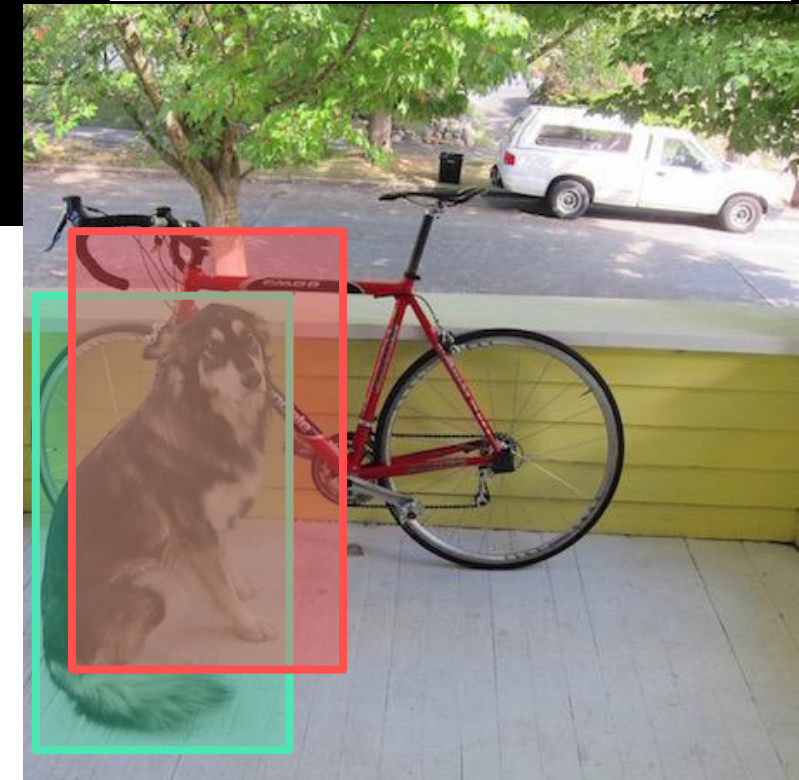
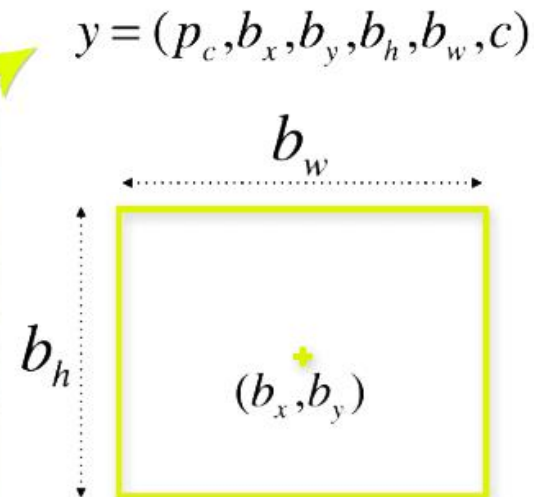
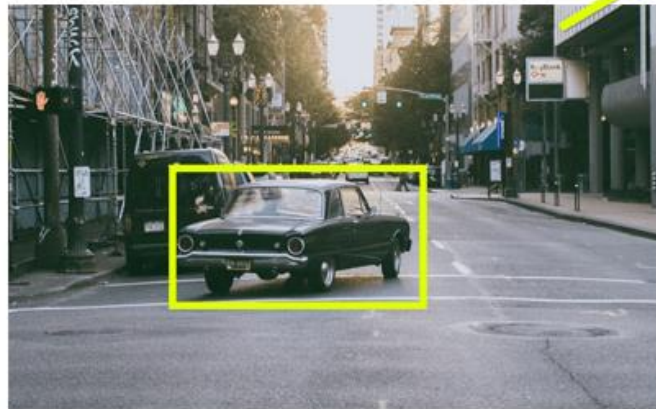
$$\begin{aligned} & \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \\ & + \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \\ & + \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\ & + \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 \\ & + \sum_{i=0}^{S^2} \mathbb{1}_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \end{aligned}$$

HOW YOLO ALGORITHM WORKS

YOLO algorithm works using the following three techniques:

- Residual Blocks
- Bounding Box Regression
- Intersection Over Union (IOU)

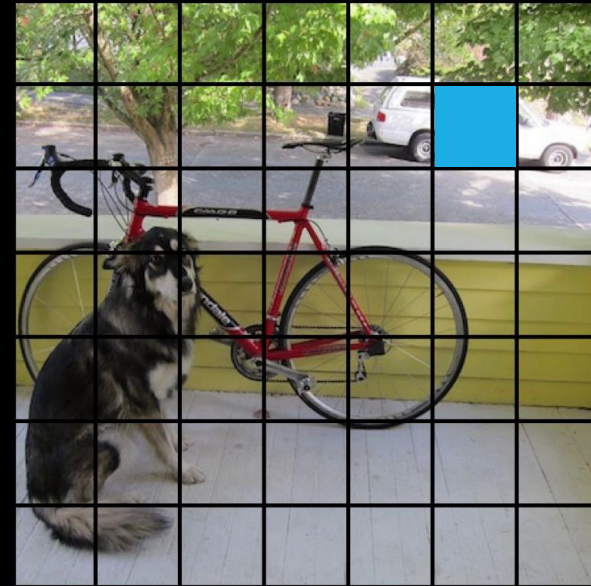
$$IOU = \frac{\text{area of overlap}}{\text{area of union}} = \frac{\text{area of intersection}}{\text{area of union}}$$




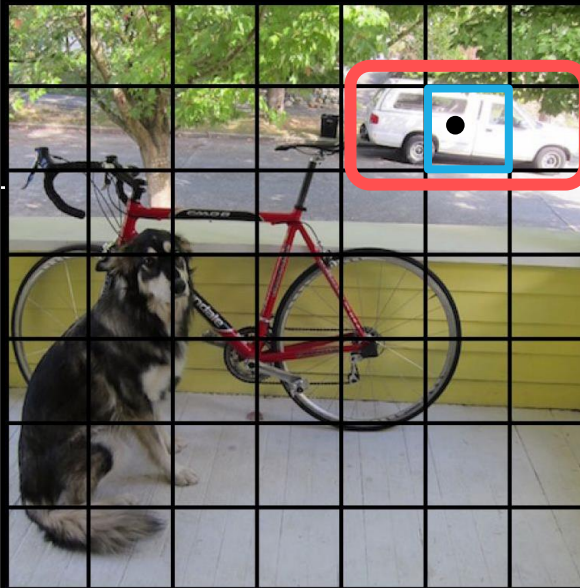
HOW YOLO ALGORITHM WORKS



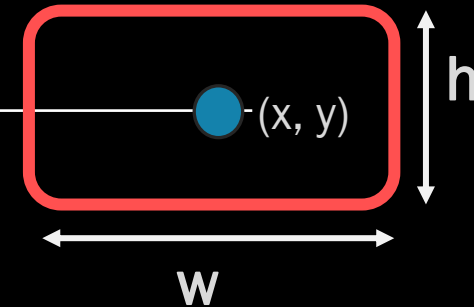
Image is divided into $S \times S$ grid



Each cell predicts B boxes (x, y, w, h) and confidence of each box: $P(\text{object})$



Predicted box's center is shown in black which is in the blue colored cell.



Anchor box specifying the object in a grid cell.

HOW YOLO ALGORITHM WORKS

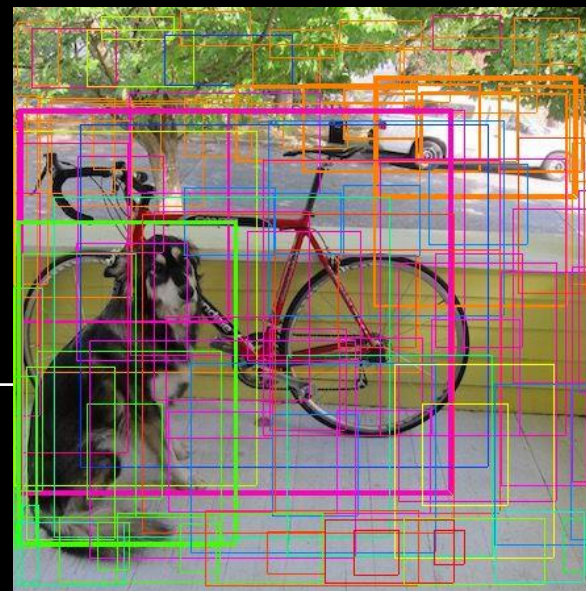


Each cell predicts boxes and confidences: $P(\text{object})$
Probability that the box contains an object.



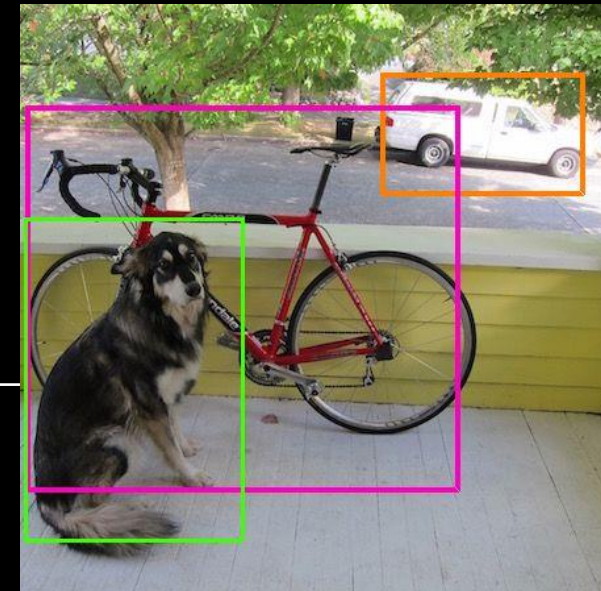
Each cell also predicts a class probability conditioning on objects:

- Green = Dog,
- Pink = Bicycle
- Orange = Car



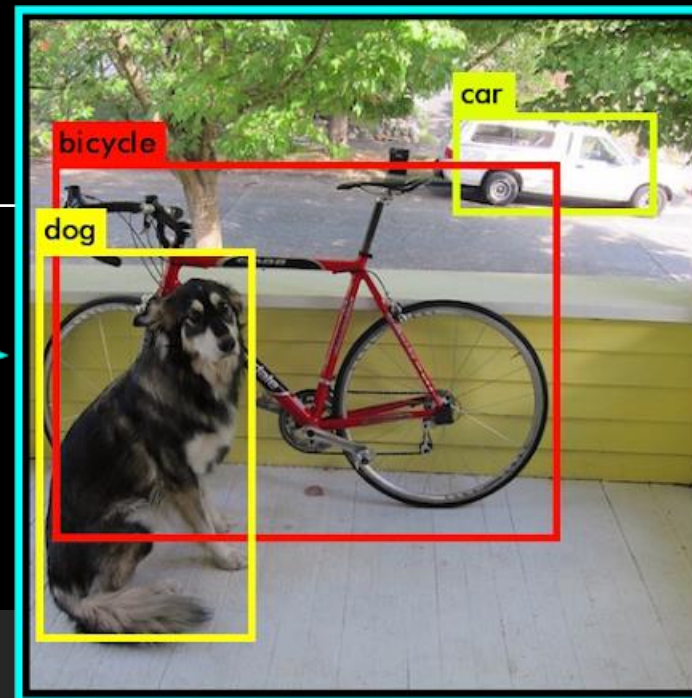
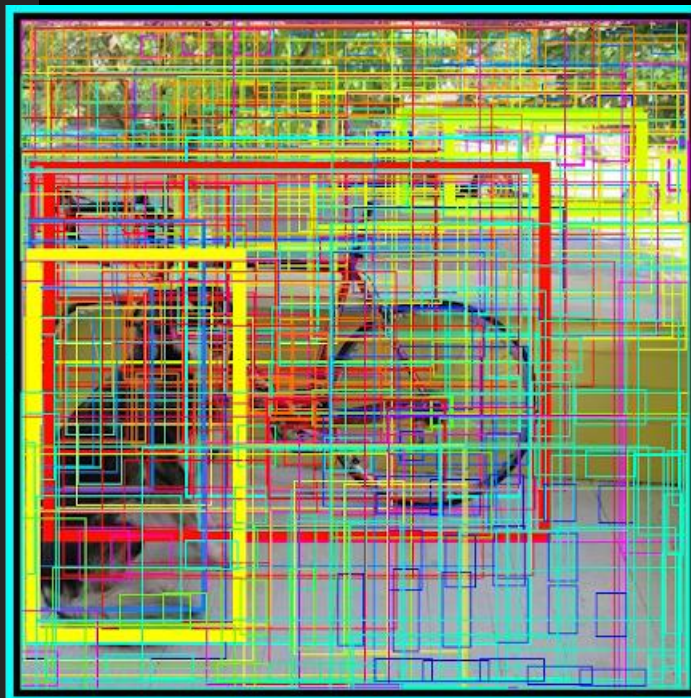
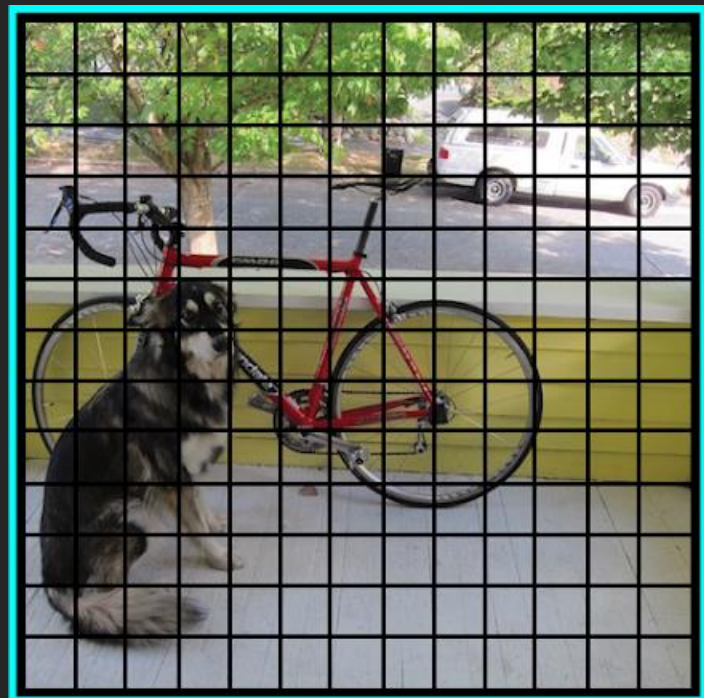
Combining the box and class predictions.

$$P(\text{class} | \text{object}) * P(\text{object}) \\ = P(\text{class})$$



After performing threshold detection and Non-max suppression.
Discard all boxes with Probability ≤ 0.6

HOW YOLO ALGORITHM WORKS

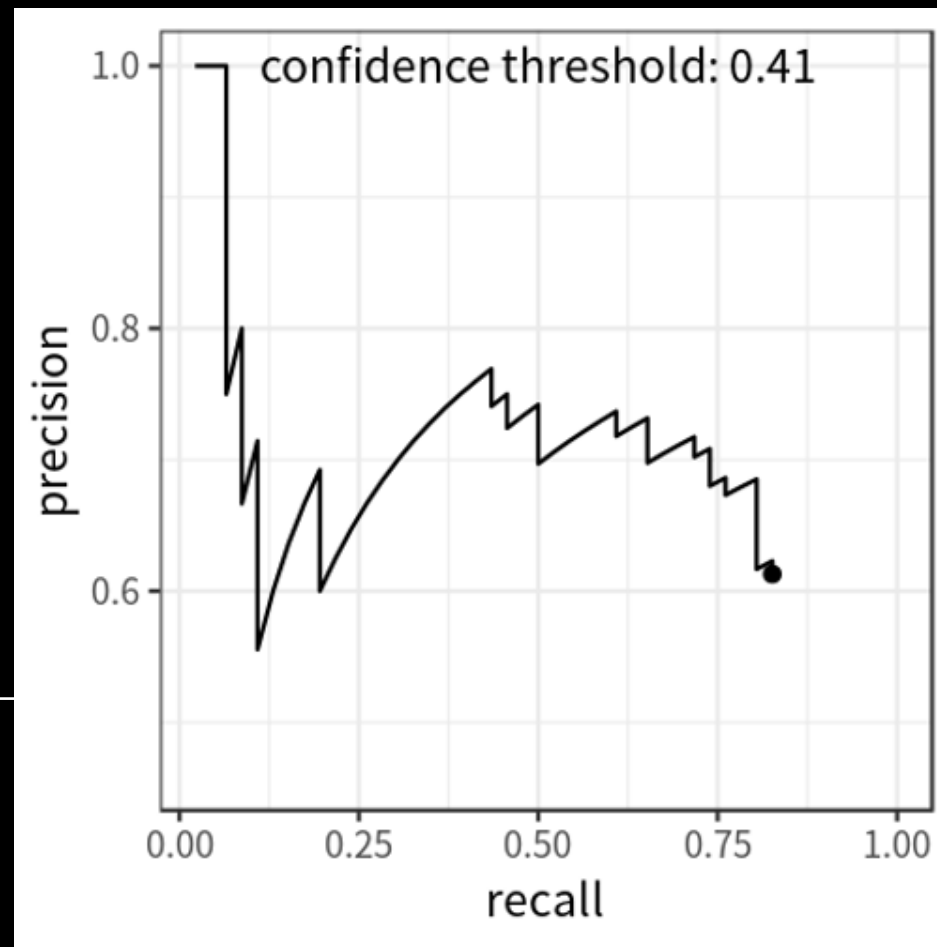


EVALUATION METRIC

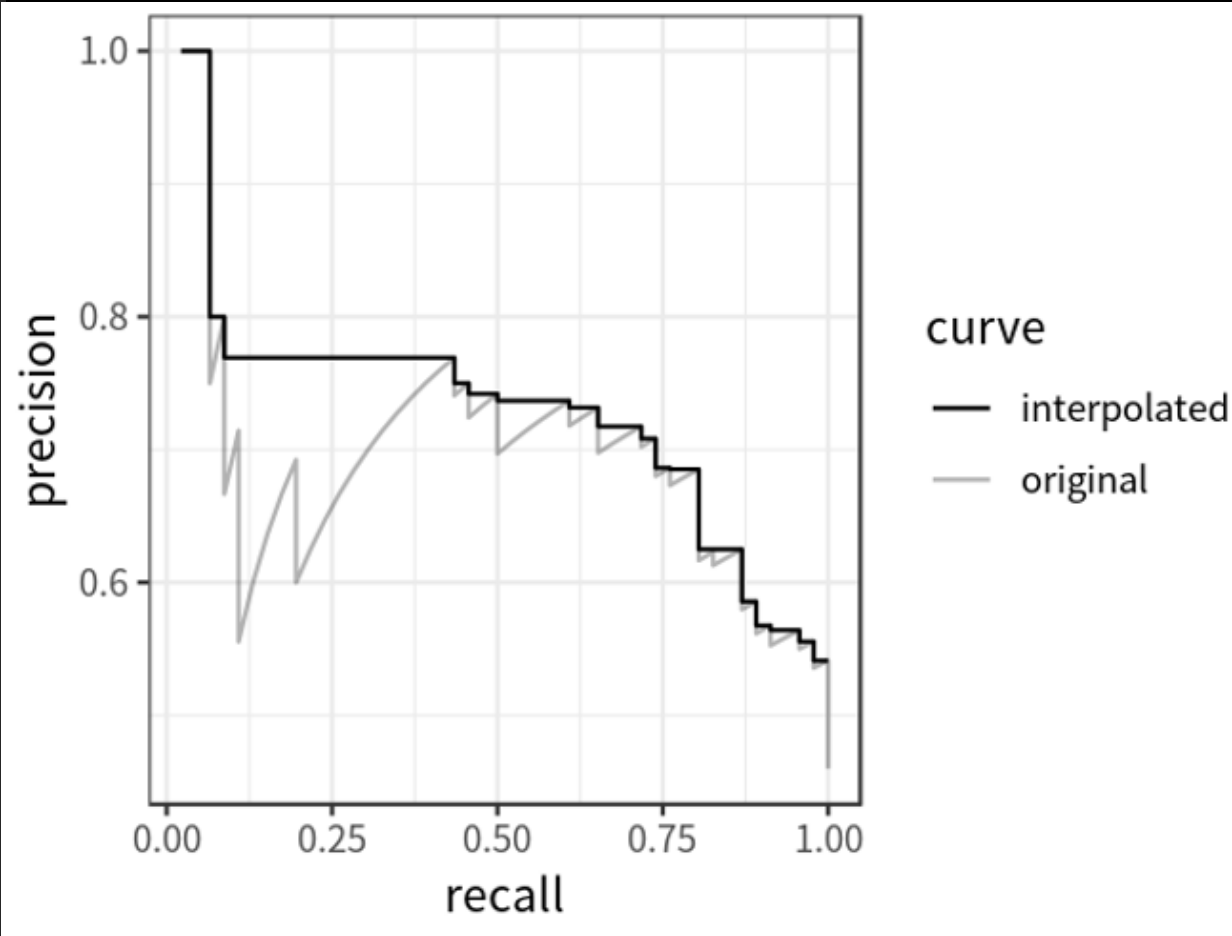
$$IoU = \frac{area(B_p \cap B_{gt})}{area(B_p \cup B_{gt})}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$



EVALUATION METRIC



AP can then be defined as the area under the interpolated precision-recall curve, which can be calculated using the following formula:

$$AP = \sum_{i=1}^{n-1} (r_{i+1} - r_i) p_{interp}(r_{i+1}) \quad (5)$$

where r_1, r_2, \dots, r_n is the recall levels (in an ascending order) at which the precision is first interpolated.

Mean Average
Precision:

$$mAP = \frac{\sum_{i=1}^K AP_i}{K}$$

DATASET

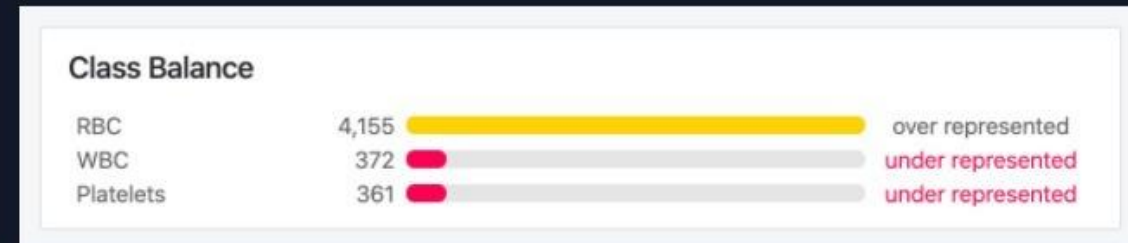
BCCD

Overview

This is a dataset of blood cells photos, originally open sourced by [cosmicad](#) and [akshaylambda](#).

There are 364 images across three classes: `WBC` (white blood cells), `RBC` (red blood cells), and `Platelets`. There are 4888 labels across 3 classes (and 0 null examples).

Here's a class count from Roboflow's Dataset Health Check:



Data Splitting:

Partition	# of Images	%
Train	205	56.32 %
Validation	87	23.90 %
Test	72	19.78 %

TRAINING

YOLO V5

100 epochs

Testing

Results

mAP@.5:.95 → 62.5 %

```
100 epochs completed in 0.543 hours.
Optimizer stripped from yolov5/runs/train/BCCM2/weights/last.pt, 14.4MB
Optimizer stripped from yolov5/runs/train/BCCM2/weights/best.pt, 14.4MB

Validating yolov5/runs/train/BCCM2/weights/best.pt...
Fusing layers...
Model Summary: 213 layers, 7018216 parameters, 0 gradients, 15.8 GFLOPs

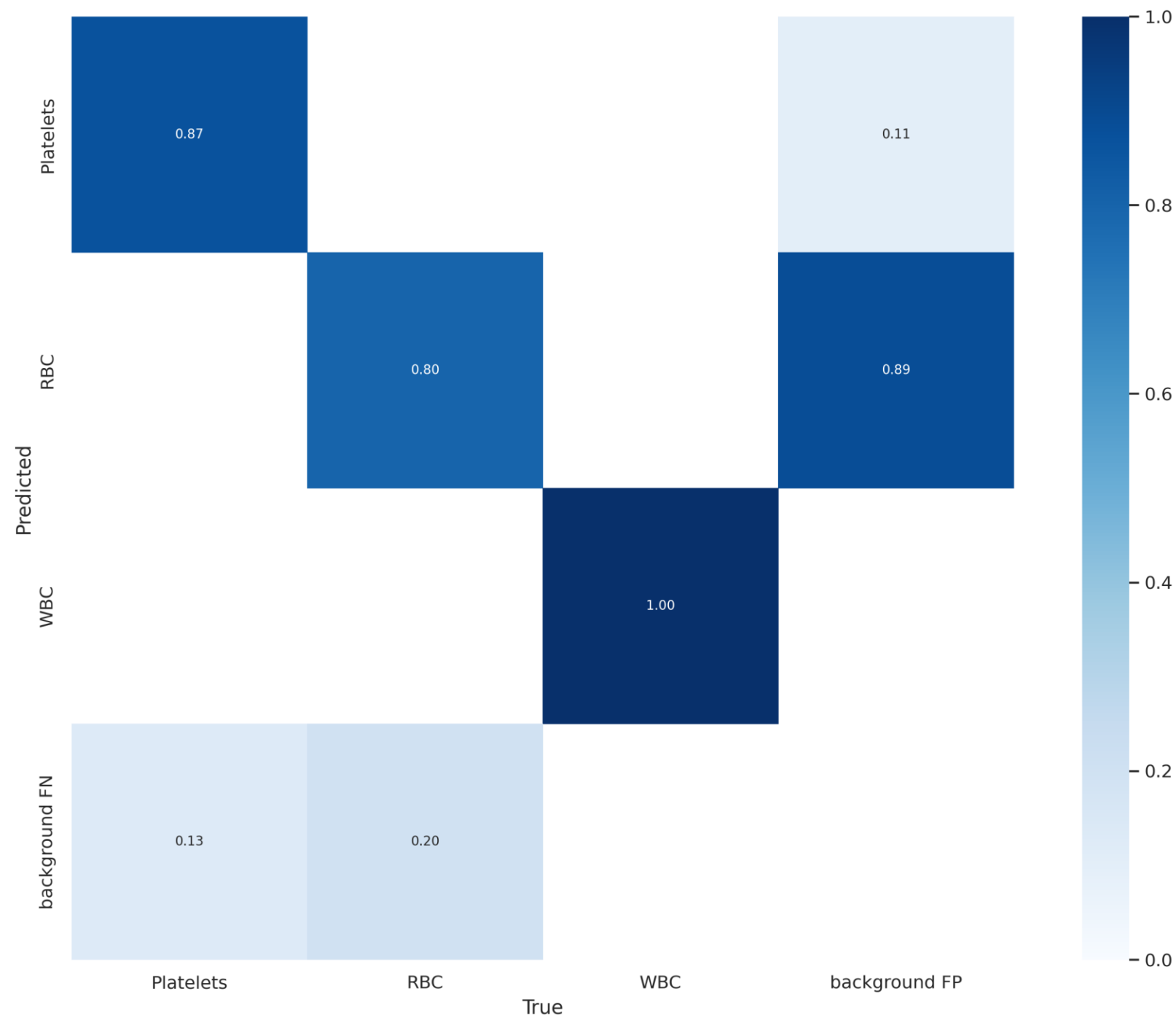
```

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95: 100% 6/6
all	87	1138	0.876	0.874	0.907	0.625
Platelets	87	83	0.818	0.865	0.879	0.454
RBC	87	968	0.825	0.756	0.854	0.61
WBC	87	87	0.984	1	0.987	0.812

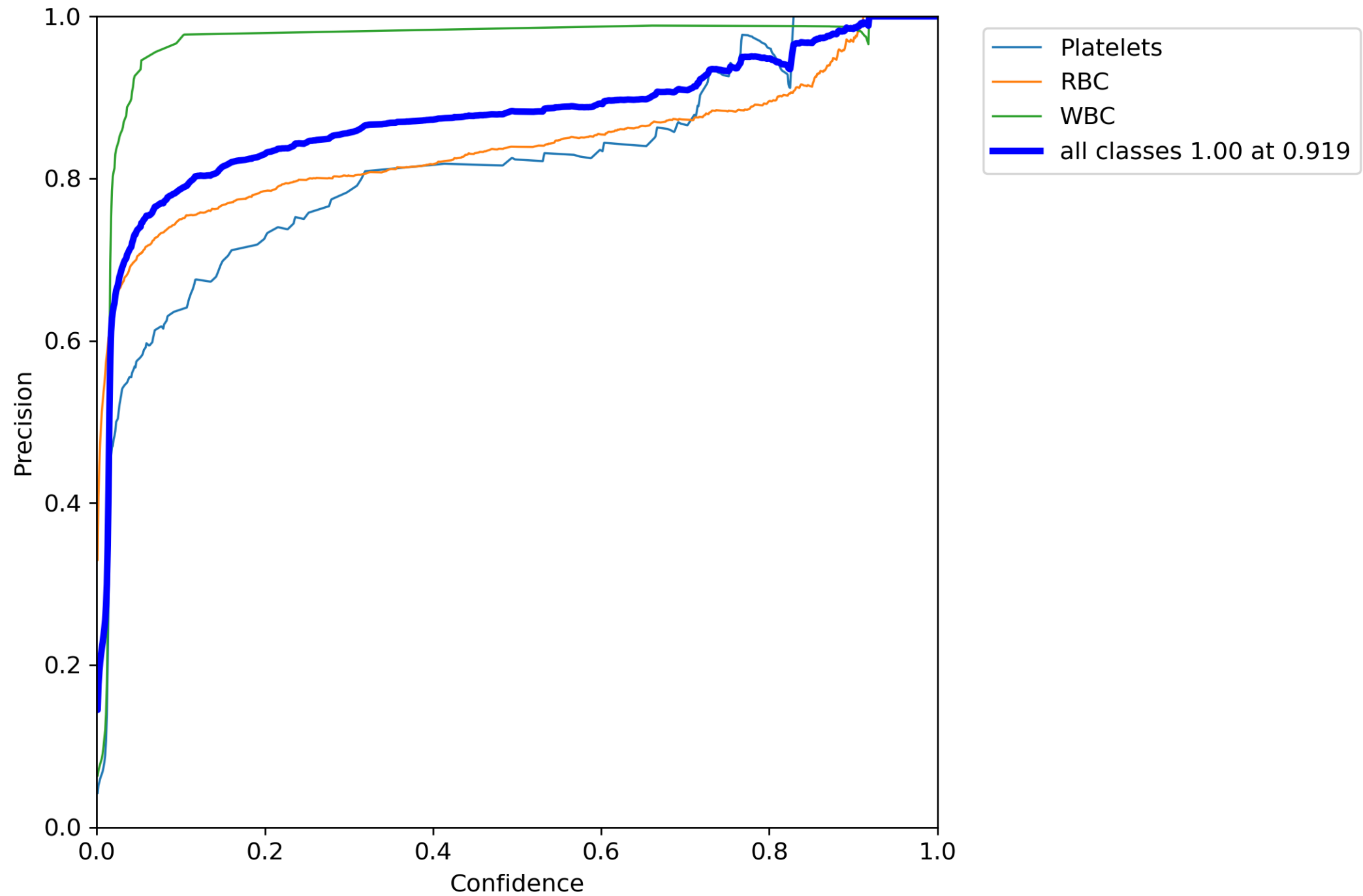
```
Results saved to yolov5/runs/train/BCCM2
CPU times: user 18.7 s, sys: 3.08 s, total: 21.8 s
Wall time: 33min 3s
```

	Platelets	RBC	WBC
Ground Truth	69	805	71
Prediction	85	1268	79

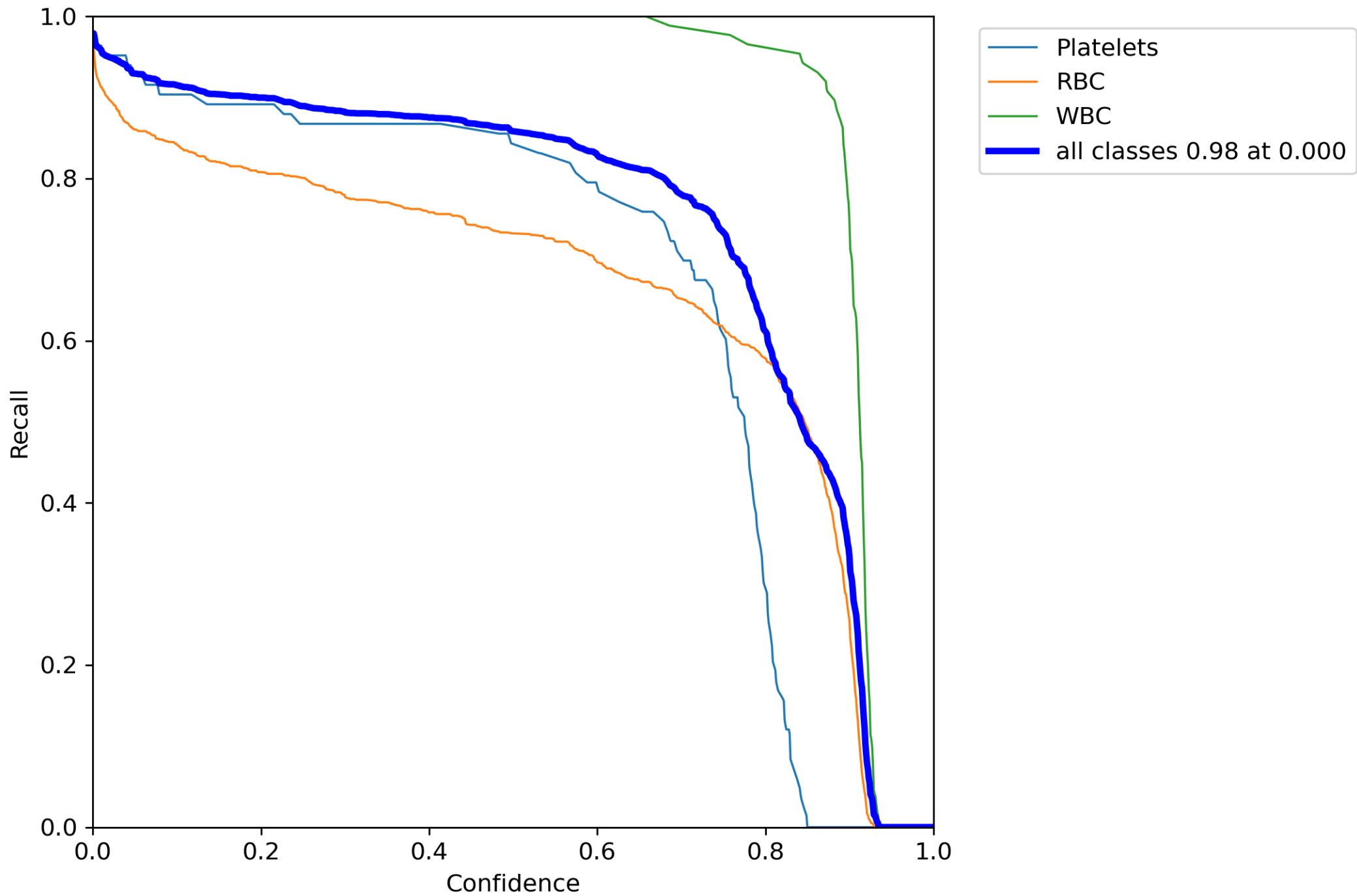
Confusion Matrix



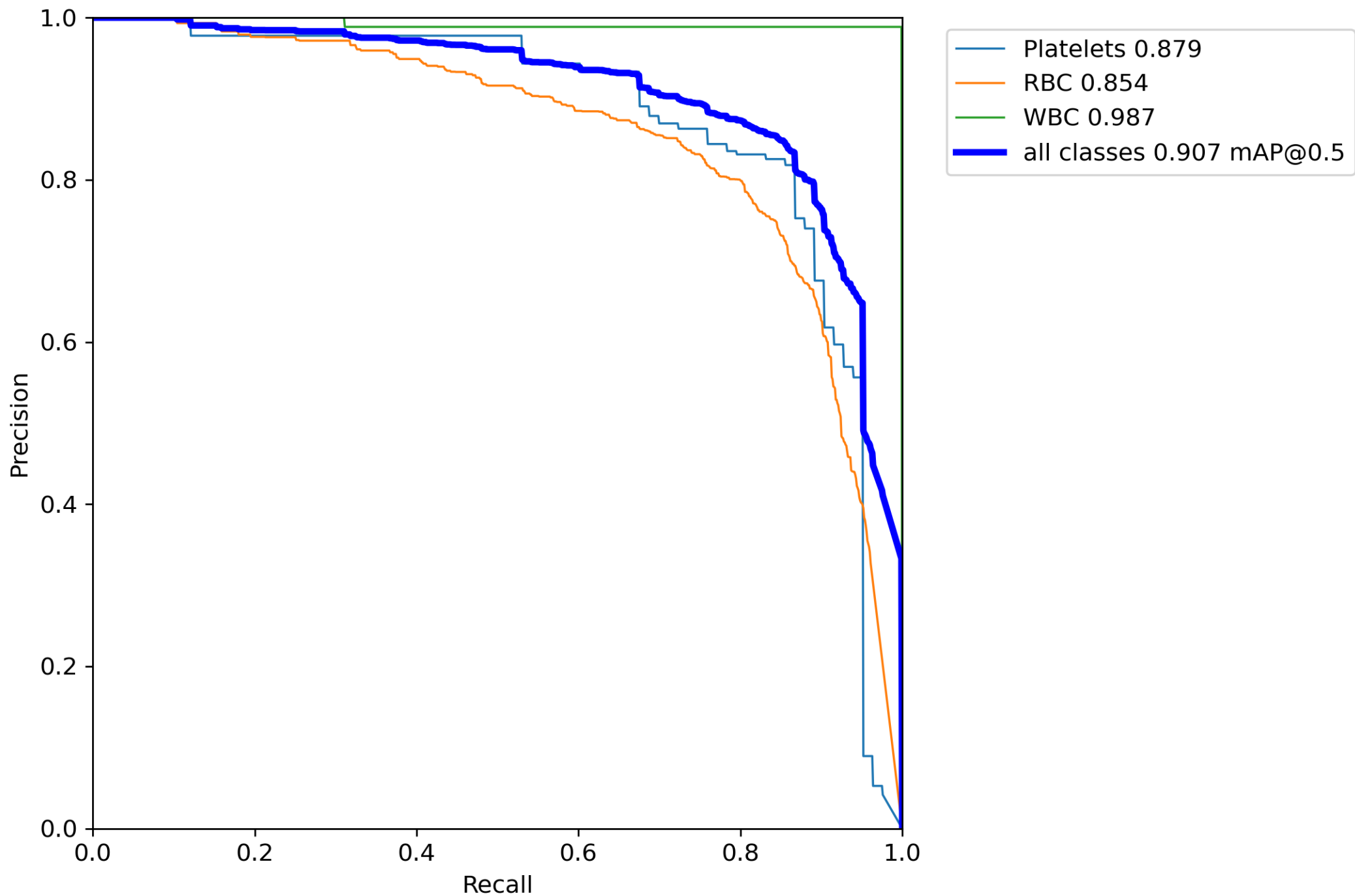
Precision (P) Curve



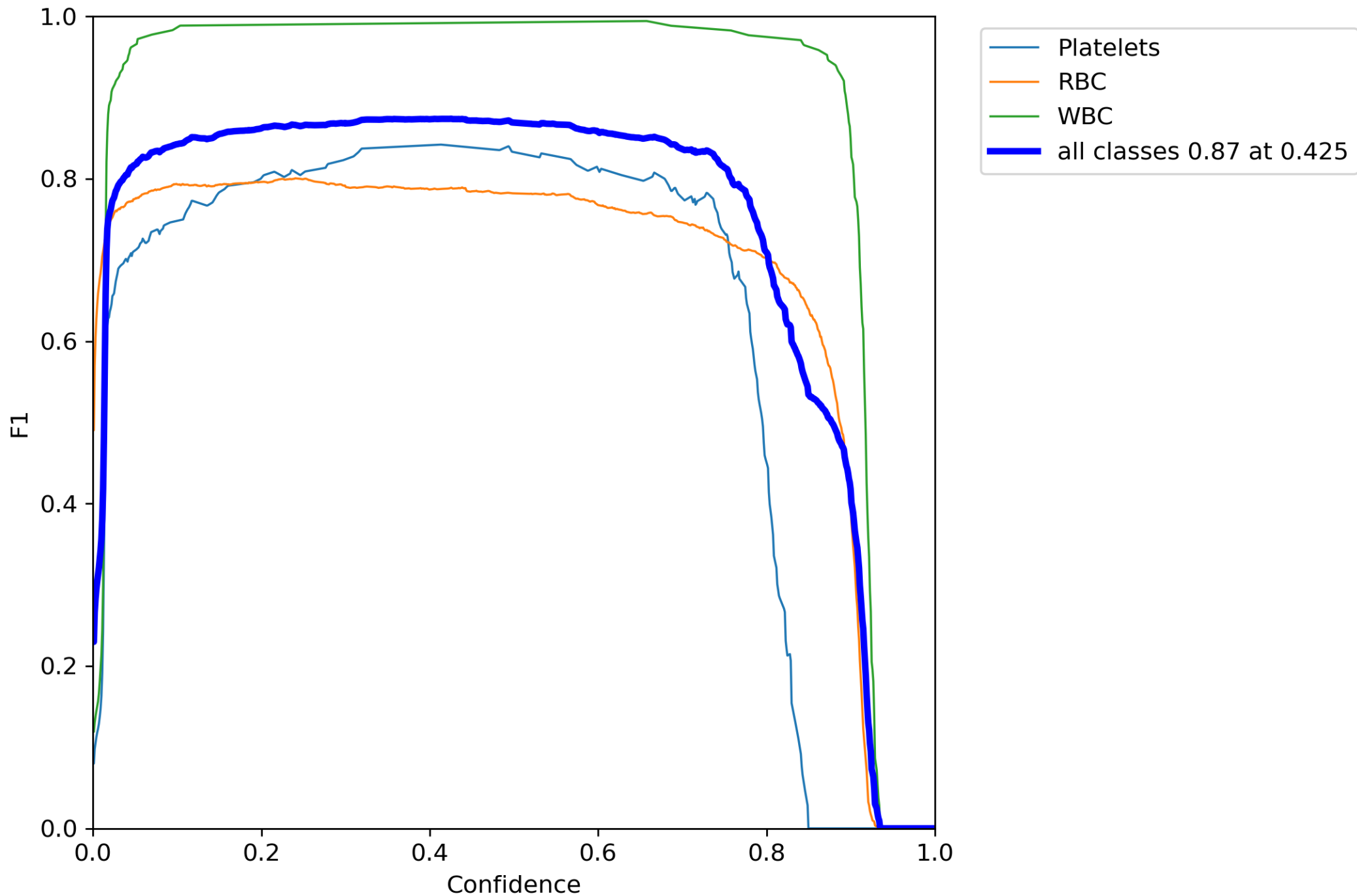
Recall (R) Curve



P-R Curve

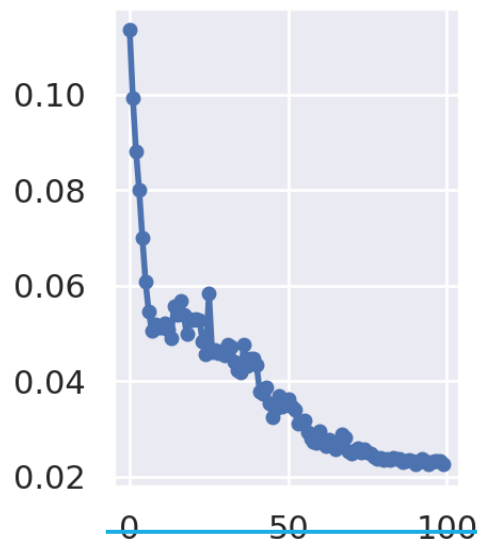


F1 Curve

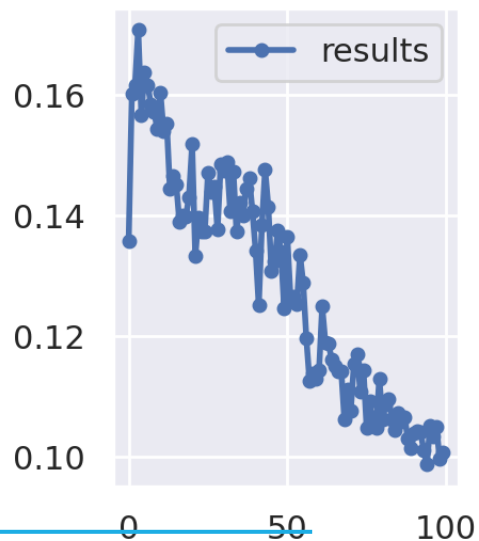


Results

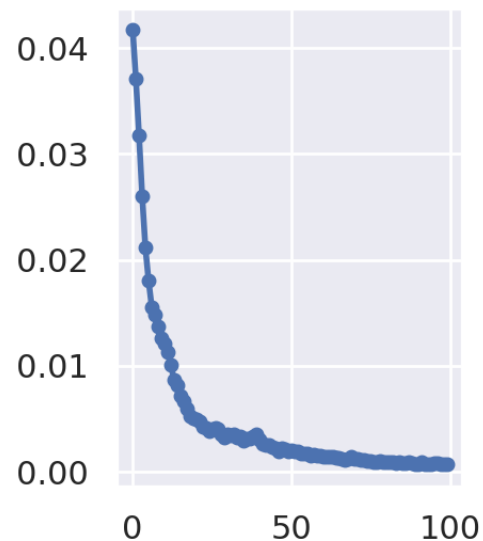
train/box_loss



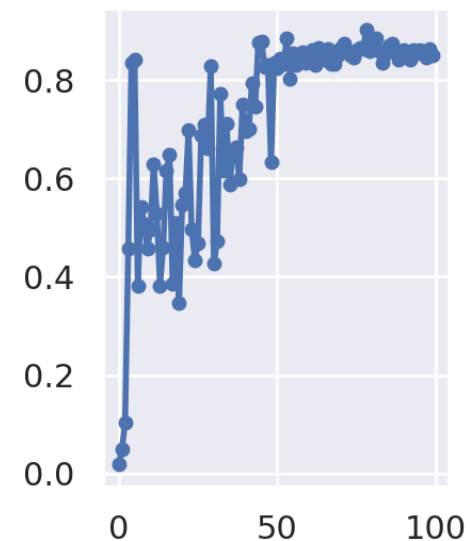
train/obj_loss



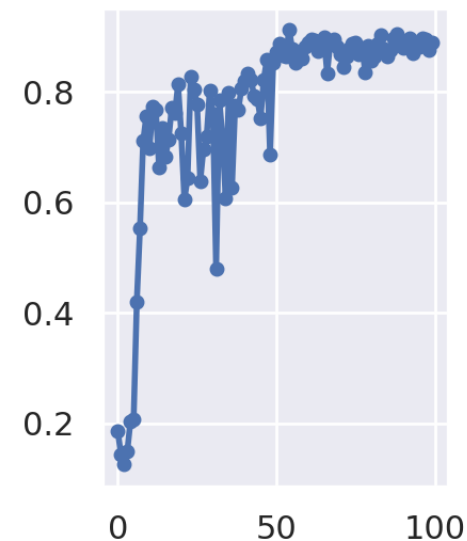
train/cls_loss



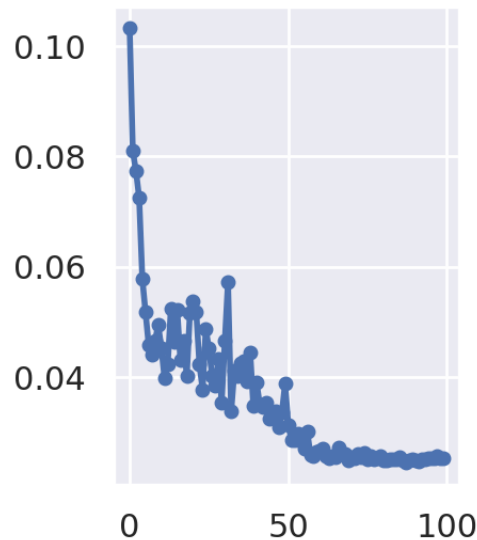
metrics/precision



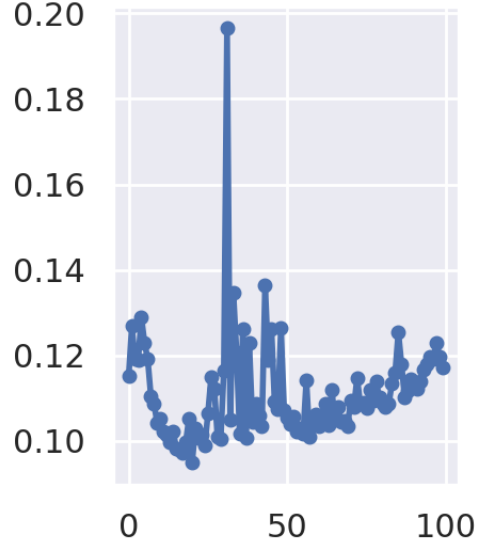
metrics/recall



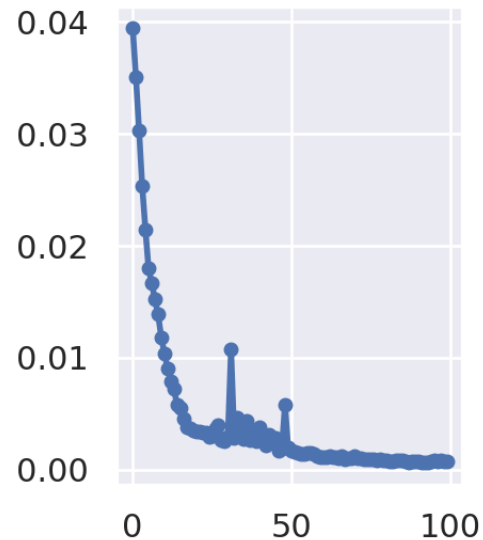
val/box_loss



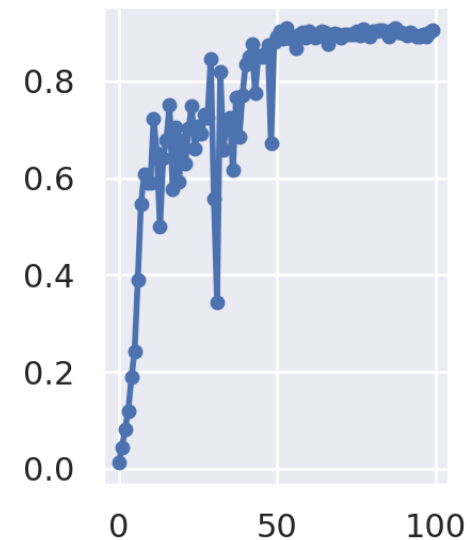
val/obj_loss



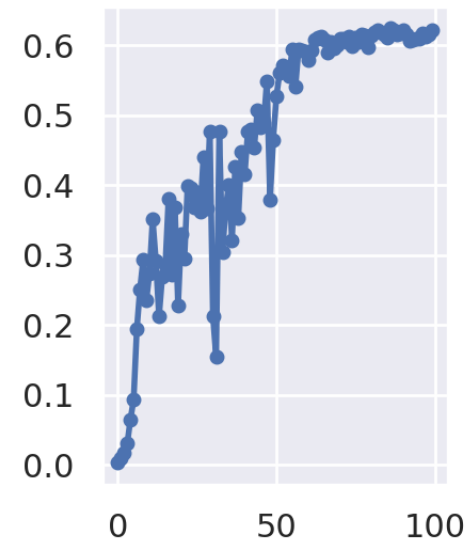
val/cls_loss



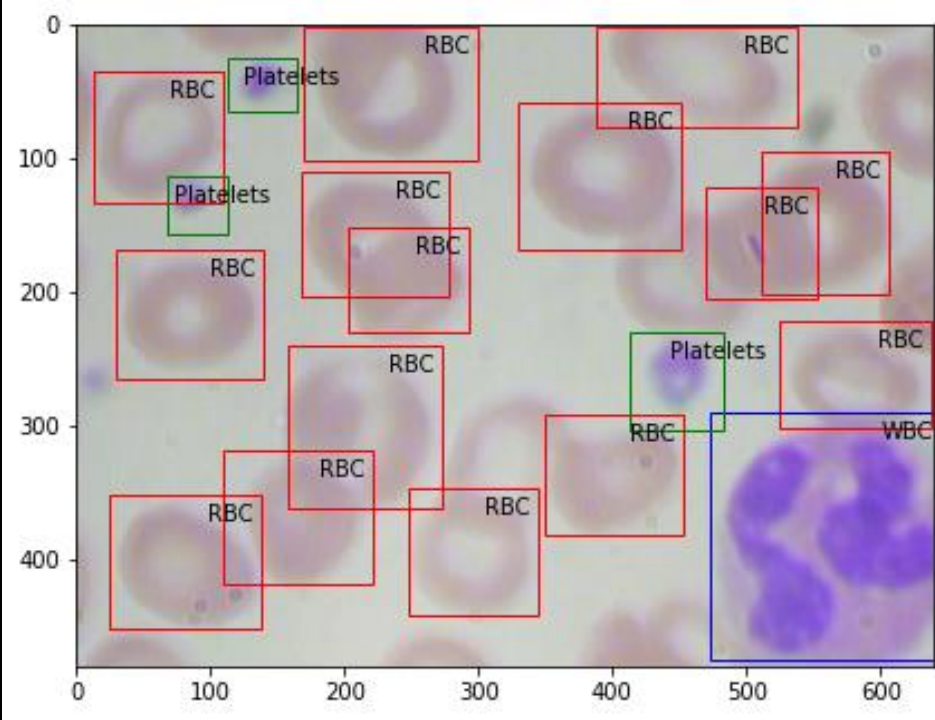
metrics/mAP_0.5



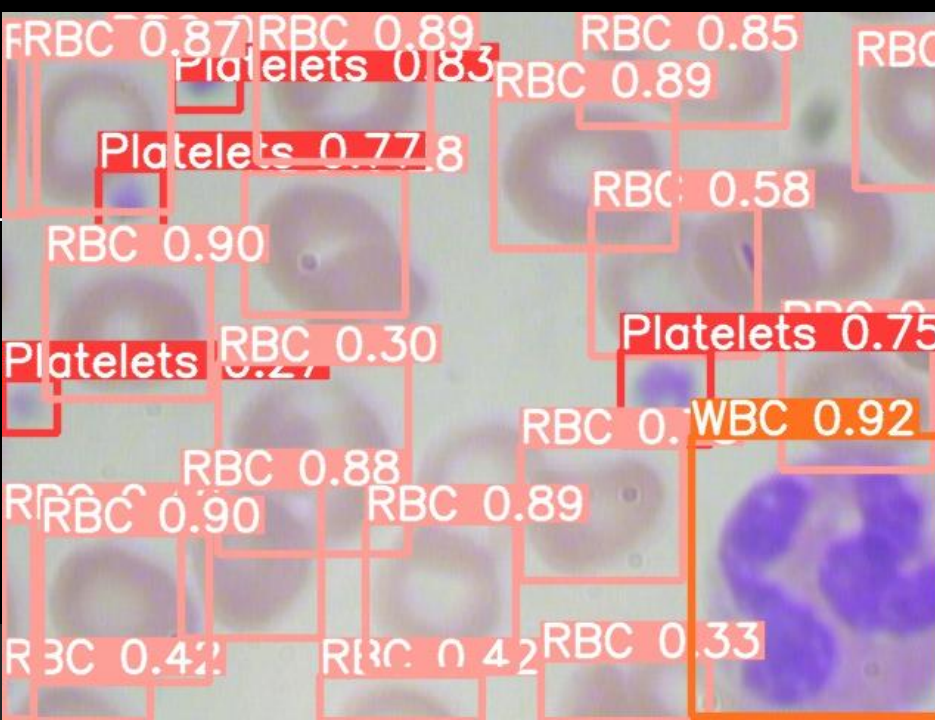
metrics/mAP_0.5:0.95



Comments on Platelets & RBC counts



	Platelets	RBC	WBC
Ground Truth	03	15	01
Prediction	04	20	01



	Platelets	RBC	WBC
Ground Truth	69	805	71
Prediction	85	1268	79

Data Augmentation

TRAIN / TEST SPLIT

Training Set

88%

765 images

Validation Set

8%

73 images

Testing Set

4%

36 images

Output Size Calculation

When you generate a version, we create a point-in-time snapshot of your dataset, locking in your preprocessing and augmentation selections for reproducibility.

Breakdown:

255 training images × 3 variants
+ 73 validation images
+ 36 testing images

≤ 874 image output size

Your version's final number of images may be smaller than this estimate because we de-duplicate images and certain options (like "Filter Null") can remove images from the output.

Done

TRAINING

YOLO V5

100 epochs

Testing Results

mAP@.5:.95 → 64.2 %

```
100 epochs completed in 1.042 hours.  
Optimizer stripped from yolov5/runs/train/BCCM/weights/last.pt, 14.3MB  
Optimizer stripped from yolov5/runs/train/BCCM/weights/best.pt, 14.3MB  
  
Validating yolov5/runs/train/BCCM/weights/best.pt...  
Fusing layers...  
Model Summary: 213 layers, 7018216 parameters, 0 gradients, 15.8 GFLOPs
```

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95: 100% 5/5
all	73	967	0.875	0.905	0.925	0.642
Platelets	73	76	0.882	0.881	0.908	0.507
RBC	73	819	0.776	0.835	0.885	0.622
WBC	73	72	0.967	1	0.983	0.796

```
Results saved to yolov5/runs/train/BCCM  
CPU times: user 45.1 s, sys: 6.88 s, total: 52 s  
Wall time: 1h 3min 17s
```

	Platelets	RBC	WBC
Ground Truth	36	398	37
Prediction	45	692	40

Transfer Learning

Comparison
with other
state-of-the-art
Object Detection Models

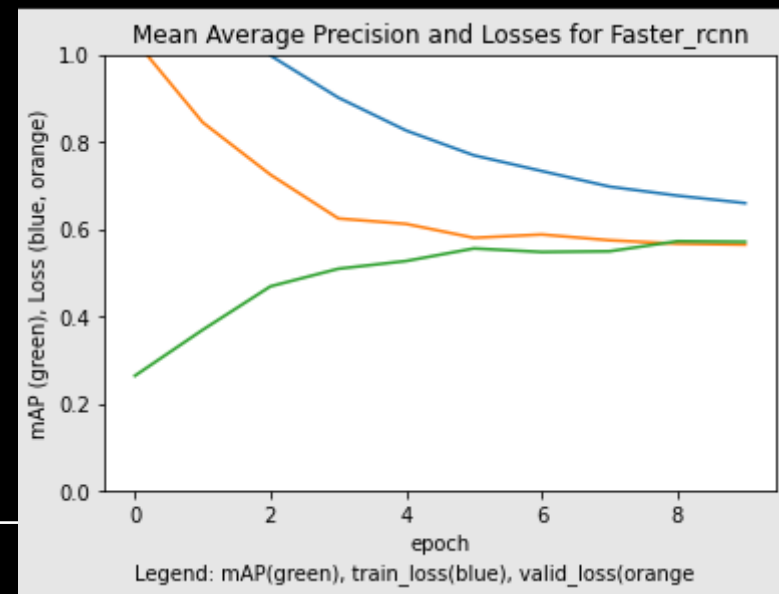
```
model_type_yolo = models.ultralytics.yolov5
backbone_yolo = model_type_yolo.backbones.small
model_yolo = model_type_yolo.model(
    backbone = backbone_yolo(pretrained=True),
    num_classes=len(parser.class_map), img_size = size)
train_dl_yolo = model_type_yolo.train_dl(train_ds,
    batch_size=16, num_workers=4, shuffle=True)
valid_dl_yolo = model_type_yolo.valid_dl(valid_ds,
    batch_size=16, num_workers=4, shuffle=False)

learn_yolo = model_type_yolo.fastai.learner(
    dls=[train_dl_yolo, valid_dl_yolo],
    model=model_yolo, metrics=metrics)

learn_yolo.lr_find()
learn_yolo.fine_tune(10, 1e-2, freeze_epochs=1)
plot_metrics(learn_yolo,
    'Mean Average Precision and Losses for YOLOv5')
```

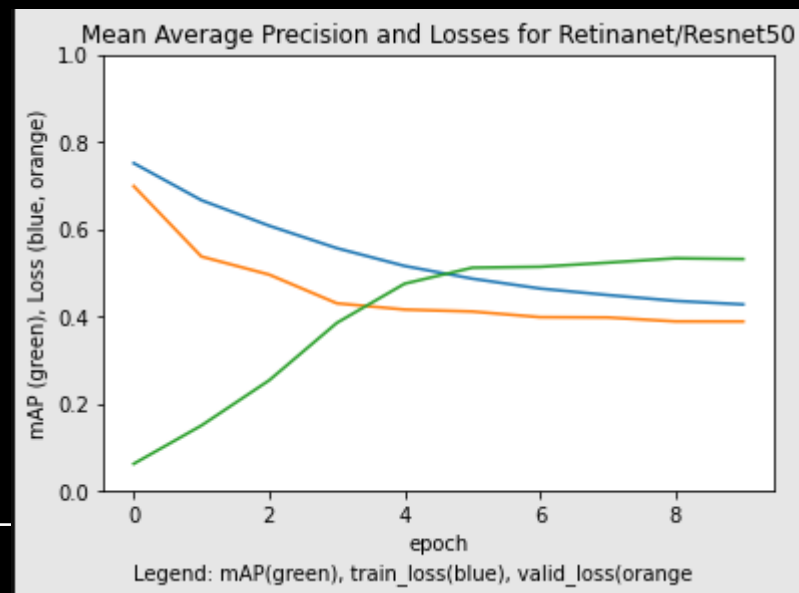
FASTER R-CNN

epoch	train_loss	valid_loss	COCOMetric	time
0	1.421260	1.033804	0.265108	01:11
1	1.162679	0.845835	0.370371	00:58
2	0.998871	0.725854	0.470032	00:58
3	0.902615	0.625586	0.510287	00:57
4	0.827155	0.613033	0.528075	00:58
5	0.770260	0.581217	0.556863	00:57
6	0.734273	0.588839	0.548724	00:57
7	0.698556	0.575590	0.550385	00:57
8	0.677905	0.567733	0.573396	00:57
9	0.660749	0.565578	0.572065	00:57



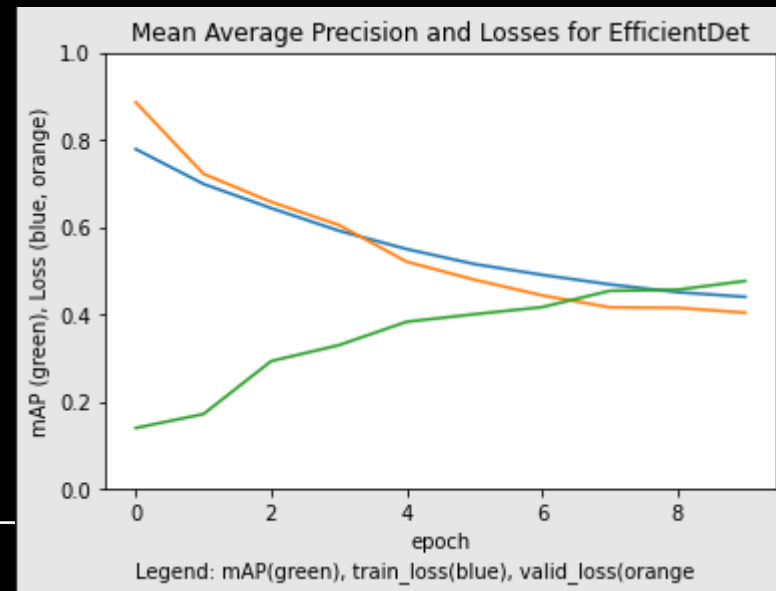
Retina Net

epoch	train_loss	valid_loss	COCOMetric	time
0	0.752289	0.699699	0.063327	00:39
1	0.667371	0.538277	0.151133	00:38
2	0.608886	0.496884	0.254696	00:38
3	0.557438	0.431085	0.386364	00:37
4	0.516701	0.416808	0.476085	00:37
5	0.487569	0.412279	0.512709	00:37
6	0.464997	0.399387	0.514859	00:37
7	0.450095	0.398680	0.524334	00:37
8	0.436650	0.389633	0.534338	00:38
9	0.428610	0.389472	0.532546	00:37



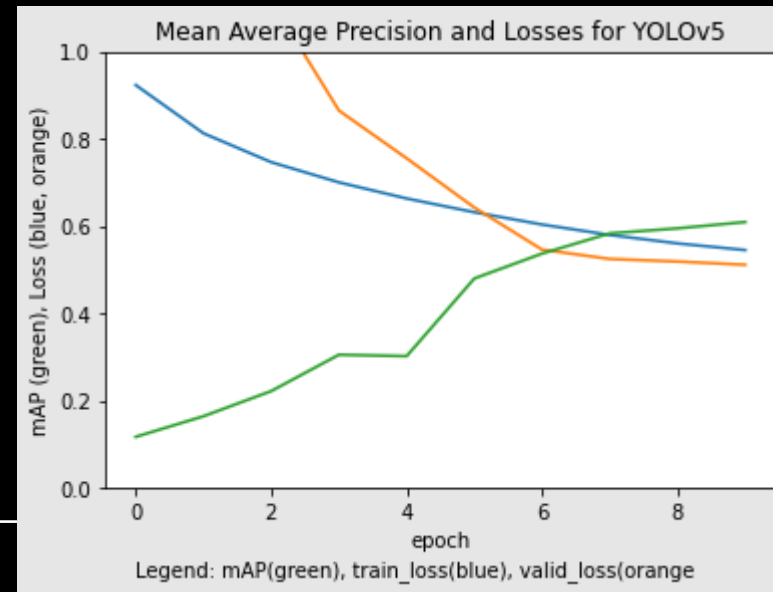
EfficientDet

epoch	train_loss	valid_loss	COCOMetric	time
0	0.779975	0.887384	0.140874	00:25
1	0.700151	0.723331	0.172714	00:23
2	0.644590	0.658918	0.294107	00:22
3	0.592794	0.606164	0.330704	00:23
4	0.550768	0.521928	0.384231	00:23
5	0.516472	0.480586	0.401486	00:23
6	0.491730	0.444813	0.417749	00:23
7	0.469823	0.417321	0.455171	00:23
8	0.451999	0.416150	0.457720	00:23
9	0.441310	0.405147	0.477708	00:23



YOLO-V5

epoch	train_loss	valid_loss	COCOMetric	time
0	0.924407	1.139100	0.118237	00:15
1	0.813875	1.455061	0.165457	00:15
2	0.747731	1.117861	0.223106	00:14
3	0.701412	0.866094	0.306402	00:14
4	0.664457	0.756519	0.303205	00:14
5	0.632931	0.643673	0.481163	00:14
6	0.604743	0.547221	0.538219	00:14
7	0.580869	0.525873	0.584507	00:14
8	0.561514	0.519982	0.595998	00:14
9	0.546258	0.512514	0.610488	00:14



Comparison

Model	LR	mAP	Avg. time
Faster R-CNN	2e-04	0.57	57 sec
YOLO-V5	1e-02	0.61	14 sec
Retina Net	8e-05	0.53	37 sec
EfficientDet	1e-02	0.48	23 sec

Best Model YOLO-V5

41	0.389574	0.548379	0.622749	00:13
42	0.384600	0.549746	0.621227	00:14
43	0.380539	0.559521	0.624182	00:14
44	0.376359	0.552600	0.612266	00:14
45	0.371917	0.554087	0.622479	00:14
46	0.370168	0.553329	0.615118	00:14
47	0.369631	0.555480	0.619671	00:14
48	0.368694	0.554739	0.618568	00:14
49	0.366679	0.554078	0.619776	00:14

Better model found at epoch 0 with COCOMetric value: 0.11712814851744503.
Better model found at epoch 1 with COCOMetric value: 0.23050699305620143.
Better model found at epoch 2 with COCOMetric value: 0.3785265946222327.
Better model found at epoch 3 with COCOMetric value: 0.4446381264126172.
Better model found at epoch 5 with COCOMetric value: 0.46801126206937094.
Better model found at epoch 8 with COCOMetric value: 0.5182532786877971.
Better model found at epoch 12 with COCOMetric value: 0.5223814597991697.
Better model found at epoch 13 with COCOMetric value: 0.5452902918600457.
Better model found at epoch 17 with COCOMetric value: 0.5495939167804712.
Better model found at epoch 22 with COCOMetric value: 0.5847185619932614.
Better model found at epoch 24 with COCOMetric value: 0.5997363300132839.
Better model found at epoch 32 with COCOMetric value: 0.6171018943293074.
Better model found at epoch 38 with COCOMetric value: 0.6210552059955694.
Better model found at epoch 41 with COCOMetric value: 0.6227487698173754.
Better model found at epoch 43 with COCOMetric value: 0.6241815784979853.

Challenges

- Scarcity of Computational Resources
(Google Colab Free Account Restrictions)
 - Small Dataset
 - Error Handling
 - RBC, Platelets overlapping problem
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THANK
YOU

