

# MULTI-CLASS WILDLIFE SPECIES CLASSIFICATION

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01

OBJECTIVE

02

DATASET

03

APPROACH

04

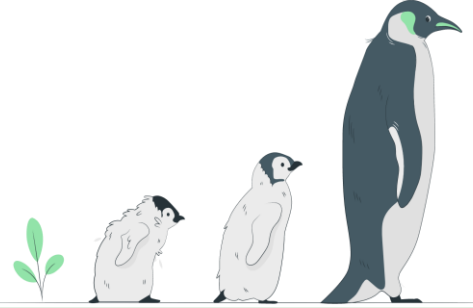
RESULTS

05

NEXT STEPS



# Objective



## Detect and classify over 80 species of wildlife captured by wildlife cameras

1.

Recognize predatory animals which may pose threat to other species or humans

2.

Monitor endangered species and determine long term viability

3.

Reduce the number of traffic accidents in various regions

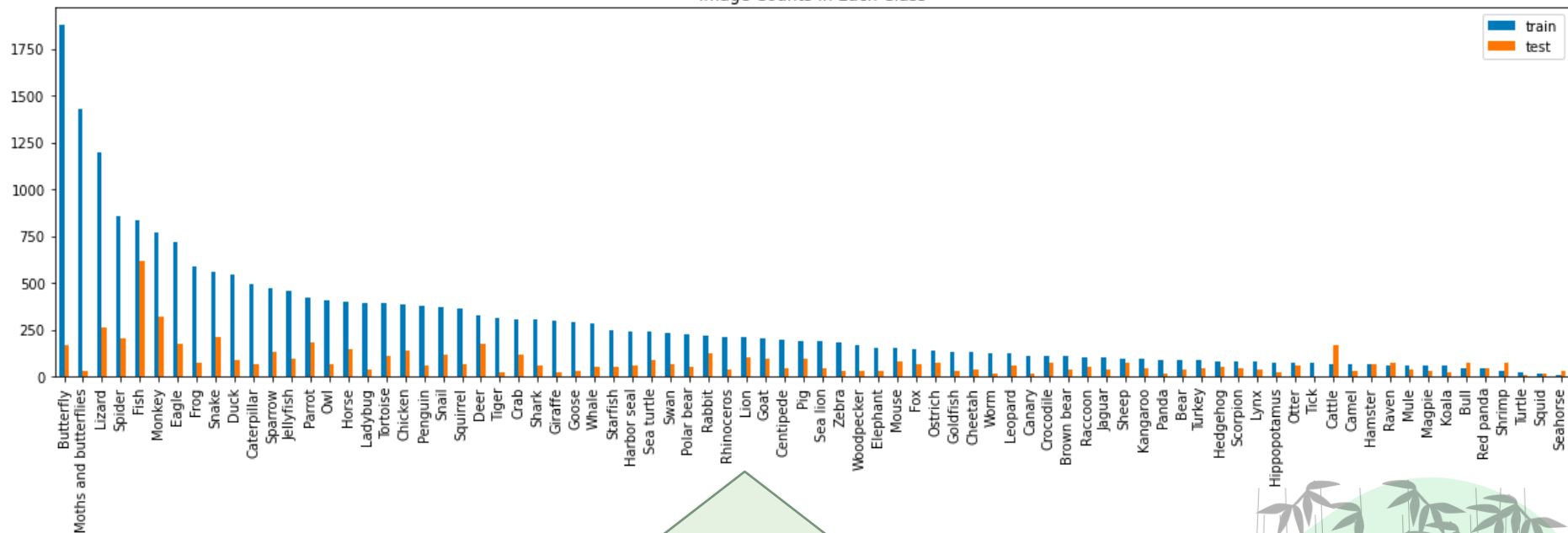
4.

Regulate poaching in restricted areas by keeping a count of the number of animals



# Dataset

Image Counts in Each Class



Public  
dataset  
on  
Kaggle

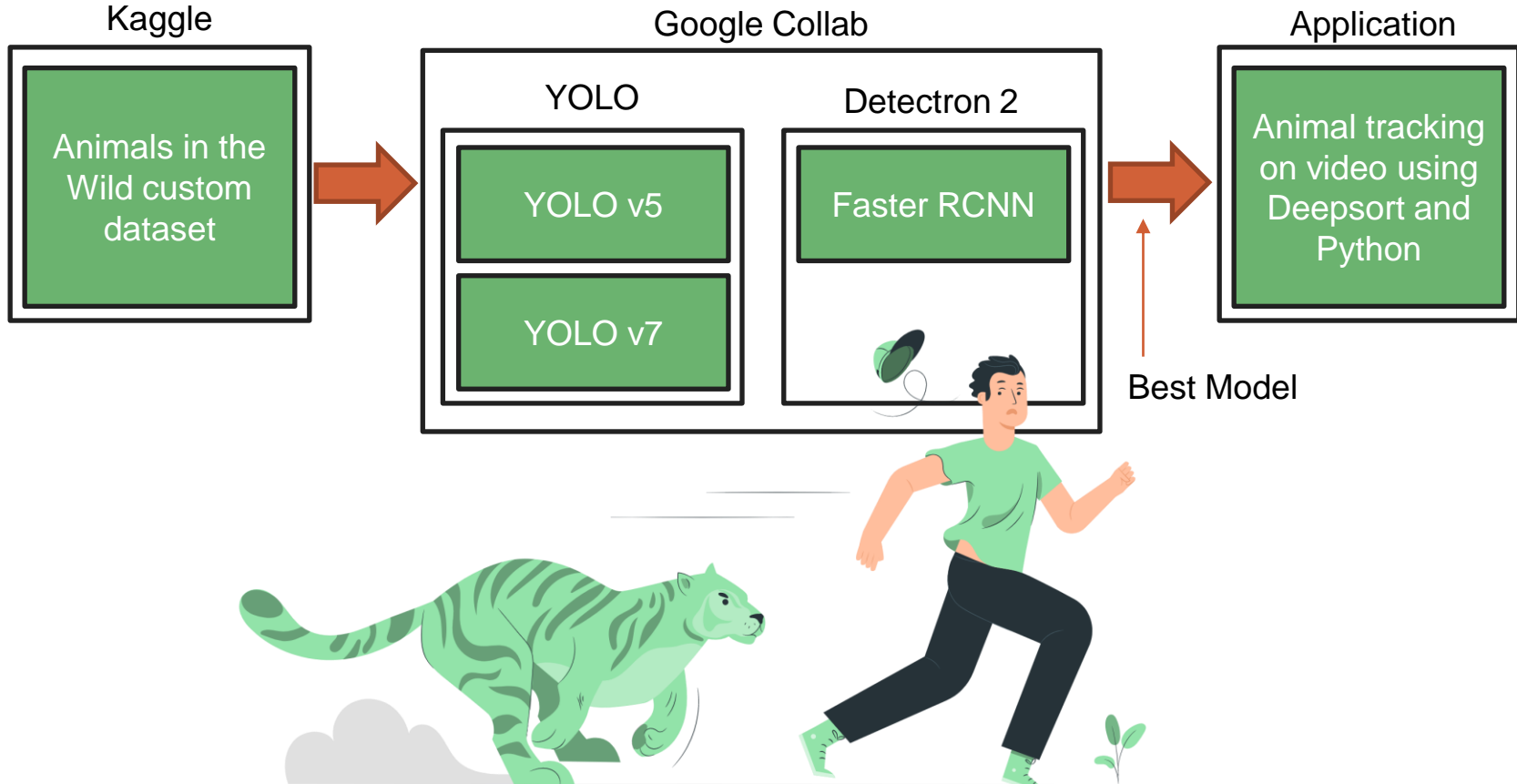
29,000  
wildlife  
images

80  
wildlife  
classes



# Approach

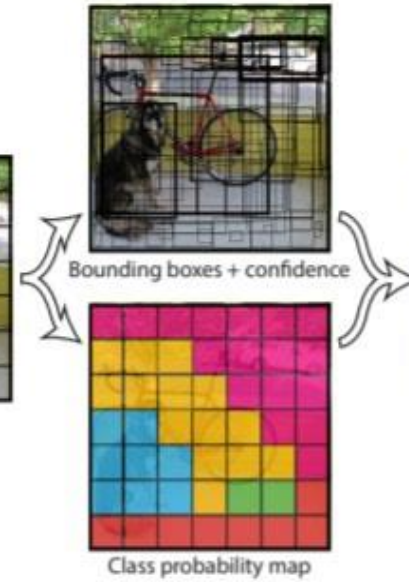
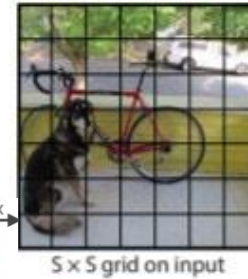
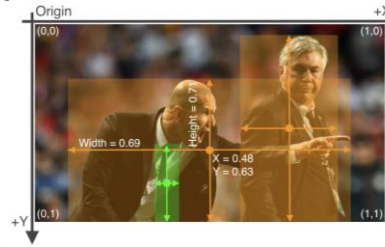
- We trained 3 models using transfer learning on our dataset for object detection



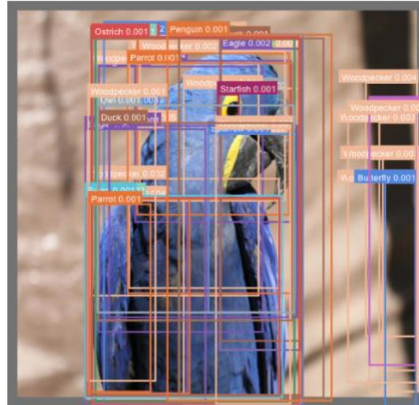


# How does YOLO work?

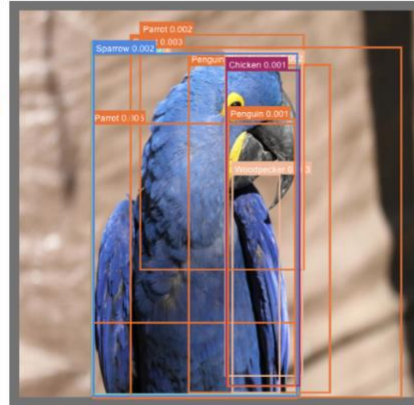
- YOLO system divides the input image into an  $S \times S$  grid
- Each grid cell predicts B bounding boxes. Each bounding box consists of 5 predictions-  $x, y, w, h$ , and confidence
- Each grid cell also predicts C conditional class probabilities,  $\Pr(\text{Class}|\text{Object})$



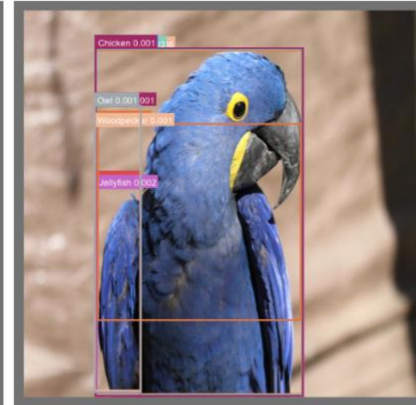
Step 3



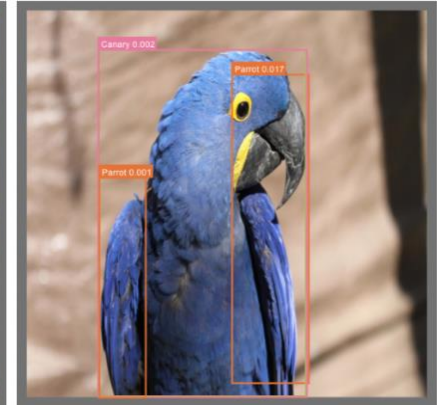
Step 15



Step 23



Step 39

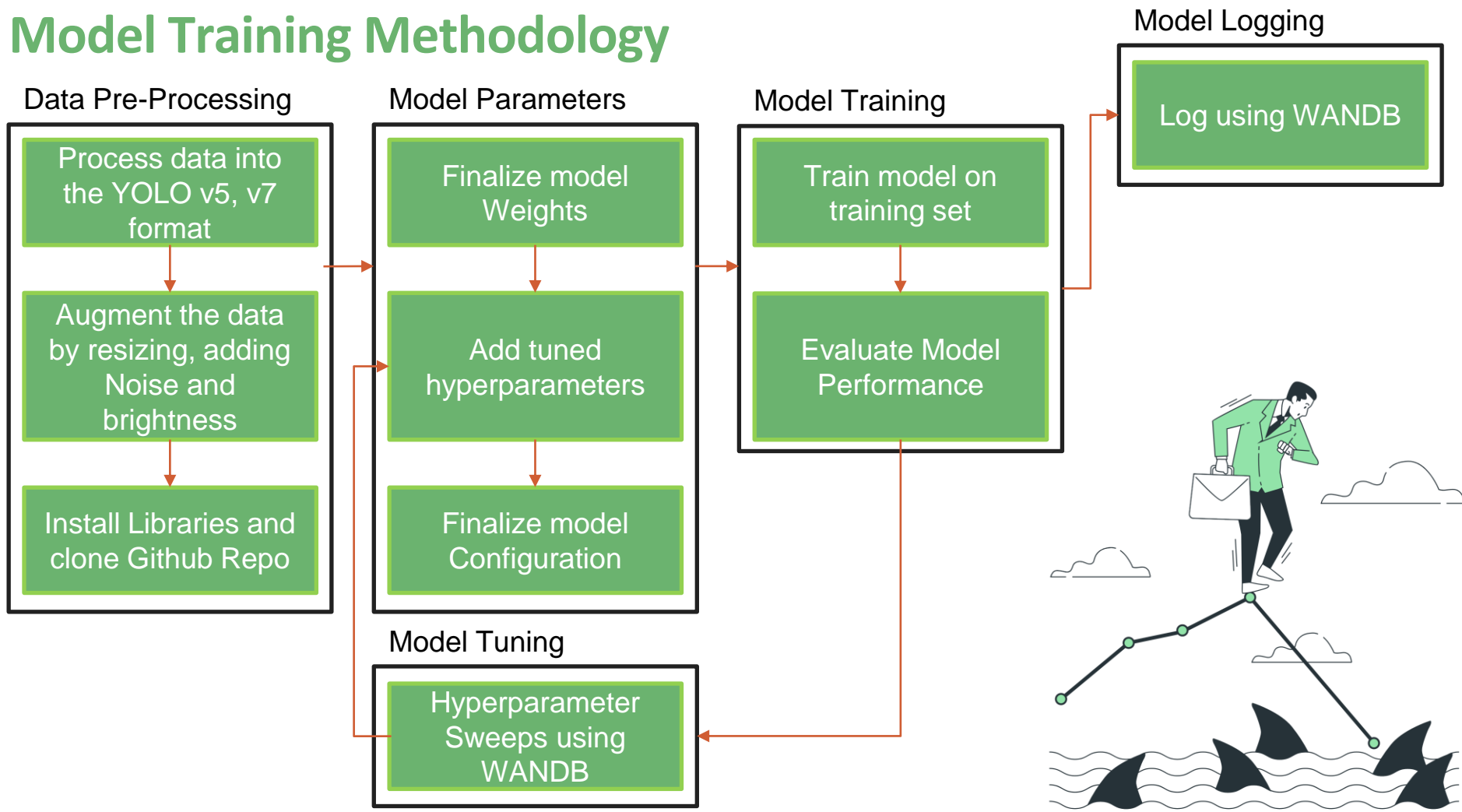


# YOLO v5,v7 IMPLEMENTATION AND RESULTS

elephant 0.95



# Model Training Methodology





# YOLO v5 Setup for training on custom dataset using transfer learning

- `!python train.py`
- `--data animal_detect1.yaml`
- `--weights yolov5s.pt`
- `--batch-size 16`
- `--epochs 50`
- `--cfg yolov5s.yaml`
- `--hyp hyp.scratch-low.yaml`

```
lr0: 0.01 # initial learning rate (SGD=1E-2, Adam=1E-3)
lrf: 0.01 # final OneCycleLR learning rate (lr0 * lrf)
momentum: 0.937 # SGD momentum/Adam beta1
weight_decay: 0.0005 # optimizer weight decay 5e-4
warmup_epochs: 3.0 # warmup epochs (fractions ok)
warmup_momentum: 0.8 # warmup initial momentum
warmup_bias_lr: 0.1 # warmup initial bias lr
box: 0.05 # box loss gain
cls: 0.5 # cls loss gain
cls_pw: 1.0 # cls BCELoss positive_weight
obj: 1.0 # obj loss gain (scale with pixels)
obj_pw: 1.0 # obj BCELoss positive_weight
iou_t: 0.20 # IoU training threshold
anchor_t: 4.0 # anchor-multiple threshold
# anchors: 3 # anchors per output layer (0 to ignore)
fl_gamma: 0.0 # focal loss gamma (efficientDet default gamma=1.5)
hsv_h: 0.015 # image HSV-Hue augmentation (fraction)
hsv_s: 0.7 # image HSV-Saturation augmentation (fraction)
hsv_v: 0.4 # image HSV-Value augmentation (fraction)
degrees: 0.0 # image rotation (+/- deg)
translate: 0.1 # image translation (+/- fraction)
scale: 0.5 # image scale (+/- gain)
shear: 0.0 # image shear (+/- deg)
perspective: 0.0 # image perspective (+/- fraction), range 0-0.001
flipud: 0.0 # image flip up-down (probability)
fliplr: 0.5 # image flip left-right (probability)
mosaic: 1.0 # image mosaic (probability)
mixup: 0.0 # image mixup (probability)
copy_paste: 0.0 # segment copy-paste (probability)
```

```
# Parameters
nc: 80 # number of classes
depth_multiple: 0.67 # model depth multiple
width_multiple: 0.75 # layer channel multiple
anchors:
  - [10,13, 16,30, 33,23] # P3/8
  - [30,61, 62,45, 59,119] # P4/16
  - [116,90, 156,198, 373,326] # P5/32
```

```
# YOLOv5 v6.0 backbone
backbone:
  # [from, number, module, args]
  [[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2
  [-1, 1, Conv, [128, 3, 2]], # 1-P2/4
  [-1, 3, C3, [128]],
  [-1, 1, Conv, [256, 3, 2]], # 3-P3/8
  [-1, 6, C3, [256]],
  [-1, 1, Conv, [512, 3, 2]], # 5-P4/16
  [-1, 9, C3, [512]],
  [-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
  [-1, 3, C3, [1024]],
  [-1, 1, SPPF, [1024, 5]], # 9
  ]
```

```
# YOLOv5 v6.0 head
head:
  [[-1, 1, Conv, [512, 1, 1]],
  [-1, 1, nn.Upsample, [None, 2, 'nearest']],
  [[-1, 6], 1, Concat, [1]], # cat backbone P4
  [-1, 3, C3, [512, False]], # 13

  [-1, 1, Conv, [256, 1, 1]],
  [-1, 1, nn.Upsample, [None, 2, 'nearest']],
  [[-1, 4], 1, Concat, [1]], # cat backbone P3
  [-1, 3, C3, [256, False]], # 17 (P3/8-small)

  [-1, 1, Conv, [256, 3, 2]],
  [[-1, 14], 1, Concat, [1]], # cat head P4
  [-1, 3, C3, [512, False]], # 20 (P4/16-medium)
```



Nano  
YOLOv5n

4 MB<sub>FP16</sub>  
6.3 ms<sub>V100</sub>  
28.4 mAP<sub>COCO</sub>



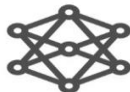
Small  
YOLOv5s

14 MB<sub>FP16</sub>  
6.4 ms<sub>V100</sub>  
37.2 mAP<sub>COCO</sub>



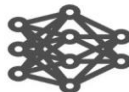
Medium  
YOLOv5m

41 MB<sub>FP16</sub>  
8.2 ms<sub>V100</sub>  
45.2 mAP<sub>COCO</sub>



Large  
YOLOv5l

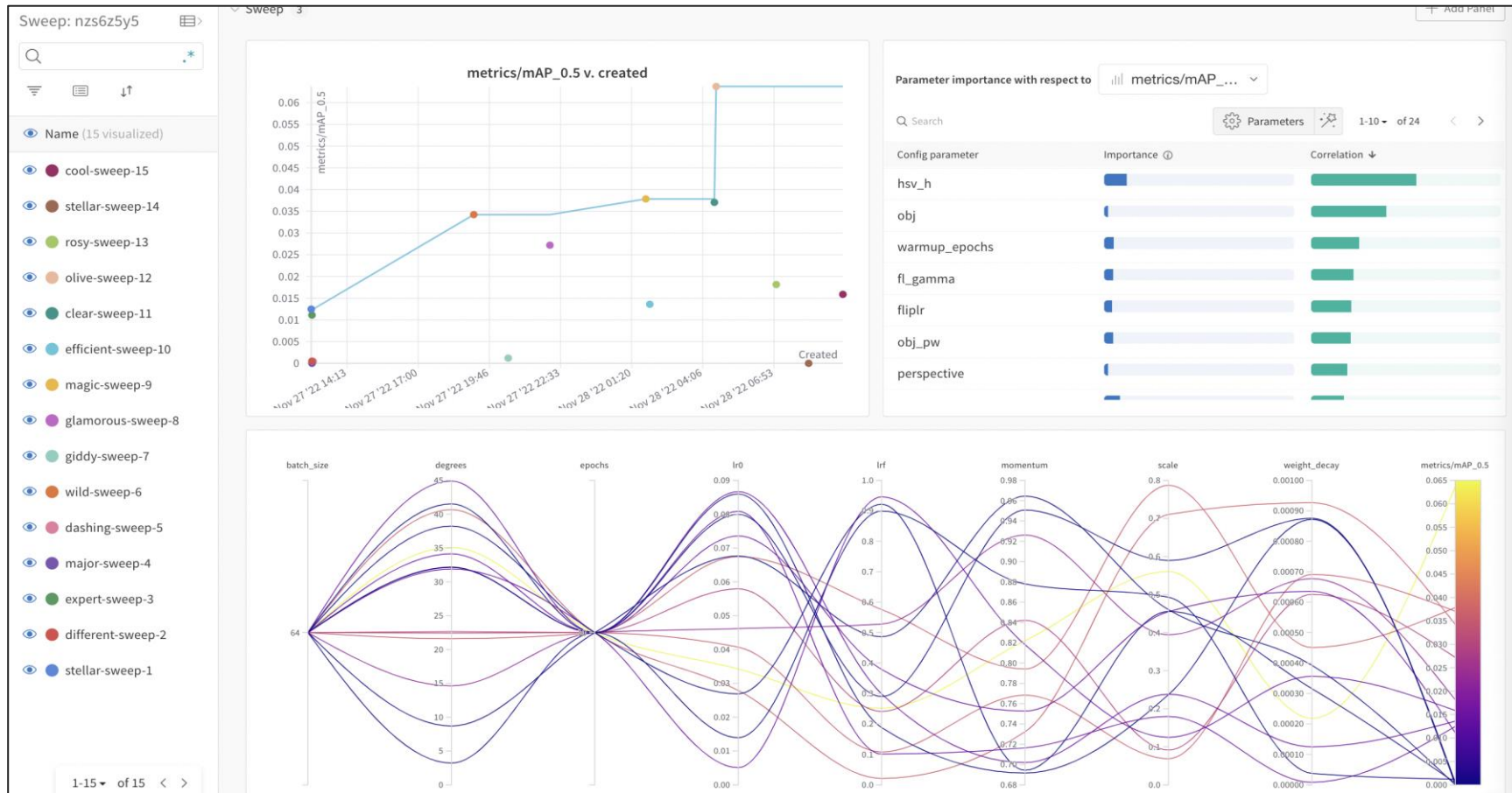
89 MB<sub>FP16</sub>  
10.1 ms<sub>V100</sub>  
48.8 mAP<sub>COCO</sub>



XLarge  
YOLOv5x

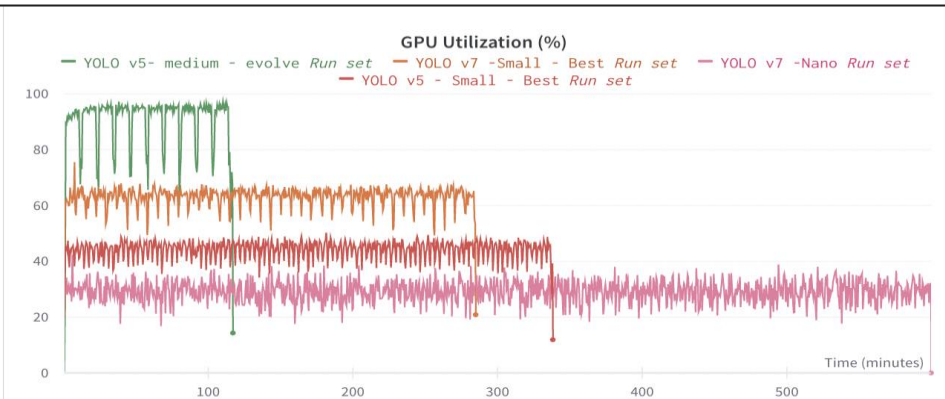
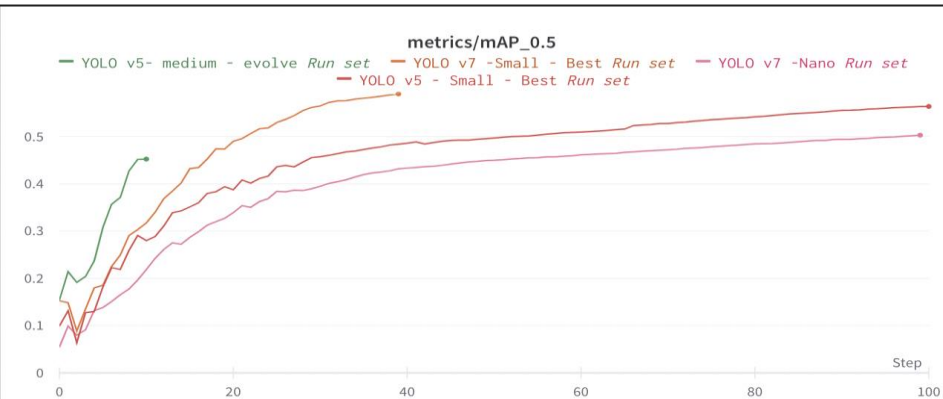
166 MB<sub>FP16</sub>  
12.1 ms<sub>V100</sub>  
50.7 mAP<sub>COCO</sub>

# Yolo Hyperparameter Tuning using Sweeps



# YOLO Run Metrics

<https://wandb.ai/amritangshu/YOLOR/reports/Multi-Class-wildlife-detection-using-YOLOv5-and-YOLOv7--VmldzozMDE1NDcy>



Name	Runtime	GPU Type	epochs
YOLO v5- medium-evolve	1.95 hr	Tesla T4	10
YOLO v7 - Final - Small	4.75 hr	A100-SXM4-40GB	40
YOLO v7 - Run 2 - Nano	9.99 hr	A100-SXM4-40GB	100
YOLO v5 - Final - Small	5.64 hr	A100-SXM4-40GB	100

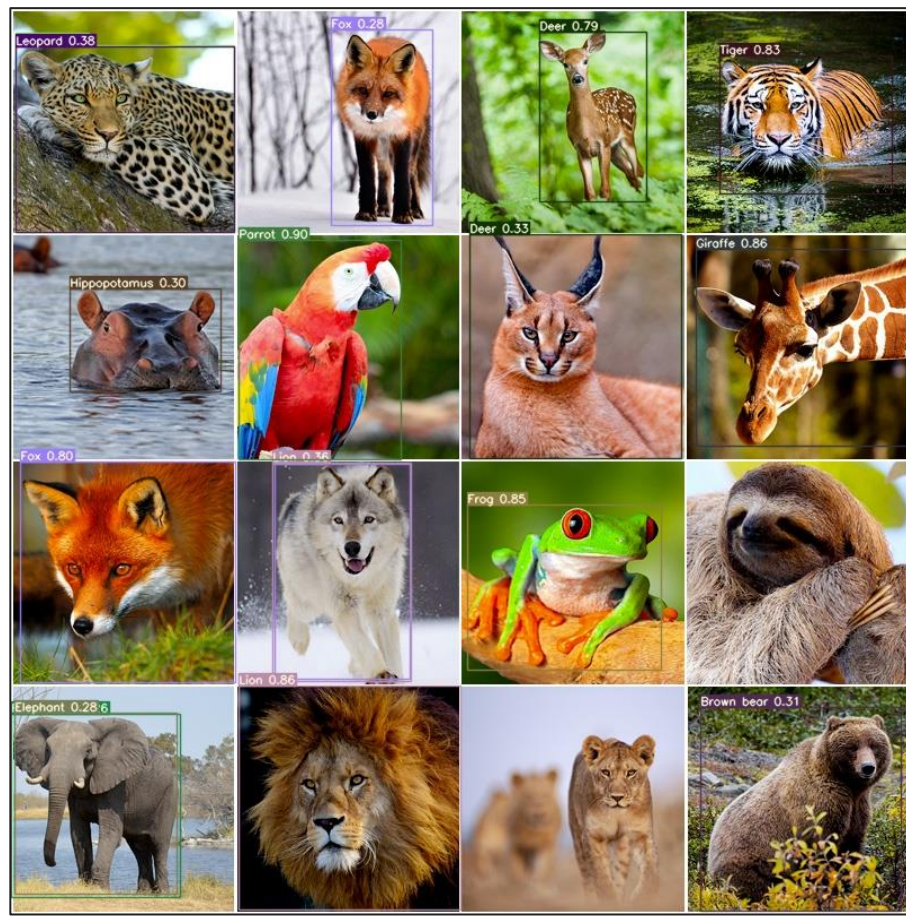


# YOLO V5 vs V7 Prediction

YOLO v5



YOLO v7





# Testing YOLO models with Changes in Noise and Colors



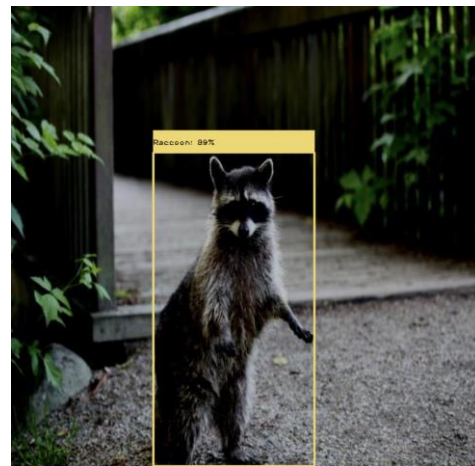
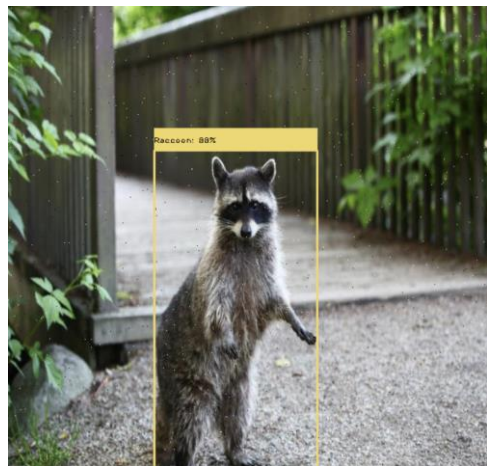
Black and white  
grainy (animal  
not detected)

Vintage color  
palette (84%)

Original Image  
Confidence: 88%

Decreased  
brightness and  
grainy (88%)

Increased  
contrast (89%)



# Alternative Approach - Detectron2's Faster RCNN

- Developed by Facebook, collection of models
- Uses 9 anchor boxes of different scales and aspect ratios to obtain ROIs (region of interest)
- Reduces number of ROIs with binary classifier and Softmax layer
- 25000 Images labeled with bounding boxes
- Uploaded images to Roboflow, which is linked to in our Colab notebook
- Used pre-trained weights on COCO dataset to initialize model
- 1000 iterations



COCO pretrained model predictions



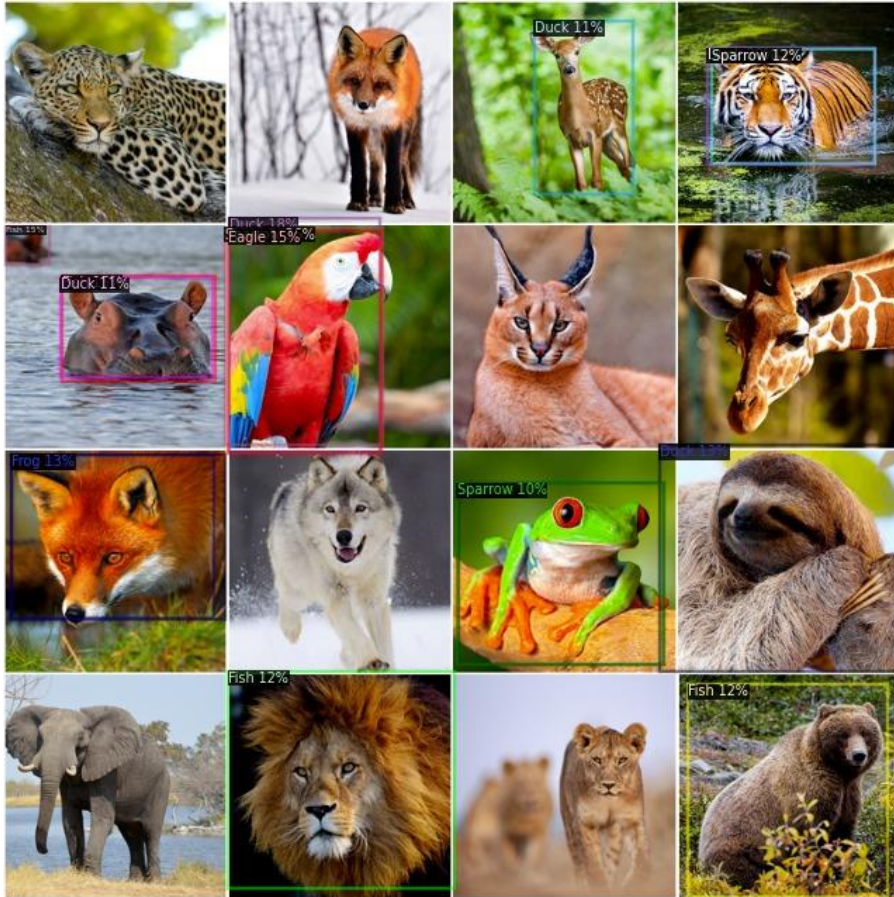
Instance segmentation model



panoptic segmentation model



# Detectron2 Predictions



Name	Runtime	GPU Type	epochs
YOLO v5-medium-evolve	1.95 hr	Tesla T4	10
YOLO v7 - Final - Small	4.75 hr	A100-SXM4-40GB	40
YOLO v7 - Run 2 - Nano	9.99 hr	A100-SXM4-40GB	100
YOLO v5 - Final - Small	5.64 hr	A100-SXM4-40GB	100
Detectron2 Faster RCNN	20 min	Tesla T4	1000 Iterations

**The Predictions here are not accurate for our custom dataset due to some data formatting issues in COCO Json format and GPU limitations**

# Application/ Next Steps

Inference on Video using our best model from Yolo V7  
and using the python library for Deepsort

<https://www.youtube.com/watch?v=WrxIrYdzy4>



Semantic Segmentation with  
YOLO V5 default model





# Thank You

Questions?

