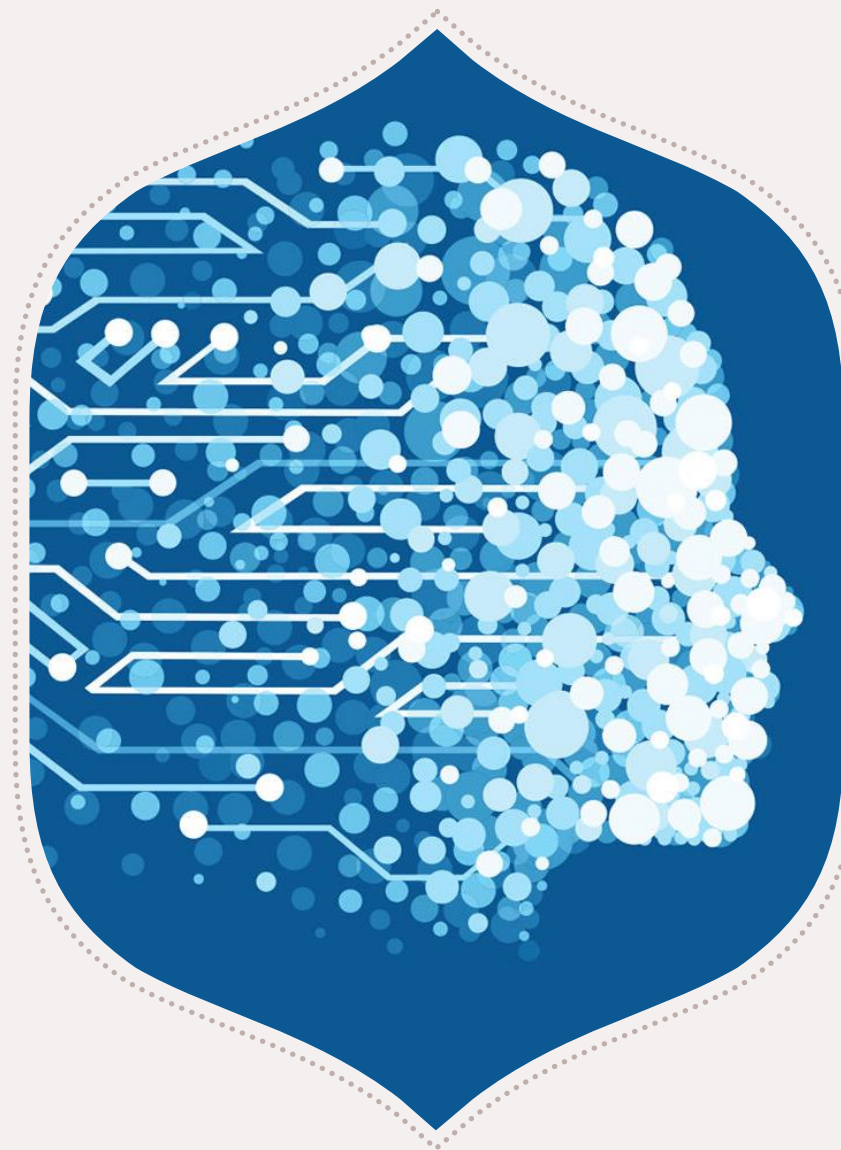




Pythius+
TensorFlow For Social Good
Agrifood

by, Jonathan Rivera,
Lorenzo Stewart,
Edison Tran



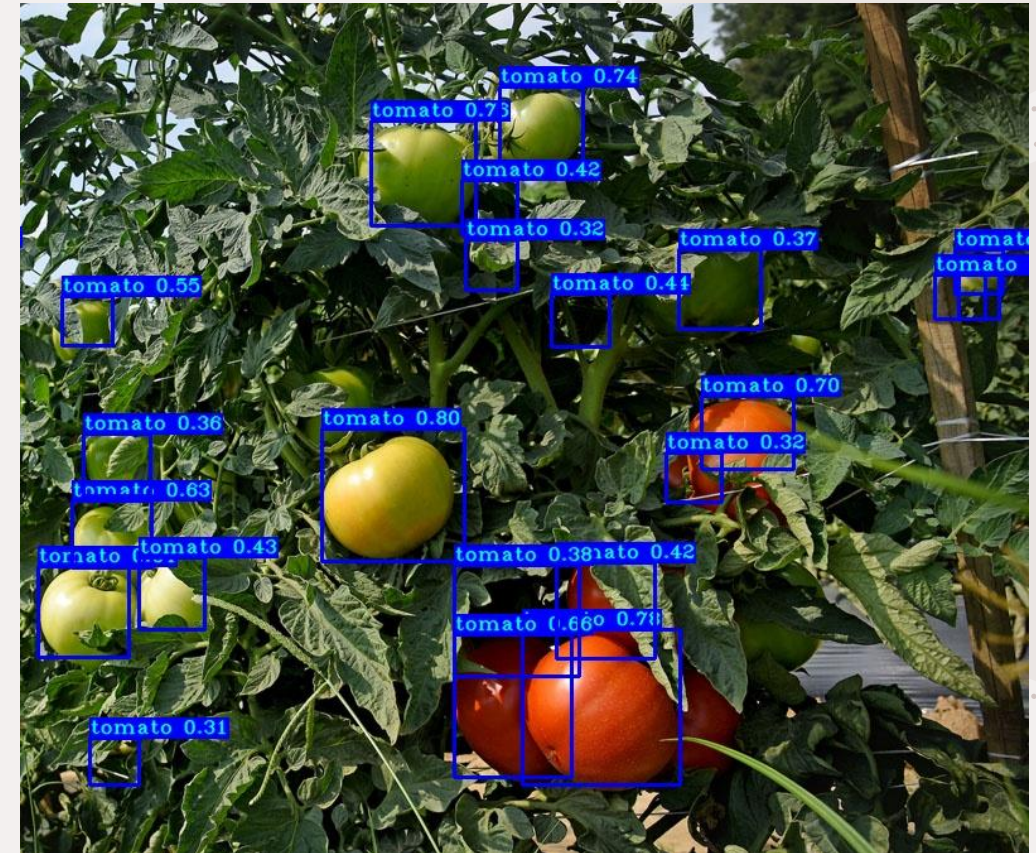
The image is a collage of three photographs arranged in a triangular pattern on the left side of the slide. The top photograph shows a vast vineyard with rows of grapevines stretching towards a horizon under a warm, golden sunset sky. The middle photograph is a close-up of several ripe, red tomatoes hanging from a green vine. The bottom photograph shows a person wearing a white protective suit and mask, working in a modern greenhouse with rows of plants growing in elevated beds.

Problem

- While brainstorming about problems that we face in the central valley, we decided to pick one based on agriculture.
- The problem specifically that we are trying to solve is food production.
- Worldwide diseases can lay waste to 40% of crops. A massive problem, to an ever expanding increasing population.
- Tomatoes are the 7th most popular crop in California and the state is the leader in vegetable production in the U.S.
- We came up with a solution that could help reduce the loss of crops, benefiting the hungry, the farmers, and everyone else.

Solution

- Using machine learning, more specifically object detection. We have created a program that can detect diseases on tomatoes.
- Using YOLO, we can identify diseases fast and accurately, allowing the resulting infections to be located and treated immediately.
- This will increase the efficiency of the “pipeline” of identifying, treating, and producing larger crop yields, creating more food while turning a larger profit.

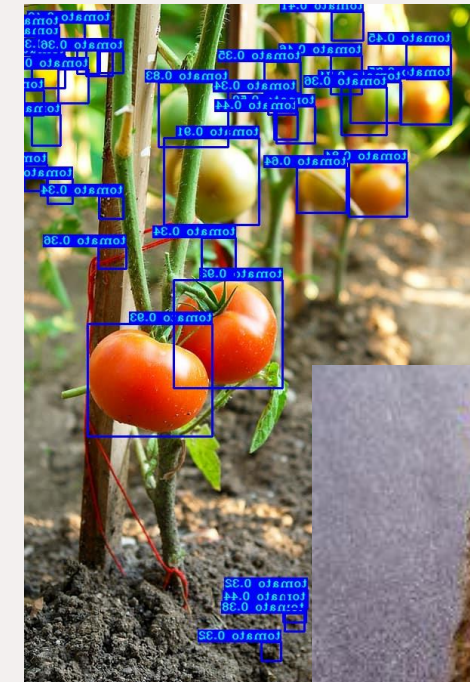


Implementation

- Our solution uses the YOLOv4 model, models from “[TensorFlow-2.x-YOLOv3](#)”, models from the TensorFlow Model Zoo, TensorFlow 2 framework, Darknet framework, virtual environments and image labeling software.
- We gathered and created datasets on common tomato diseases like verticillium wilt, blossom end rot, and early/late blight.

```
# YOLO options
YOLO_TYPE = "yolov4" # yolov4 or yolov3
YOLO_FRAMEWORK = "tf" # "tf" or "trt"
YOLO_V3_WEIGHTS = "model_data/yolov3.weights"
YOLO_V4_WEIGHTS = "model_data/yolov4.weights"
YOLO_V3_TINY_WEIGHTS = "model_data/yolov3-tiny.weights"
YOLO_V4_TINY_WEIGHTS = "model_data/yolov4-tiny.weights"
YOLO_TRT_QUANTIZE_MODE = "INT8" # INT8, FP16, FP32
YOLO_CUSTOM_WEIGHTS = True # "checkpoints/yolov3_custom" # used in evaluation
# YOLO_CUSTOM_WEIGHTS also used with TensorRT and custom
YOLO_CUSTOM_CLASSES = "model_data/coco/coco.names"
YOLO_STRIDES = [8, 16, 32]
YOLO_IOU_LOSS_THRESH = 0.5
YOLO_ANCHOR_PER_SCALE = 3
YOLO_MAX_BBOX_SCALE = 100
YOLO_INPUT_SIZE = 416
if YOLO_TYPE == "yolov4":
    YOLO_ANCHORS = [[12, 16], [19, 36], [40, 28]],
                    [[36, 75], [76, 55], [72, 146]],
                    [[142, 110], [192, 243], [459, 401]]
if YOLO_TYPE == "yolov3":
    YOLO_ANCHORS = [[10, 13], [16, 30], [33, 23]],
                    [[30, 61], [62, 45], [59, 119]],
                    [[116, 90], [156, 198], [373, 326]]

# Train options
TRAIN_YOLO_TINY = False
TRAIN_SAVE_BEST_ONLY = True # saves only best model according validation loss
TRAIN_SAVE_CHECKPOINT = False # saves all best validated checkpoints in training
TRAIN_CLASSES = "datasets/blossom_rot/labels.txt"
TRAIN_ANNOT_PATH = "datasets/blossom_rot/train.txt"
TRAIN_LOGDIR = "log"
TRAIN_CHECKPOINTS_FOLDER = "checkpoints"
TRAIN_MODEL_NAME = f"{YOLO_TYPE}_custom"
TRAIN_LOAD_IMAGES_TO_RAM = True # With True faster training, but need more RAM
TRAIN_BATCH_SIZE = 4
TRAIN_INPUT_SIZE = 416
TRAIN_DATA_AUG = True
TRAIN_TRANSFER = True
TRAIN_FROM_CHECKPOINT = True # "checkpoints/yolov3_custom"
TRAIN_LR_INIT = 1e-4
TRAIN_LR_END = 1e-6
TRAIN_WARMUP_EPOCHS = 2
TRAIN_EPOCHS = 32
```



Pythus+

1) Code

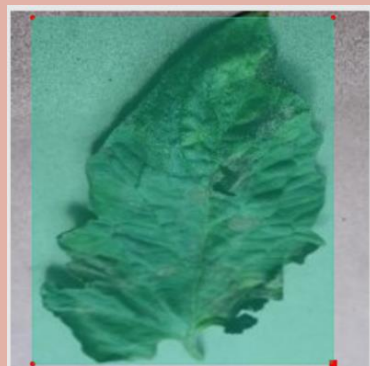
```
# YOLO options
YOLO_TYPE = "yolov4" # yolov4 or yolov3
YOLO_FRAMEWORK = "tf" # "tf" or "trt"
YOLO_V3_WEIGHTS = "model_data/yolov3.weights"
YOLO_V4_WEIGHTS = "model_data/yolov4.weights"
YOLO_V3_TINY_WEIGHTS = "model_data/yolov3-tiny.weights"
YOLO_V4_TINY_WEIGHTS = "model_data/yolov4-tiny.weights"
YOLO_TRT_QUANTIZE_MODE = "INT8" # INT8, FP16, FP32
YOLO_CUSTOM_WEIGHTS = True # "checkpoints/yolov3_custom" # used in evaluation
# YOLO_CUSTOM_WEIGHTS also used with TensorRT and custom models
YOLO_COCO_CLASSES = "model_data/coco/coco.names"
YOLO_STRIDES = [8, 16, 32]
YOLO_IOU_LOSS_THRESH = 0.5
YOLO_ANCHOR_PER_SCALE = 3
YOLO_MAX_BBOX_PER_SCALE = 100
YOLO_INPUT_SIZE = 416
if YOLO_TYPE == "yolov4":
    YOLO_ANCHORS = [
        [[12, 16], [19, 36], [40, 28]],
        [[36, 75], [76, 55], [72, 146]],
        [[142, 110], [192, 243], [459, 401]]
    ]
elif YOLO_TYPE == "yolov3":
    YOLO_ANCHORS = [
        [[10, 13], [16, 30], [33, 23]],
        [[30, 61], [62, 45], [59, 119]],
        [[116, 90], [156, 198], [373, 326]]
    ]

# Train options
TRAIN_YOLO_TINY = False
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TRAIN_SAVE_CHECKPOINT = False # saves all best validated checkpoints in train
TRAIN_CLASSES = "datasets/blossom_rot/labels.txt"
TRAIN_ANNOT_PATH = "datasets/blossom_rot/train.txt"
TRAIN_LOGDIR = "log"
TRAIN_CHECKPOINTS_FOLDER = "checkpoints"
TRAIN_MODEL_NAME = f"{YOLO_TYPE}_custom"
TRAIN_LOAD_IMAGES_TO_RAM = True # With True faster training, but need more RAM
TRAIN_BATCH_SIZE = 4
TRAIN_INPUT_SIZE = 416
TRAIN_DATA_AUG = True
TRAIN_TRANSFER = True
TRAIN_FROM_CHECKPOINT = True # "checkpoints/yolov3_custom"
TRAIN_LR_INIT = 1e-4
TRAIN_LR_END = 1e-6
TRAIN_WARMUP_EPOCHS = 2
TRAIN_EPOCHS = 32
```

2) Collect Dataset

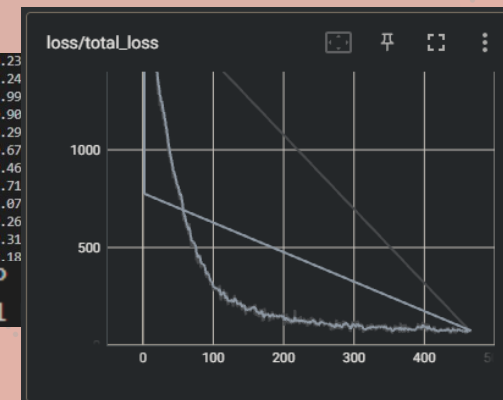


3) Label

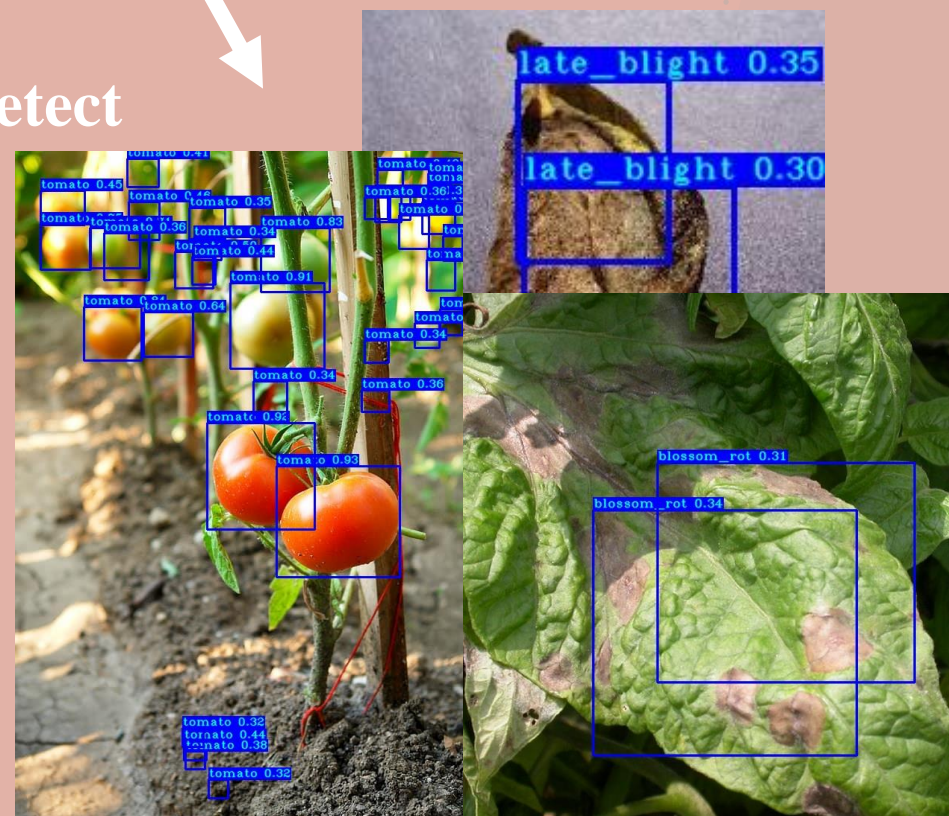


4) Train/Improve

```
epoch:10 step: 111/151, lr:0.000069, giou_loss: 7.25, conf_loss: 8.86, prob_loss: 0.11, total_loss: 16.23
epoch:10 step: 112/151, lr:0.000069, giou_loss: 5.17, conf_loss: 7.99, prob_loss: 0.08, total_loss: 13.24
epoch:10 step: 113/151, lr:0.000069, giou_loss: 4.88, conf_loss: 8.08, prob_loss: 0.03, total_loss: 12.99
epoch:10 step: 114/151, lr:0.000069, giou_loss: 5.26, conf_loss: 5.60, prob_loss: 0.04, total_loss: 10.90
epoch:10 step: 115/151, lr:0.000069, giou_loss: 1.38, conf_loss: 4.90, prob_loss: 0.01, total_loss: 6.29
epoch:10 step: 116/151, lr:0.000069, giou_loss: 4.91, conf_loss: 5.71, prob_loss: 0.05, total_loss: 10.67
epoch:10 step: 117/151, lr:0.000069, giou_loss: 4.21, conf_loss: 5.24, prob_loss: 0.02, total_loss: 9.46
epoch:10 step: 118/151, lr:0.000068, giou_loss: 6.66, conf_loss: 7.00, prob_loss: 0.05, total_loss: 13.71
epoch:10 step: 119/151, lr:0.000068, giou_loss: 12.87, conf_loss: 11.98, prob_loss: 0.22, total_loss: 25.07
epoch:10 step: 120/151, lr:0.000068, giou_loss: 8.56, conf_loss: 10.63, prob_loss: 0.07, total_loss: 19.26
epoch:10 step: 121/151, lr:0.000068, giou_loss: 3.55, conf_loss: 5.74, prob_loss: 0.02, total_loss: 9.31
epoch:10 step: 122/151, lr:0.000068, giou_loss: 4.03, conf_loss: 4.14, prob_loss: 0.01, total_loss: 8.18
epoch:10 step: 123/151, lr:0.000068, giou_loss: 3.30, conf_loss: 5.00, prob_loss: 0.02, total_loss: 9.40
epoch:10 step: 124/151, lr:0.000068, giou_loss: 13.37, conf_loss: 9.40, prob_loss: 0.183% = tomato AP
mAP = 0.183%, 9.01
```



5) Detect



Implementation

Low Epochs = Low mAP

epoch: 4 step: 139/151, lr:0.000096, giou_loss: 6.35, conf_loss: 18.76, prob_loss: 0.23, total_loss: 25.33
epoch: 4 step: 140/151, lr:0.000096, giou_loss: 11.87, conf_loss: 19.80, prob_loss: 0.71, total_loss: 32.38
epoch: 4 step: 141/151, lr:0.000096, giou_loss: 4.17, conf_loss: 18.14, prob_loss: 0.25, total_loss: 22.56
epoch: 4 step: 142/151, lr:0.000096, giou_loss: 13.64, conf_loss: 28.24, prob_loss: 0.86, total_loss: 42.73
epoch: 4 step: 143/151, lr:0.000096, giou_loss: 3.76, conf_loss: 19.65, prob_loss: 0.16, total_loss: 23.58
epoch: 4 step: 144/151, lr:0.000096, giou_loss: 13.58, conf_loss: 26.72, prob_loss: 0.68, total_loss: 40.98
epoch: 4 step: 145/151, lr:0.000096, giou_loss: 9.16, conf_loss: 20.39, prob_loss: 0.34, total_loss: 29.89
epoch: 4 step: 146/151, lr:0.000096, giou_loss: 6.30, conf_loss: 16.64, prob_loss: 0.19, total_loss: 23.13
epoch: 4 step: 147/151, lr:0.000096, giou_loss: 9.03, conf_loss: 19.93, prob_loss: 0.39, total_loss: 29.34
epoch: 4 step: 148/151, lr:0.000096, giou_loss: 11.06, conf_loss: 22.51, prob_loss: 0.55, total_loss: 34.13
epoch: 4 step: 149/151, lr:0.000096, giou_loss: 16.10, conf_loss: 28.36, prob_loss: 0.82, total_loss: 45.27
epoch: 4 step: 150/151, lr:0.000096, giou_loss: 5.67, conf_loss: 18.40, prob_loss: 0.17, total_loss: 24.24
epoch: 4 step: 0/151, lr:0.000096, giou_loss: 3.30, conf_loss: 16.85, prob_loss: 0.07, total_loss: 20.23
epoch: 4 step: 1/151, lr:0.000096, giou_loss: 8.71, conf_loss: 18.44, prob_loss: 0.37, total_loss: 27.52

↓ Train with more Epochs (but takes more time)

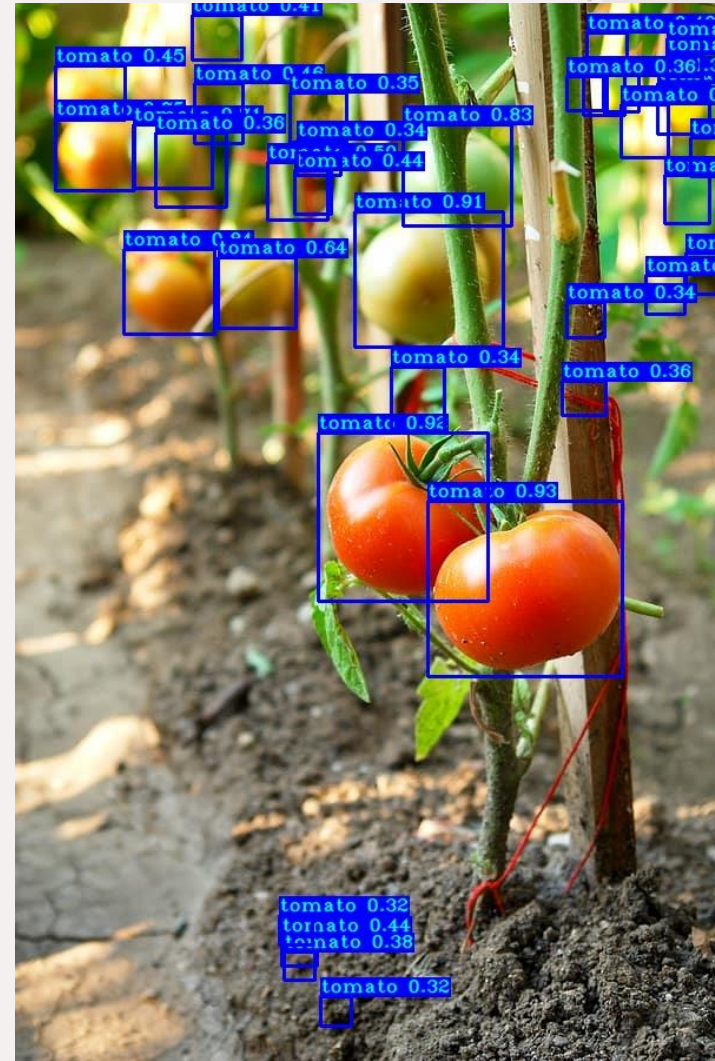
epoch:10 step: 111/151, lr:0.000069, giou_loss: 7.25, conf_loss: 8.86, prob_loss: 0.11, total_loss: 16.23
epoch:10 step: 112/151, lr:0.000069, giou_loss: 5.17, conf_loss: 7.99, prob_loss: 0.08, total_loss: 13.24
epoch:10 step: 113/151, lr:0.000069, giou_loss: 4.88, conf_loss: 8.08, prob_loss: 0.03, total_loss: 12.99
epoch:10 step: 114/151, lr:0.000069, giou_loss: 5.26, conf_loss: 5.60, prob_loss: 0.04, total_loss: 10.90
epoch:10 step: 115/151, lr:0.000069, giou_loss: 1.38, conf_loss: 4.90, prob_loss: 0.01, total_loss: 6.29
epoch:10 step: 116/151, lr:0.000069, giou_loss: 4.91, conf_loss: 5.71, prob_loss: 0.05, total_loss: 10.67
epoch:10 step: 117/151, lr:0.000069, giou_loss: 4.21, conf_loss: 5.24, prob_loss: 0.02, total_loss: 9.46
epoch:10 step: 118/151, lr:0.000068, giou_loss: 6.66, conf_loss: 7.00, prob_loss: 0.05, total_loss: 13.71
epoch:10 step: 119/151, lr:0.000068, giou_loss: 12.87, conf_loss: 11.98, prob_loss: 0.22, total_loss: 25.07
epoch:10 step: 120/151, lr:0.000068, giou_loss: 8.56, conf_loss: 10.63, prob_loss: 0.07, total_loss: 19.26
epoch:10 step: 121/151, lr:0.000068, giou_loss: 3.55, conf_loss: 5.74, prob_loss: 0.02, total_loss: 9.31
epoch:10 step: 122/151, lr:0.000068, giou_loss: 4.03, conf_loss: 4.14, prob_loss: 0.01, total_loss: 8.18
epoch:10 step: 123/151, lr:0.000068, giou_loss: 3.30, conf_loss: 5.00, prob_loss: 0.03, total_loss: 8.33
epoch:10 step: 124/151, lr:0.000068, giou_loss: 13.37, conf_loss: 9.40, prob_loss: 0.16, total_loss: 22.94



0.183% = tomato AP
mAP = 0.183%, 9.01 FPS

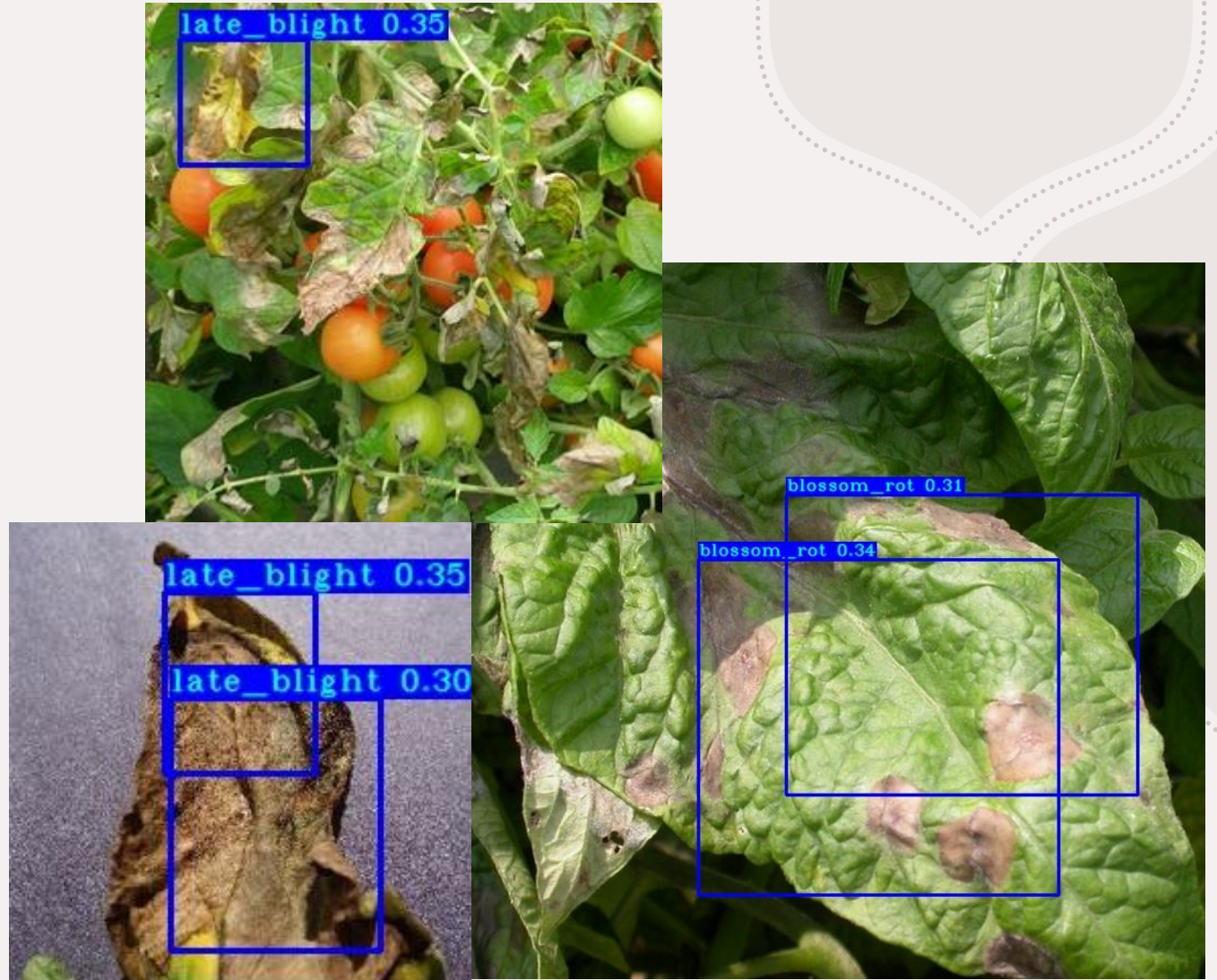
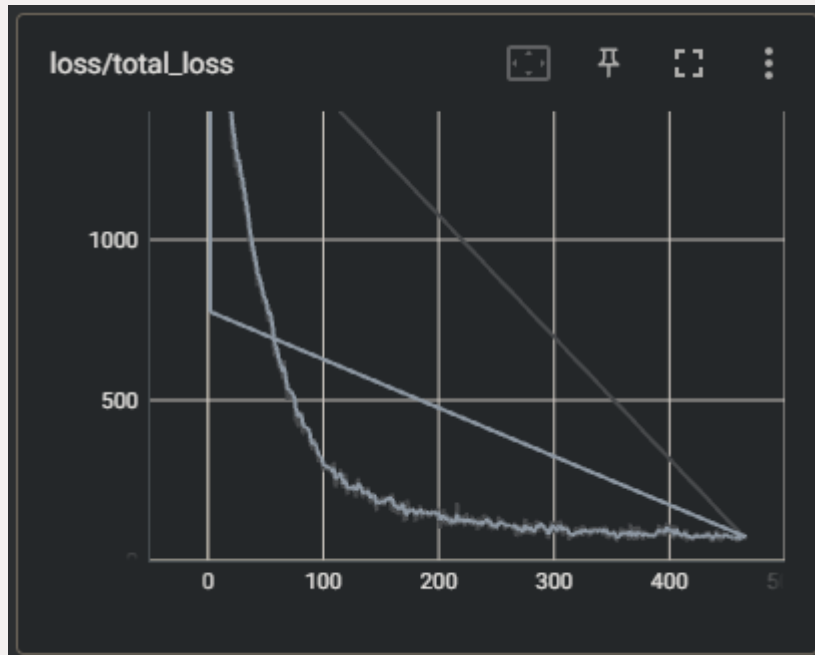
more
Accurate
Testing
Results

Leads
to Accurate
Image/object
detection



Results

- Using YOLO v4 and TensorFlow we were able to train and successfully detect early & late blight diseases as well as tomatoes themselves.
- Many issues we ran into, mostly where with documentation, and compatibility between dependencies and chunks of code.



Improvements

Our detections didn't provide the highest level of accuracies, this is to be expected since some of the labeling of images contain shadows, random artifacts and in general YOLOV4, and other lightweight models are not accurate due to their speed and purpose of implementation. However, we can repurpose our code and convert to TFRecords, TFJS and whatever necessary to be able to run on on hardware like Jetson Nano's, Raspberry Pi's, Android/IOS devices and even Drones.



Sources

- Huang, Mei-Ling; Chang, Ya-Han (2020), “Dataset of Tomato Leaves”, Mendeley Data, V1, doi: 10.17632/ngdgg79rzb.1
- <https://github.com/pythonlessons/TensorFlow-2.x-YOLOv3.git>
- [GitHub - nicknochnack/TFODCourse](#)
- [models/tf2_detection_zoo.md at master · tensorflow/models · GitHub](#)
- [API Documentation | TensorFlow v2.11.0](#)
- <https://www.kaggle.com/datasets/andrewmvd/tomato-detection?resource=download>
- [When to Plant Tomatoes in California? \(Region By Region\) - GFL Outdoors](#)