IESTI05 – Edge AI

Machine Learning System Engineering

8. Object Detection: Fundamentals

UNIFEI

Marcelo Rovai
Professor Honoris Causa

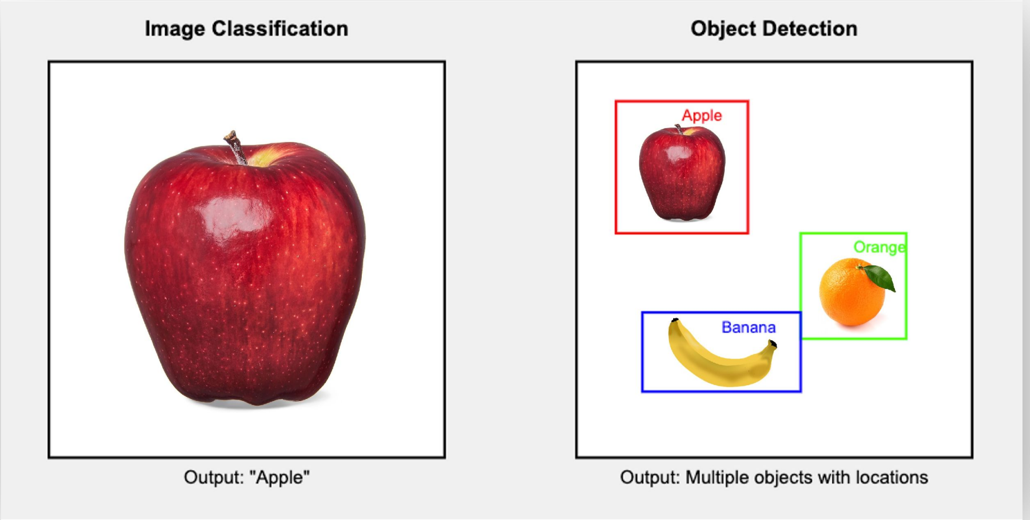
Object Detection
Fundamentals & SSD-Mobilenet Model

What is Object Detection?

Object detection is a computer vision task that identifies and locates objects within an image or video. Unlike simple image classification, it doesn't just say "there is an apple in this image," but rather "here is an apple at these specific coordinates.”

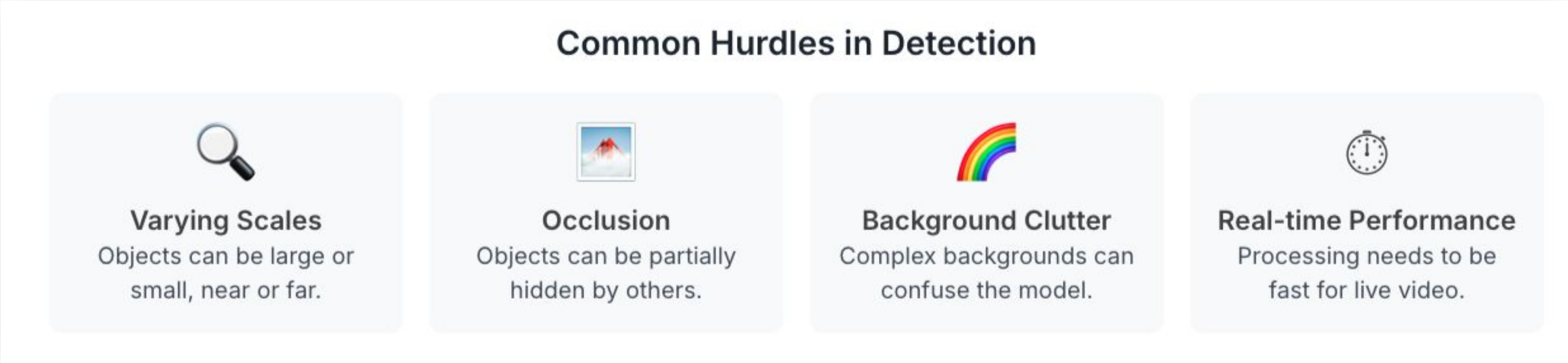
- Identifies: Determines the class of an object (e.g., car, person).

- Localizes: Provides a bounding box to indicate precisely where the object is located.



Can identify multiple objects with locations in the image

Key Challenges in Detection



- **Multiple Objects:** Images often contain multiple objects of different classes, sizes, and positions, making it challenging to detect and classify each one accurately.
- **Real-Time Performance:** Many applications require fast inference times, especially on edge devices with limited computational resources; striking a balance between accuracy and speed is essential.

Two-Stage vs Single-Stage

Two-Stage Detectors

Models like Faster R-CNN first propose regions of interest and then classify each region. This approach is accurate but computationally intensive.

Single-Stage Detectors

Models such as SSD-MobileNet, YOLO, and EfficientDet predict bounding boxes and class probabilities in one forward pass, making them faster and more suitable for edge devices.

Trade-offs

While two-stage detectors offer higher accuracy, single-stage detectors provide a better balance between speed and accuracy, crucial for real-time applications.

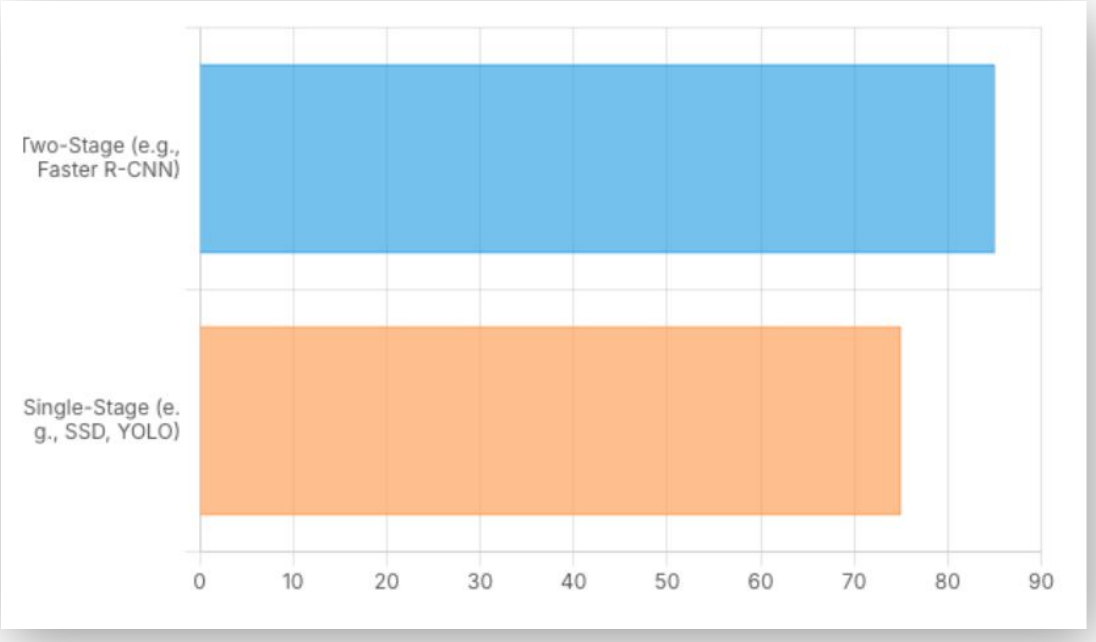
Examples

SSD MobileNet is a popular single-stage detector that combines the efficiency of SSD with the lightweight MobileNet backbone, ideal for edge deployment.

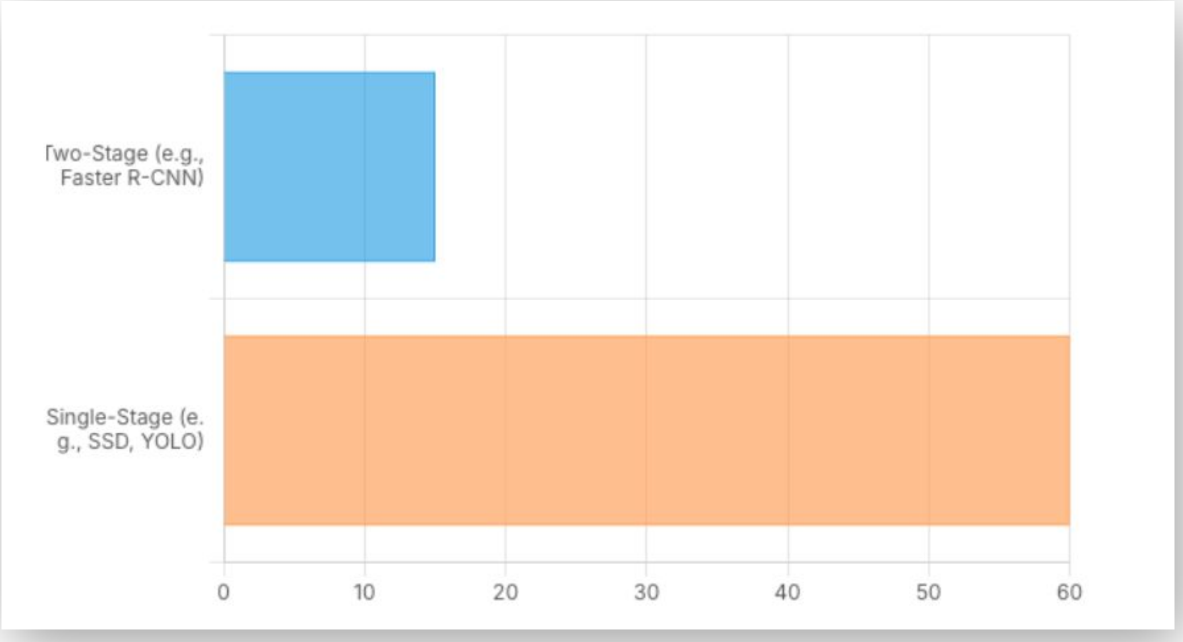
Detector Architectures: A Trade-Off

Models generally fall into two categories, each balancing accuracy and speed in different ways.

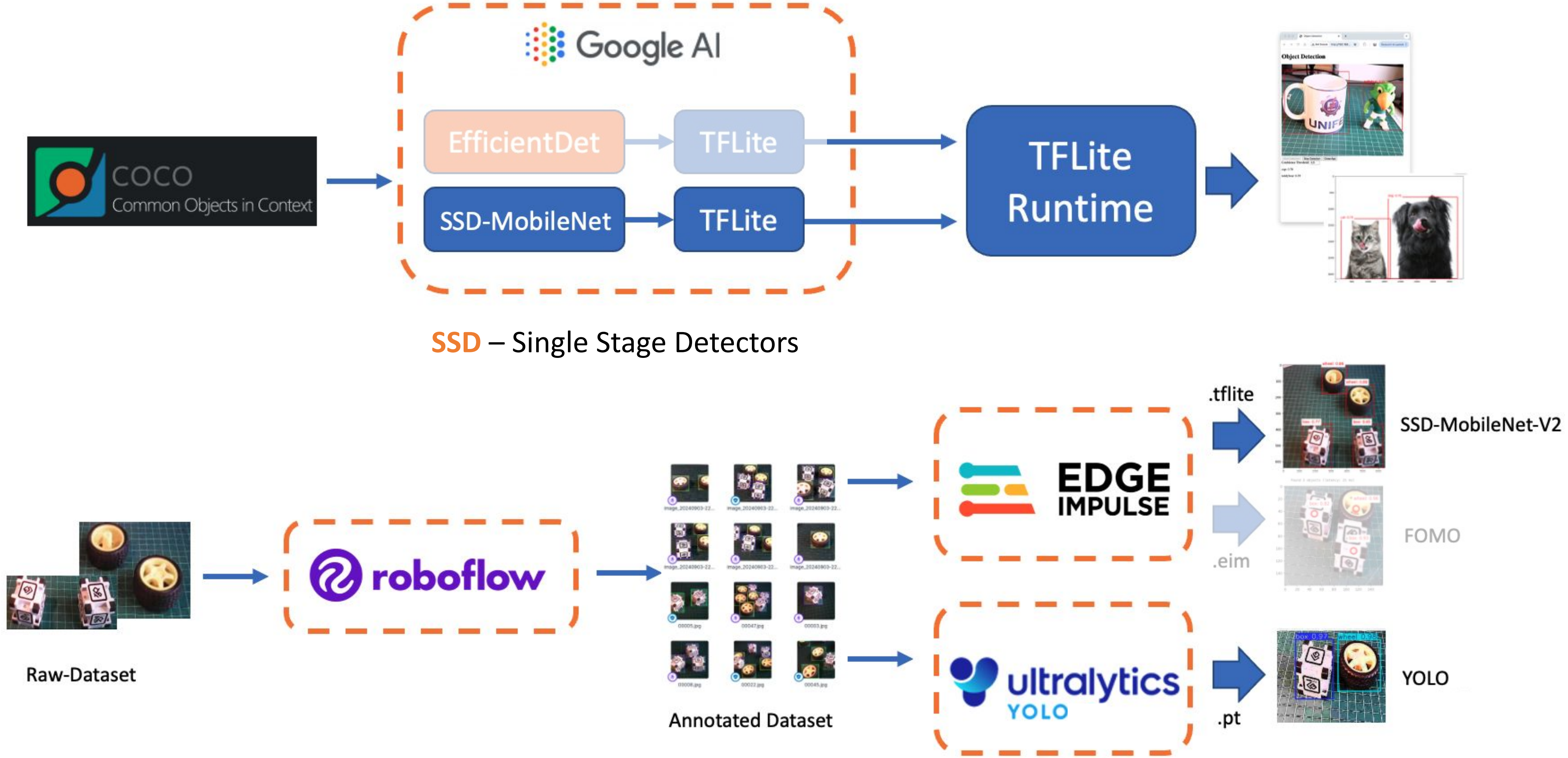
Accuraccy



Speed



Models covered in the course



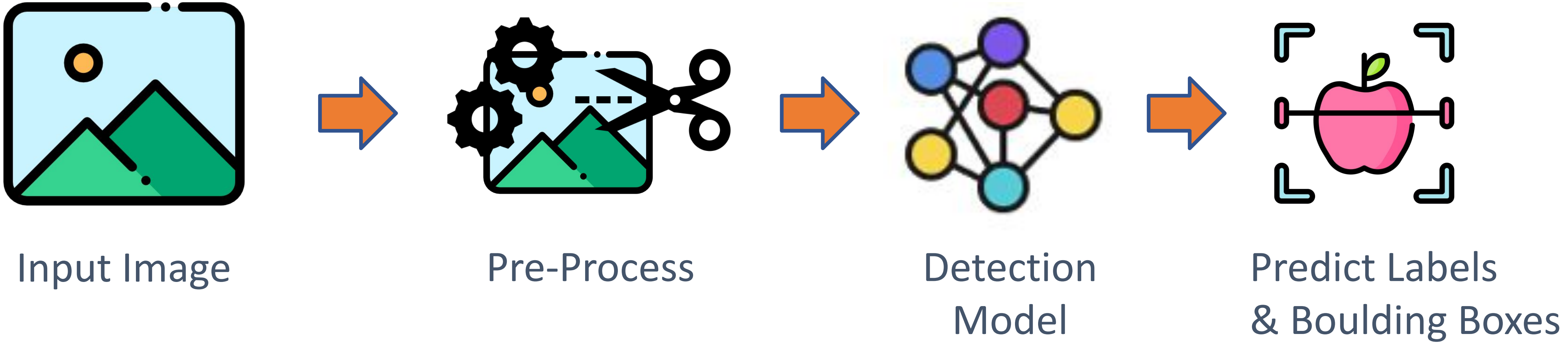
SSD-MobileNet: The best of two worlds

SSD (Single Shot Detector)
A fast, single-stage detection framework that finds objects in one pass.
🏃

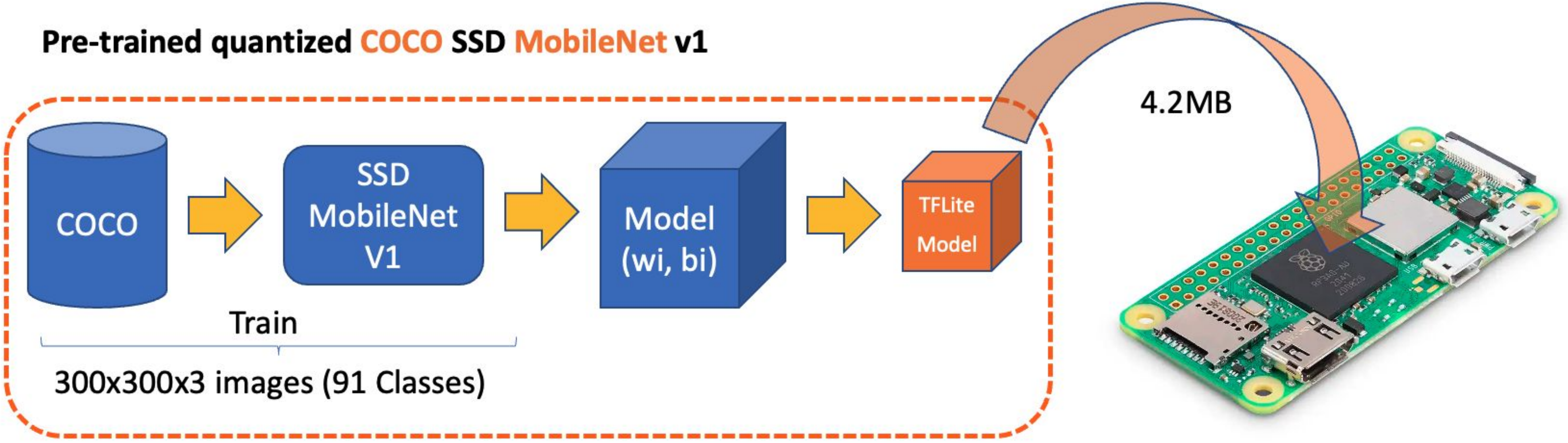
+

MobileNet
A lightweight backbone network designed for efficiency on mobile/edge devices.
📱

Object Detection: Inference Pipeline



The SSD-MobileNet V1 model

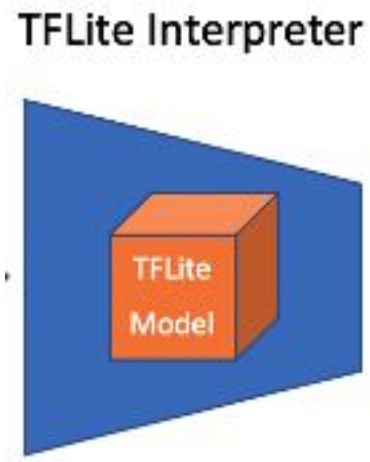


It outputs up **to ten detections per image**, including bounding boxes, class IDs, and confidence scores

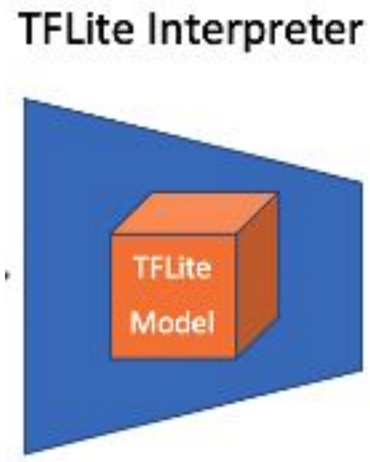
Model Input

```
input_details
```

```
[{'name': 'normalized_input_image_tensor',
  'index': 175,
  'shape': array([  1, 300, 300,   3], dtype=int32),
  'shape_signature': array([  1, 300, 300,   3], dtype=int32),
  'dtype': numpy.uint8,
  'quantization': (0.0078125, 128),
  'quantization_parameters': {'scales': array([0.0078125], dtype=float32),
   'zero_points': array([128], dtype=int32),
   'quantized_dimension': 0},
  'sparsity_parameters': {}}]
```



Model Output



1.Boxes [1,10,4]: Location (normalized coordinates)
2.Scores [1,10]: Confidence (0.0-1.0)
3.Classes [1,10]: Class (COCO class IDs 0-90)
4.Count [1]: How many valid detections (0-10)

```
output_details
```

1. Boxes

```
[{'name': 'TFLite_Detection_PostProcess',
  'index': 167,
  'shape': array([ 1, 10,  4], dtype=int32),
  'shape_signature': array([ 1, 10,  4], dtype=int32),
  'dtype': numpy.float32,
  'quantization': (0.0, 0),
  'quantization_parameters': {'scales': array([], dtype=float32),
   'zero_points': array([], dtype=int32),
   'quantized_dimension': 0},
  'sparsity_parameters': {}},
```

2. Scores

```
 {'name': 'TFLite_Detection_PostProcess:1',
  'index': 168,
  'shape': array([ 1, 10], dtype=int32),
  'shape_signature': array([ 1, 10], dtype=int32),
  'dtype': numpy.float32,
  'quantization': (0.0, 0),
  'quantization_parameters': {'scales': array([], dtype=float32),
   'zero_points': array([], dtype=int32),
   'quantized_dimension': 0},
  'sparsity_parameters': {}},
```

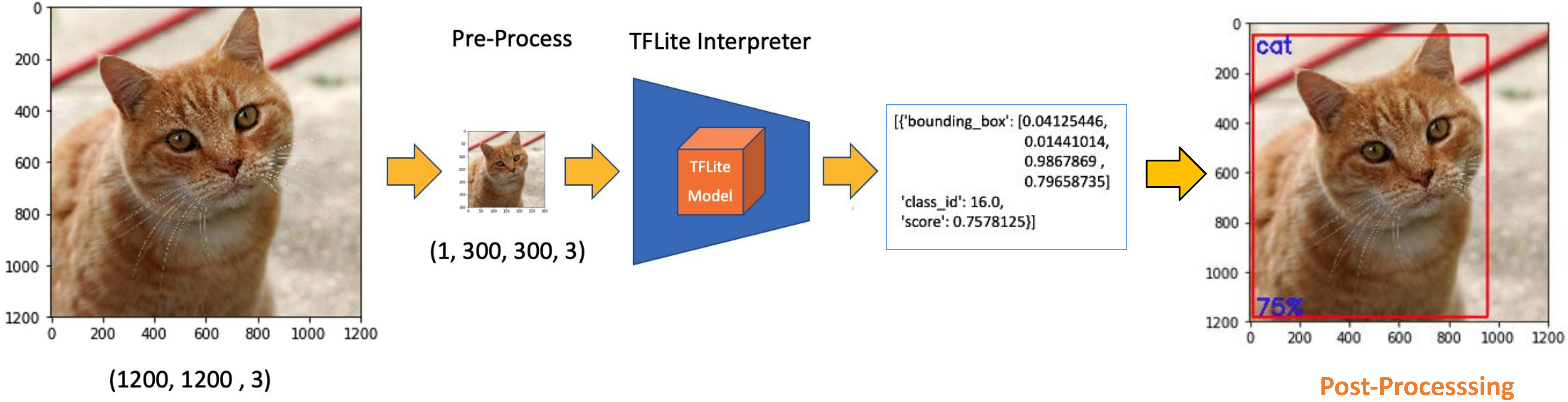
3. Classes

```
 {'name': 'TFLite_Detection_PostProcess:2',
  'index': 169,
  'shape': array([ 1, 10], dtype=int32),
  'shape_signature': array([ 1, 10], dtype=int32),
  'dtype': numpy.float32,
  'quantization': (0.0, 0),
  'quantization_parameters': {'scales': array([], dtype=float32),
   'zero_points': array([], dtype=int32),
   'quantized_dimension': 0},
  'sparsity_parameters': {}},
```

4. Count

```
 {'name': 'TFLite_Detection_PostProcess:3',
  'index': 170,
  'shape': array([1], dtype=int32),
  'shape_signature': array([1], dtype=int32),
  'dtype': numpy.float32,
  'quantization': (0.0, 0),
  'quantization_parameters': {'scales': array([], dtype=float32),
   'zero_points': array([], dtype=int32),
   'quantized_dimension': 0},
  'sparsity_parameters': {}}]
```

Making inferences with the SSD-MobileNet V1

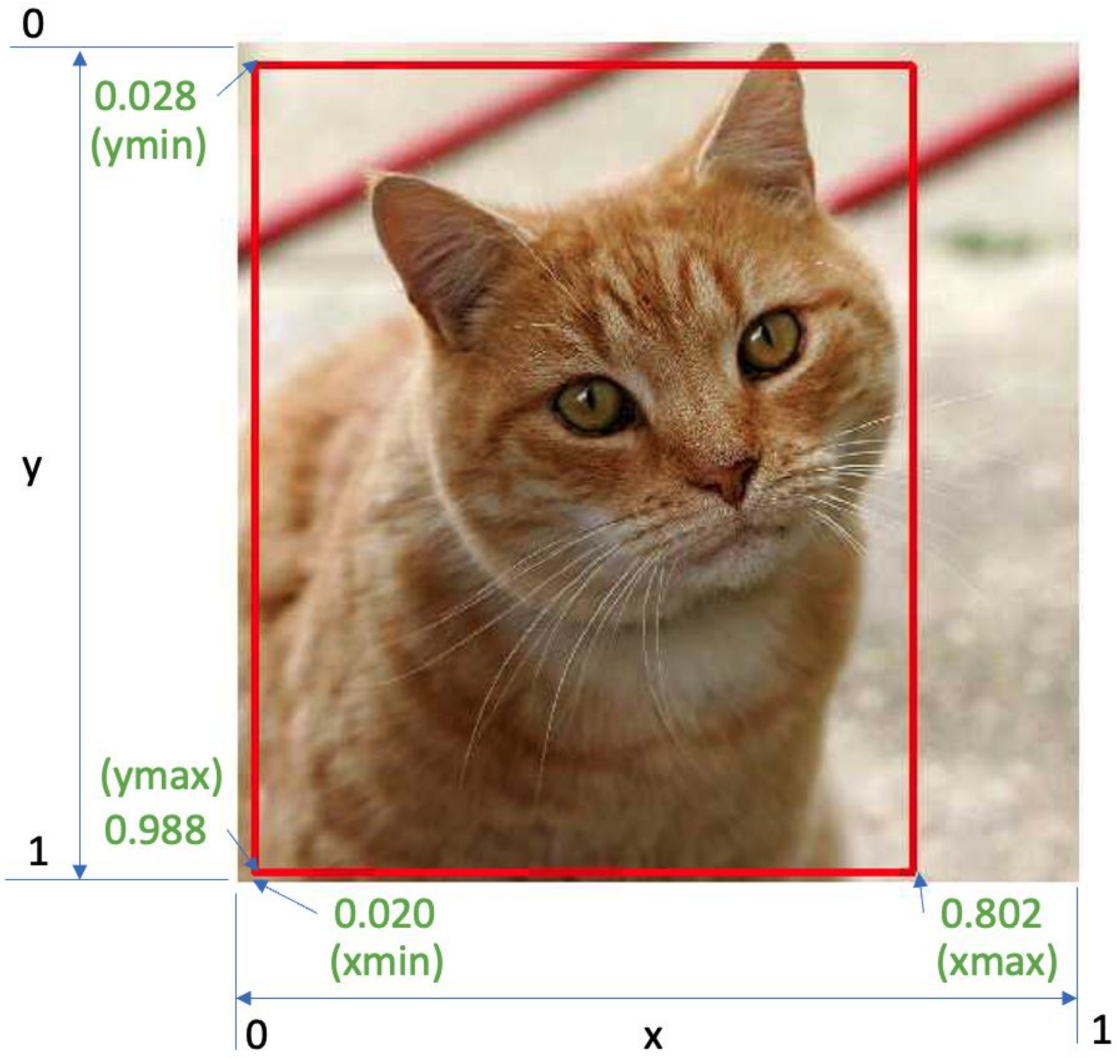


Bounding Boxes

bounding box:

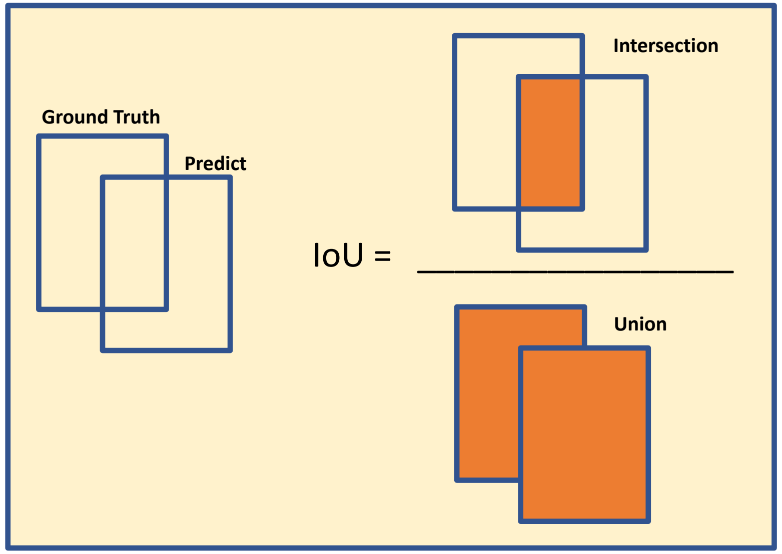
[0.028011084, 0.020121813, 0.9886069, 0.802299]

ymin xmin, ymax xmax

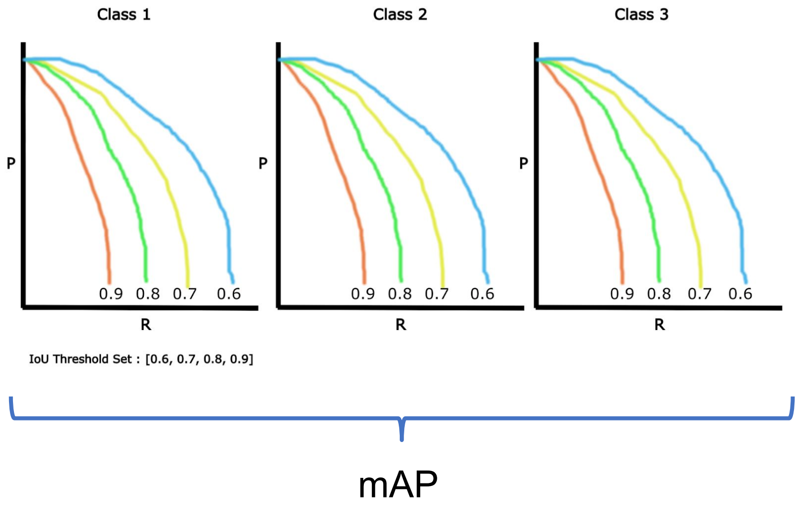


Evaluation Metrics

Intersection over Union (IoU) is a metric used to evaluate the accuracy of an object detector. It measures the overlap between two bounding boxes: the **Ground Truth** box (the manually labeled correct box) and the **Predicted** box (the box generated by the object detection model). The IoU value is calculated by dividing the area of the **Intersection** (the overlapping area) by the area of the **Union** (the total area covered by both boxes). A higher IoU value indicates a better prediction.



Mean Average Precision (mAP) is a widely used metric for evaluating the performance of object detection models. It provides a single number that reflects a model's ability to accurately both **classify** and **localize** objects. The "mean" in mAP refers to the average taken over all object classes in the dataset. The "average precision" (AP) is calculated for each class, and then these AP values are averaged to get the final mAP score. A high mAP score indicates that the model is excellent at identifying all objects and placing a tight-fitting, accurate bounding box around them.



Frames Per Second (FPS) for real-time performance

https://youtu.be/duBGmrxNHS8

TFLite Runtime and Model Setup

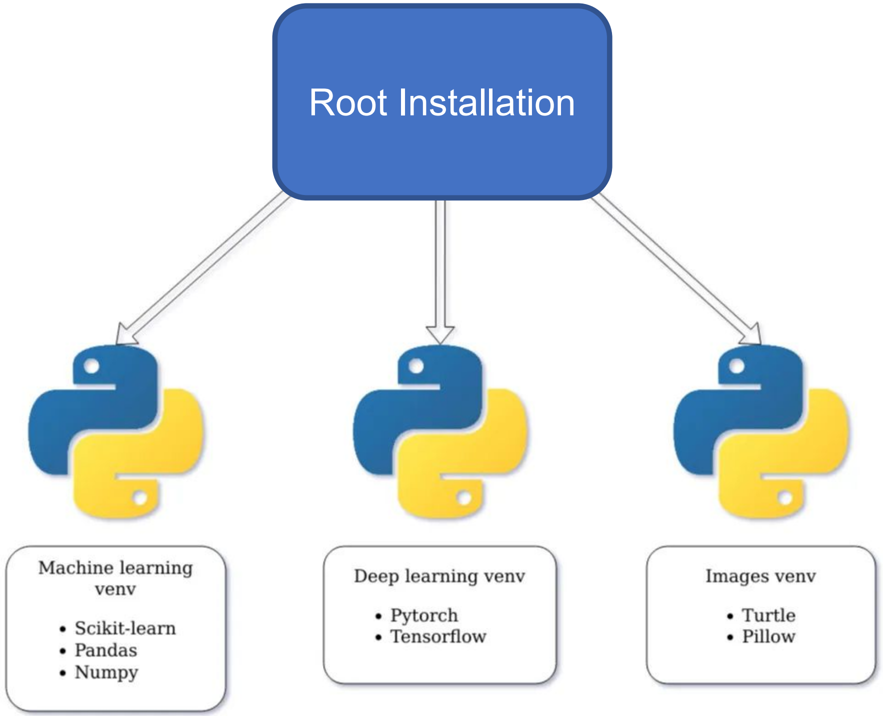
Setting up a Virtual Environment

Activate the environment:

```
source ~/tflite_env/bin/activate
```

To exit the virtual environment, use:

```
deactivate
```



Creating a working directory & get the model

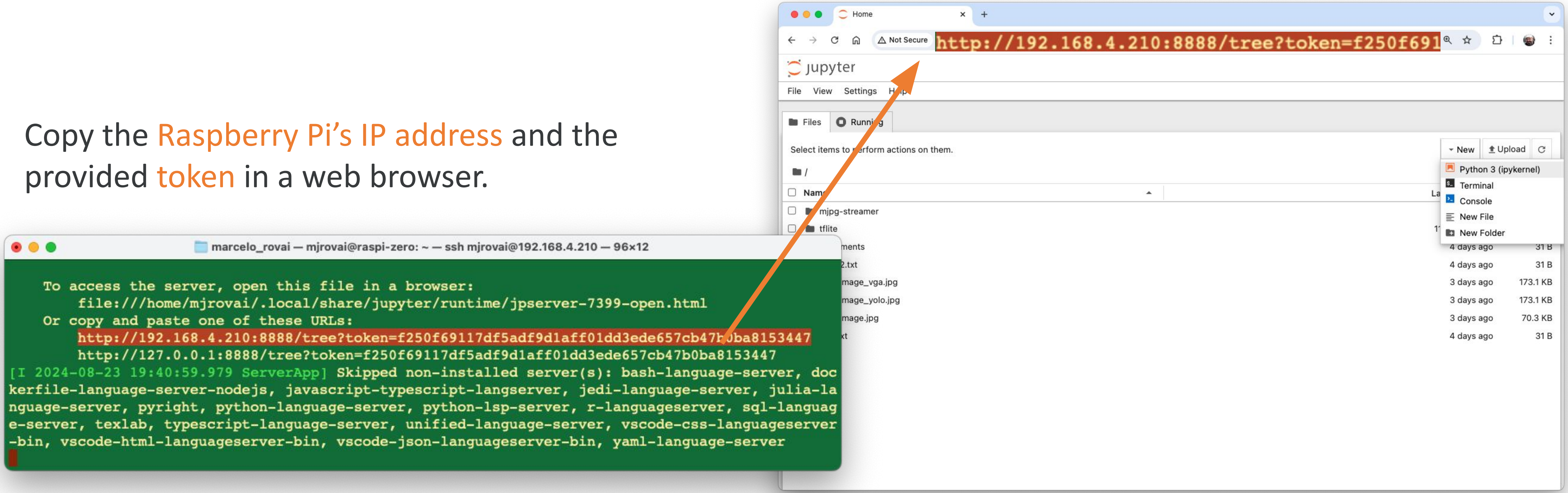
```
marcelo_rovai — mjrovai@raspi-zero: ~/Documents/TFLITE/OBJ_DETECT/models — ssh mjrovai@192.168.4.210 — 81×10
(tflite_env) mjrovai@raspi-zero:~ $
(tflite_env) mjrovai@raspi-zero:~ $ cd Documents/TFLITE/
(tflite_env) mjrovai@raspi-zero:~/Documents/TFLITE $ mkdir OBJ_DETECT
(tflite_env) mjrovai@raspi-zero:~/Documents/TFLITE $ cd OBJ_DETECT
(tflite_env) mjrovai@raspi-zero:~/Documents/TFLITE/OBJ_DETECT $ mkdir models
(tflite_env) mjrovai@raspi-zero:~/Documents/TFLITE/OBJ_DETECT $ mkdir images
(tflite_env) mjrovai@raspi-zero:~/Documents/TFLITE/OBJ_DETECT $ ls
images   models
(tflite_env) mjrovai@raspi-zero:~/Documents/TFLITE/OBJ_DETECT $ cd models
(tflite_env) mjrovai@raspi-zero:~/Documents/TFLITE/OBJ_DETECT/models $
```

```
wget
https://github.com/Mjrovai/EdgeML-with-Raspberry-Pi/raw/refs/heads/main/OBJ_DETEC/model
s/ssd-mobilenet-v1-tflite-default-v1.tar.gz

tar -xzf ssd-mobilenet-v1-tflite-default-v1.tar.gz
mv 1.tflite ssd-mobilenet-v1-tflite-default-v1.tflite

wget
https://raw.githubusercontent.com/Mjrovai/EdgeML-with-Raspberry-Pi/refs/heads/main/OBJ_
DETEC/models/coco_labels.txt
```

Running up Jupyter Notebook

jupyter notebook --ip=[YOUR IP ADDREES] --no-browser

Copy the Raspberry Pi's IP address and the provided token in a web browser.



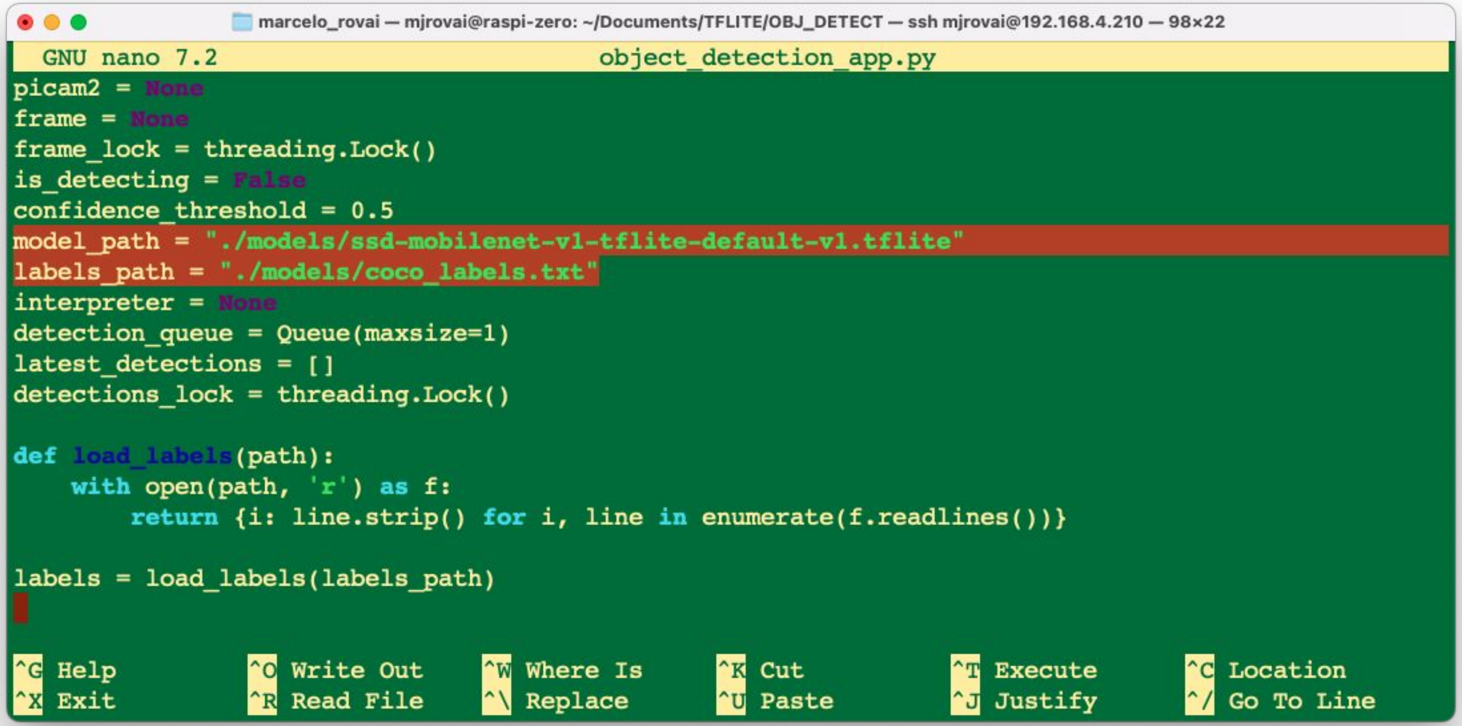
Raspberry Pi Inference:

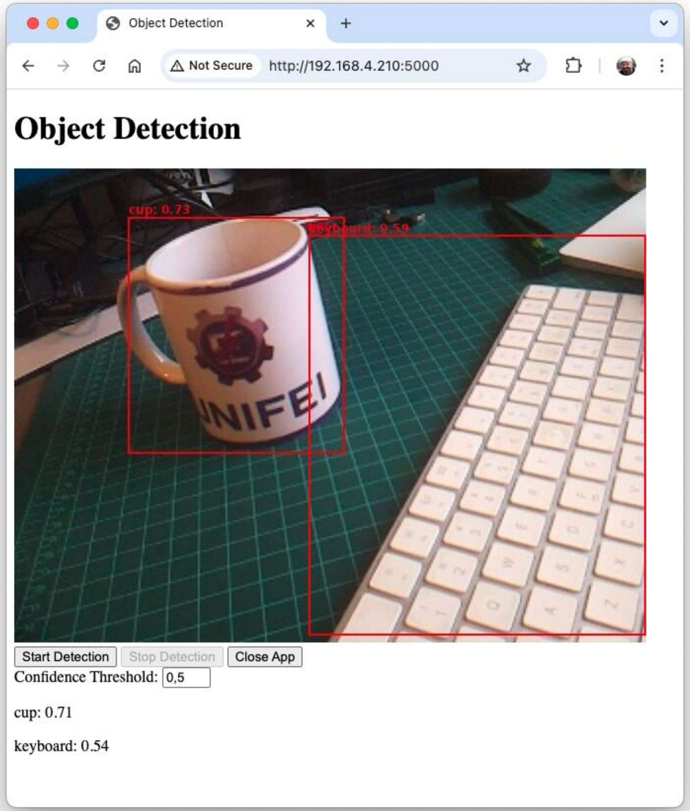
SSD_MobileNetV1.ipynb

Live Object Detection

object_detection_app.py

```
 * Running on http://192.168.4.210:5000
Press CTRL+C to quit
```





Questions?

Prof. Marcelo J. Rovai
rovai@unifei.edu.br

UNIFEI