

Untapped

Using Computer Vision to Tap into On-premise Brand Intelligence for Beverage Companies

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June 6th, 2020



THE UNIVERSITY OF CHICAGO
GRAHAM SCHOOL
CONTINUING LIBERAL AND PROFESSIONAL STUDIES

Background



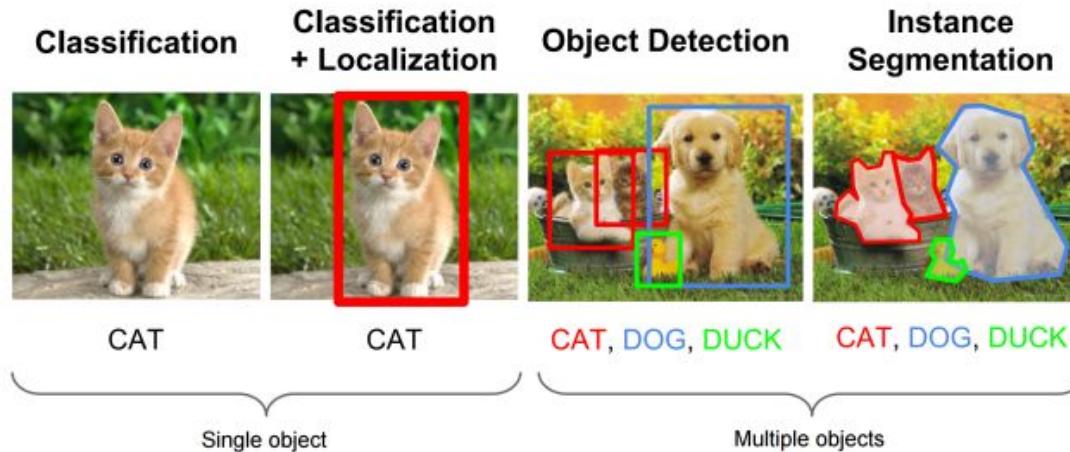
Computer vision 101

Computer Vision Tasks

Classification: “What single object is in this image?”

Object Detection: “What objects are in this image and where are they?”

Instance Segmentation: “What pixels belong to the objects in this image?”



Data



Defining the variables

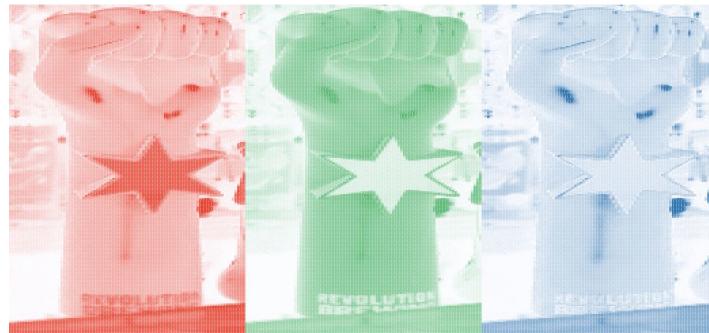
Independent Variables

Red, Green, and Blue pixel values (0-255)

Original



Image Decomposition



R: 255
G: 0
B: 0

0
255
0

0
0
255

Dependent Variables

Bounding box and brand (class) of beer tap

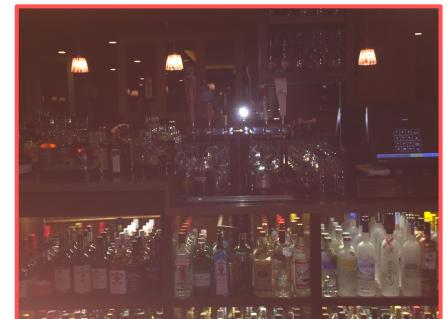
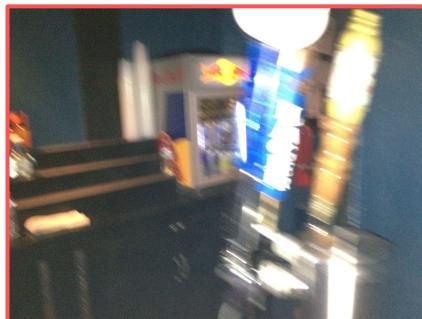
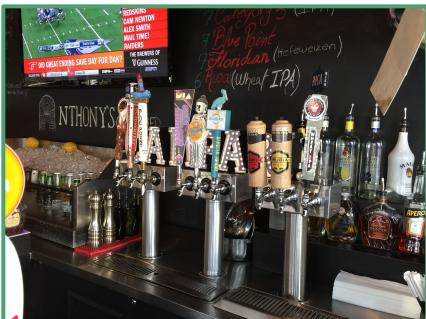


Image quality varies greatly

Good



Bad



Labeling images for consistent data capture

The screenshot shows the LabelImg application interface. On the left is a toolbar with various file operations like Open, Save, and YOLO, and drawing tools like CreateRectBox, DuplicateRectBox, DeleteRectBox, Zoom In, Zoom Out, Fit Window, and Fit Width. The main window displays a photograph of a bar tap system with several beer taps and bottles. Bounding boxes are drawn around specific items, such as a tap labeled "SAMBADA'S" and a bottle labeled "HARIBALL". To the right of the image is a "Box Labels" panel containing a list of categories: samadams, bluemoon, harp, stella, guinness, miller, and newbelgium. Below the image is a "Notepad" window titled "2012-12-29_13-52-03_625_T's_bar_&_restaurant_-_5025_N_Clark_bar2 - Notepad". It contains a table of coordinates for the labeled objects:

Object	X1	Y1	X2	Y2
5	0.094022	0.337929	0.110870	0.264706
56	0.572283	0.398591	0.092391	0.140319
72	0.594022	0.356618	0.098913	0.223039
71	0.694022	0.361673	0.086957	0.225184
20	0.957609	0.342831	0.081522	0.204657
22	0.351087	0.347733	0.102174	0.245098
68	0.280435	0.359222	0.094565	0.231311

At the bottom of the Notepad window, status bars indicate "Ln 8, Col 1", "100%", "Unix (LF)", and "UTF-8".

Methodology



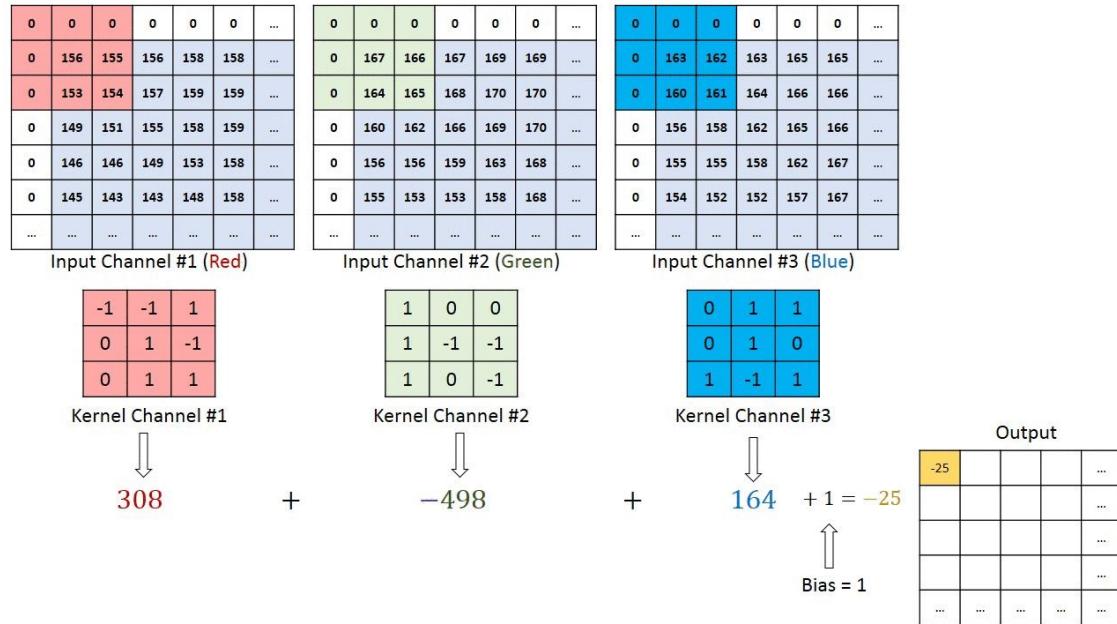
Feature extraction is critical for beer tap detection

Convolution

- Kernel weights slide left-to-right, top-to-bottom over an entire image
- Numeric pixel values are multiplied by the weights to derive output
- Operation performed iteratively to create transformations critical to detecting objects

Transfer Learning

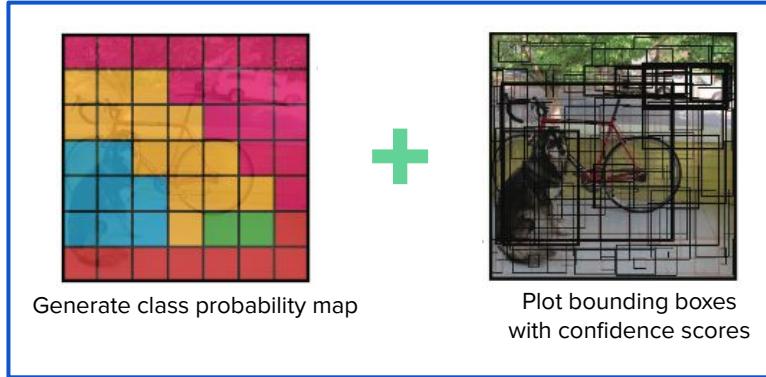
- Weights from other models can be applied to our custom model to avoid relearning patterns common to most objects



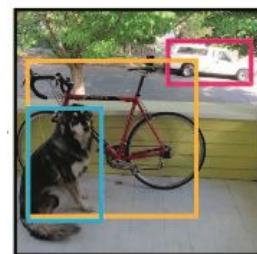
“You Only Look Once” Model Overview



Create image grid



Plot bounding boxes
with confidence scores



Show final detections

Methodology

YOLO applies a single convolutional neural network to the entire image, divides the image into regions and predicts bounding boxes with corresponding probabilities for each class.

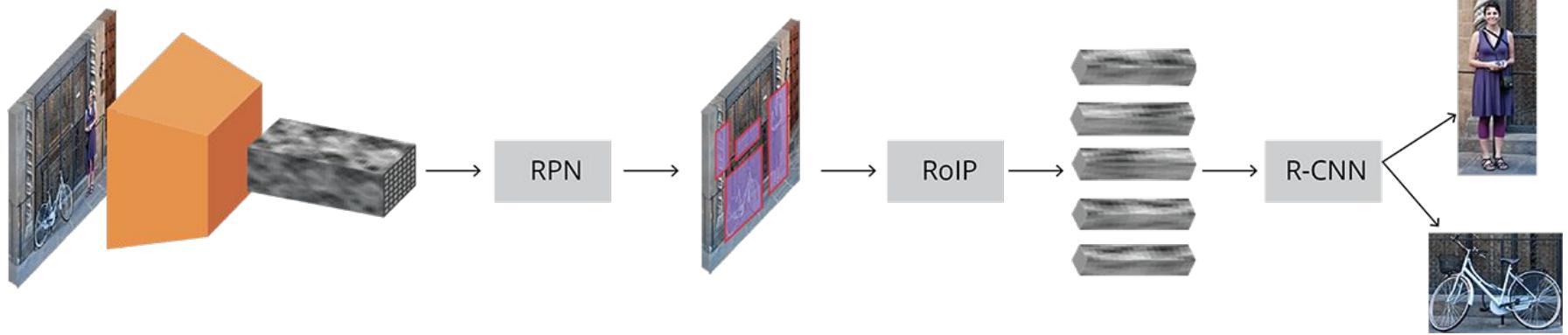
Benefits

- Higher precision, less incorrect predictions
- Supports real-time object detection

Limitations

- Tends to miss more detections
- Suffers with localization

Mask R-CNN Model Overview



Methodology

Mask R-CNN is a unified framework that first generates regions of interest and subsequently detects and predicts the probability of objects existing in these regions of interest.

Benefits

- High accuracy
- Great localization

Limitations

- Speed (compared to YOLO)
- Struggles with background noise

Evaluation Metrics

Recall: How many relevant taps are predicted?

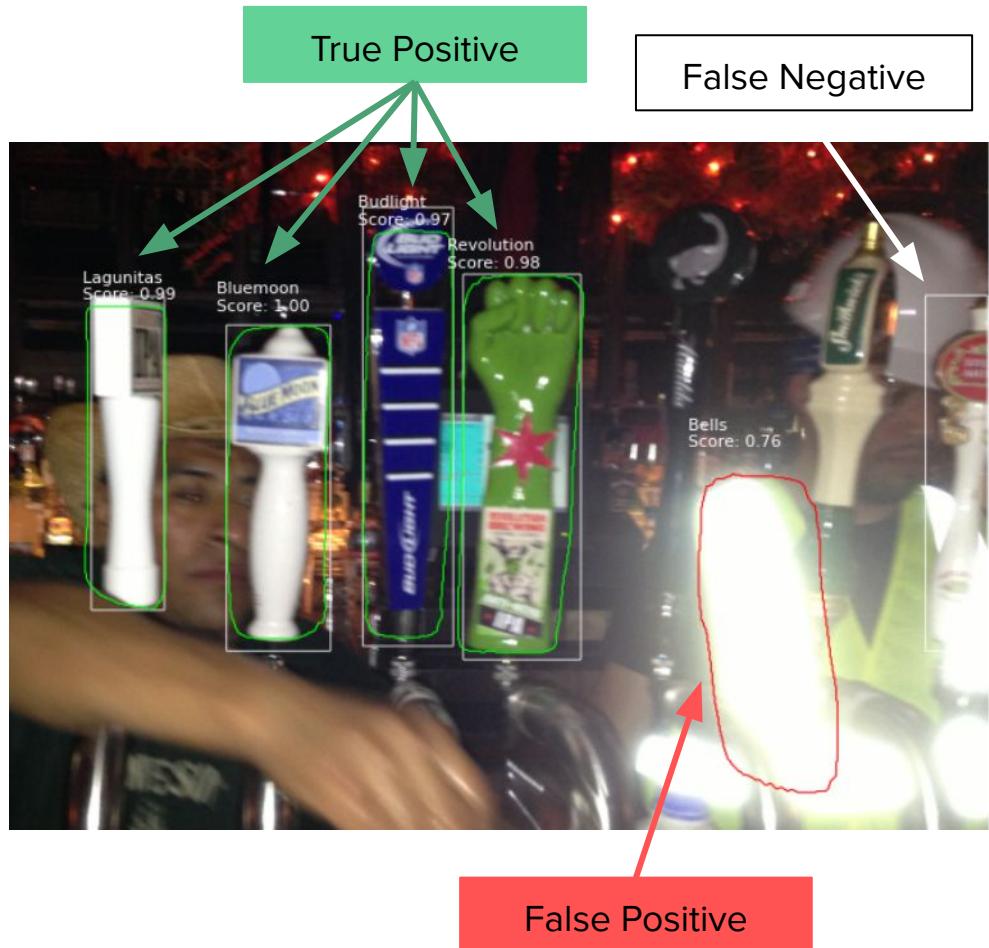
$$\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Precision: How many predicted taps are relevant?

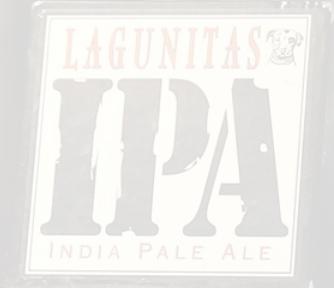
$$\frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Mean Average Precision (mAP)

The straight-average Precision at various levels of Recall

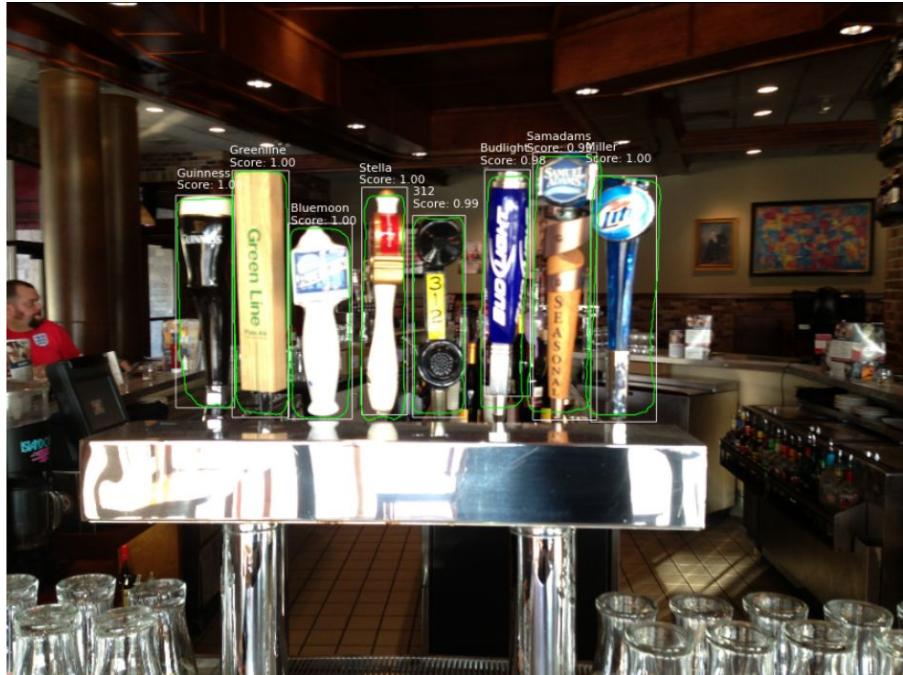


Findings

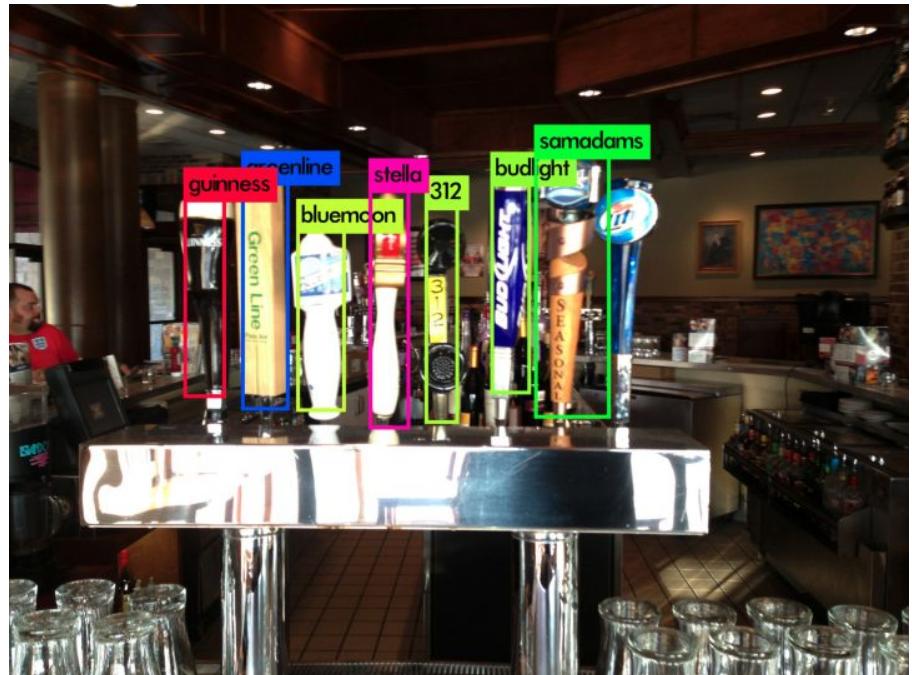


Head-to-head: Mask R-CNN vs YOLO

Mask R-CNN



YOLO



Head-to-head: Mask R-CNN vs YOLO

Mask R-CNN



YOLO



Mask R-CNN outperformed YOLO

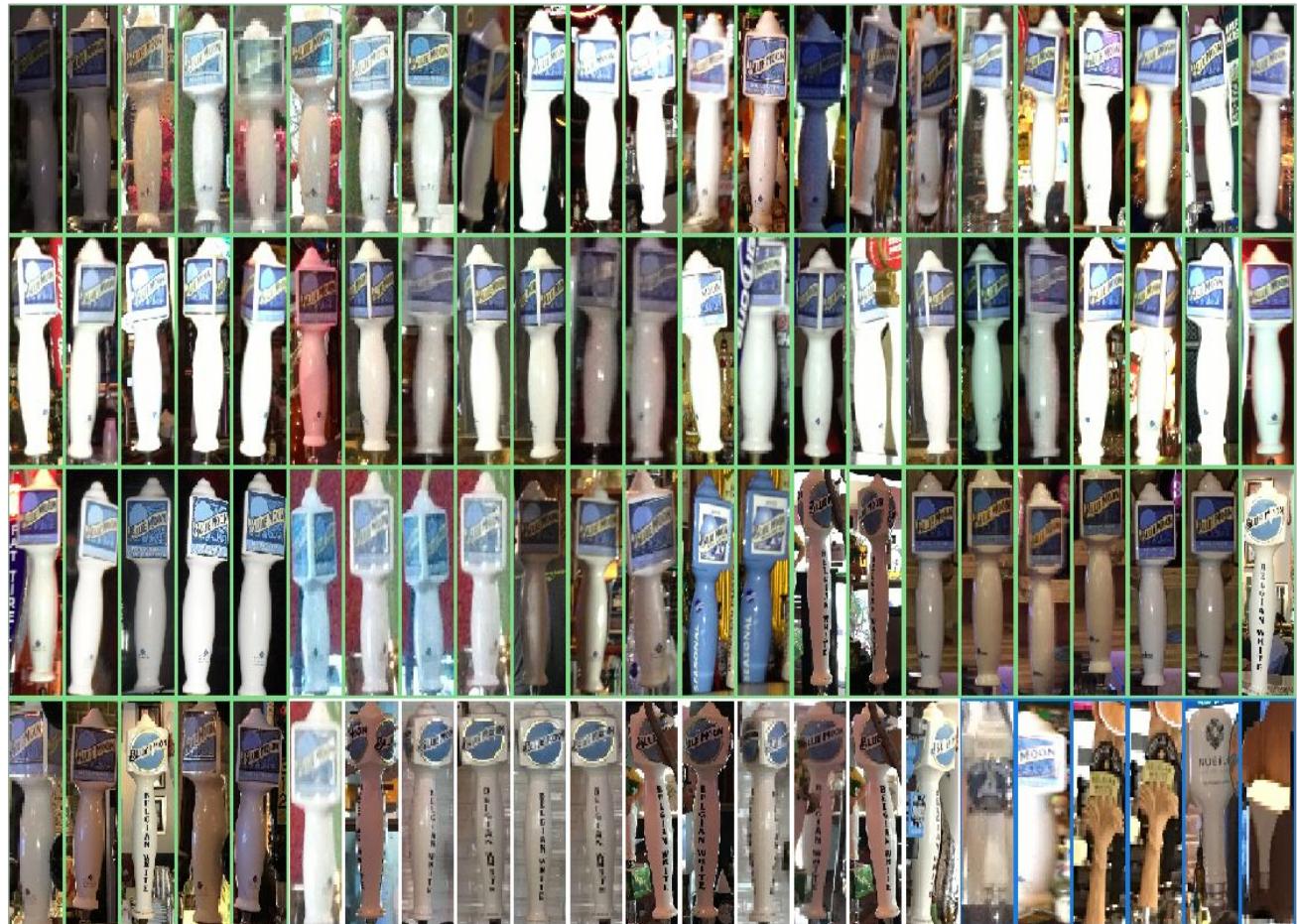
Class	Mean Average Precision (on Test)		
	YOLO	Mask R-CNN	Difference
Stella	61%	94%	33%
Lagunitas	78%	92%	14%
Sam Adams	65%	91%	26%
Guinness	81%	92%	11%
Blue Moon	86%	93%	8%
Budlight	74%	91%	17%
312	81%	96%	15%
Green Line	85%	90%	5%
Goose Island	54%	85%	31%
Miller	47%	67%	20%
Founders	74%	82%	8%
Revolution	57%	93%	37%
Bells	60%	79%	19%
Half Acre	61%	78%	17%
3 Floyds	77%	78%	0%
Heineken	46%	54%	9%
Coors	53%	65%	12%
Budweiser	60%	78%	17%
Yuengling	73%	89%	16%
Allagash	80%	94%	14%
Total	69.3%	86.5%	17.3%
Total (top-5 test classes)	73.7%	92.4%	18.7%

Detection Quilt

Brand: Blue Moon

Recall: 86%

Precision: 90%



True Positive

False Negative

False Positive - No Ground Truth

False Positive - With Ground Truth

Detection Quilt

Brand: Green Line

Recall: 83%

Precision: 78%



True Positive

False Negative

False Positive - No Ground Truth

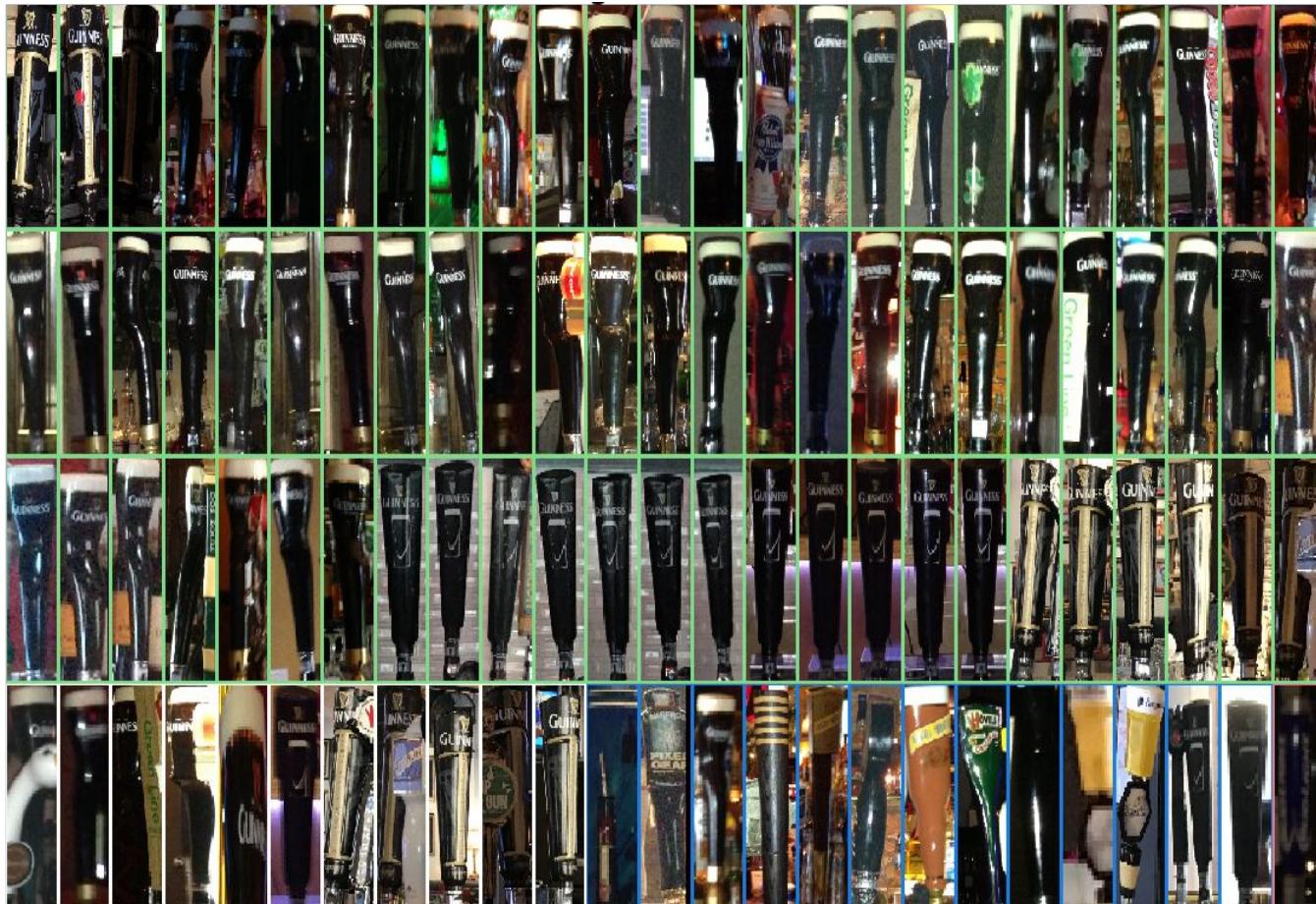
False Positive - With Ground Truth

Detection Quilt

Brand: Guinness

Recall: 87%

Precision: 83%



True Positive

False Negative

False Positive - No Ground Truth

False Positive - With Ground Truth



Cheers!