Christian Basso
Object Detection with YOLOv3
Applied ML
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Object Detection with YOLOv3 — Report

Model Performance

Provided Images

When I ran YOLOv3 on the provided images, it did a solid job overall. In most cases, the main objects in the scene were detected correctly and classified as expected. Larger and more obvious objects like people, chairs, cars, and the dog were usually identified with high confidence. The bounding boxes were generally well placed and closely matched the shape and position of the objects, as seen in Figure 1.

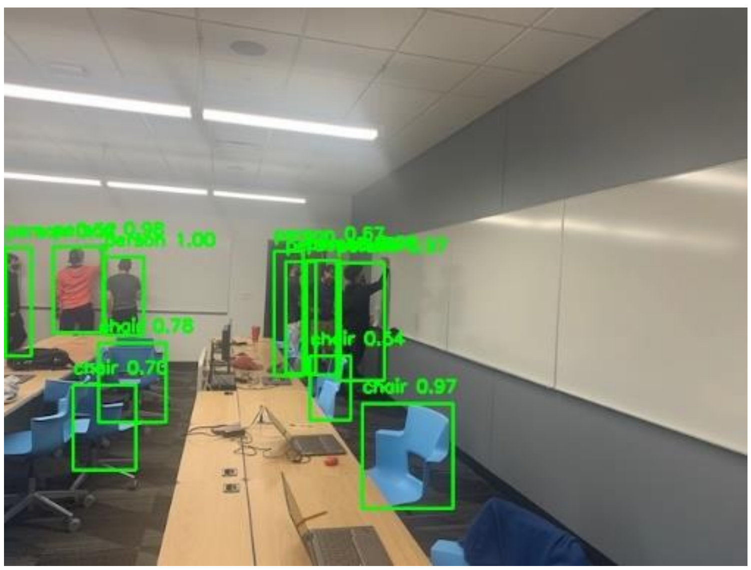

Figure 1: Most chairs and people in the photo were properly identified with appropriate borders.

There were a few imperfections. Smaller objects and partially visible objects were sometimes less precise and missed in some cases (reference Figure 2). In a couple of cases, objects near the edges of the image had slightly unstable or mis-sized boxes. I also noticed some minor false positives, like extra detections that didn't clearly correspond to real objects. Even so, the primary objects in each image were detected and localized reasonably well.

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Figure 2: The object detection was able to identify some of the chairs and people but left multiple examples undetected. Closed laptops were also not detected in any case.

Own Images

On the two additional web images I tested, YOLOv3 again performed well. In the dog image, it correctly detected the dog and also identified other objects in the scene, such as a bicycle and a truck. The bounding boxes were tight and accurately wrapped around the visible parts of each object.

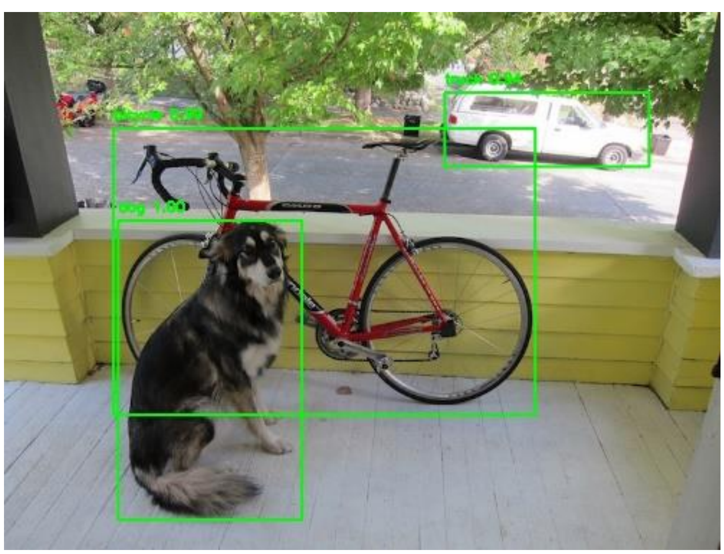

Figure 3: All three objects in the picture were identified with near-perfect borders.

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In the giraffe and zebra image, both animals were detected and correctly classified. Even though one animal was partially blocked, the model still produced a usable bounding box. Overall, the results on my own images were consistent with the included images: strong performance on clear, well-lit objects, with only minor localization issues in more complex or crowded areas.

Competing Models

Based on the YOLO paper, there are two main types of competing object detection models. Two-stage detectors like R-CNN, Fast R-CNN, and Faster R-CNN first generate region proposals and then classify them. One-stage detectors like SSD and RetinaNet predict bounding boxes and class probabilities directly in a single pass.

YOLO stands out because it treats detection as a single regression problem. Instead of proposing regions and refining them, it predicts bounding boxes and class probabilities all at once. This makes YOLO much faster and suitable for real-time applications. The trade-off is that earlier versions sometimes struggled with small objects, but YOLOv3 improves this with multi-scale predictions and stronger feature extraction.

Ethical Concerns

Privacy Concerns

Large image datasets can easily include sensitive information, such as faces, license plates, or private settings, often collected without explicit consent. Even if the dataset itself is not shared publicly, a trained model can still leak information. For example, through membership inference or model inversion attacks, someone might determine whether a specific person’s data was included in training. So, sharing a trained model can still create privacy risks.

Bias and Fairness

Researchers have shown that models trained on datasets like ImageNet may perform worse on underrepresented groups, especially people of color. This happens when the data set does not contain balanced representation across racial, ethnic, or other demographic groups.

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To check for bias, I would evaluate representation across demographics, compare error rates (false positives and false negatives) by group, and examine whether certain groups are misclassified more often. I would also look at the labels themselves to ensure they are appropriate and not offensive.

To reduce bias, strategies could include collecting more balanced data, reweighting underrepresented groups during training, reporting performance separately for different groups, and involving human review for sensitive categories. Being transparent about model limitations is also important to avoid harm when deploying these systems in real-world applications.