

## **Team 66**

# **Waste Detection using Faster RCNN and Mask R-CNN**

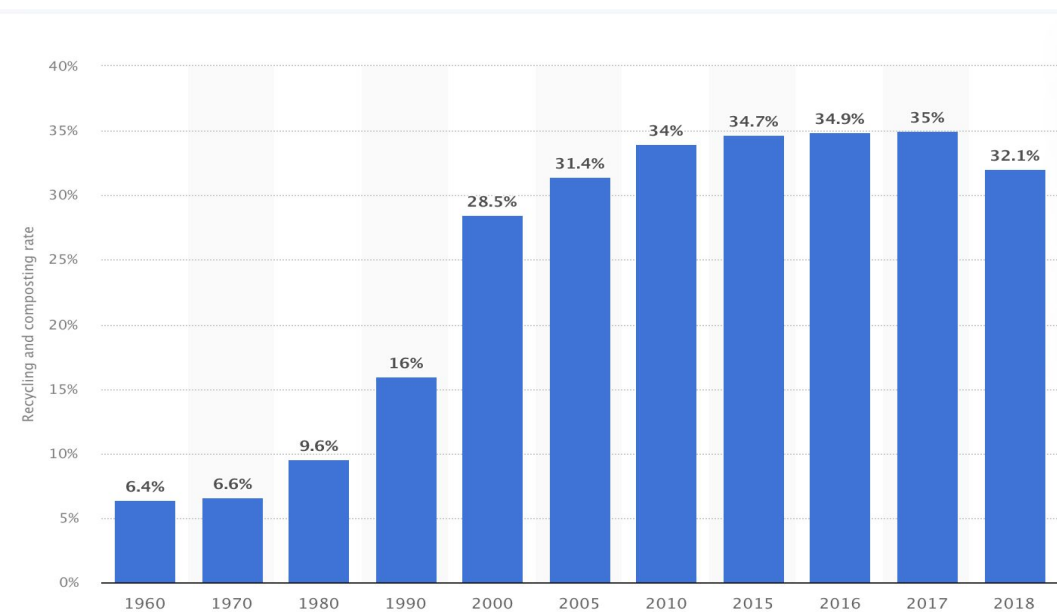
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# Motivation

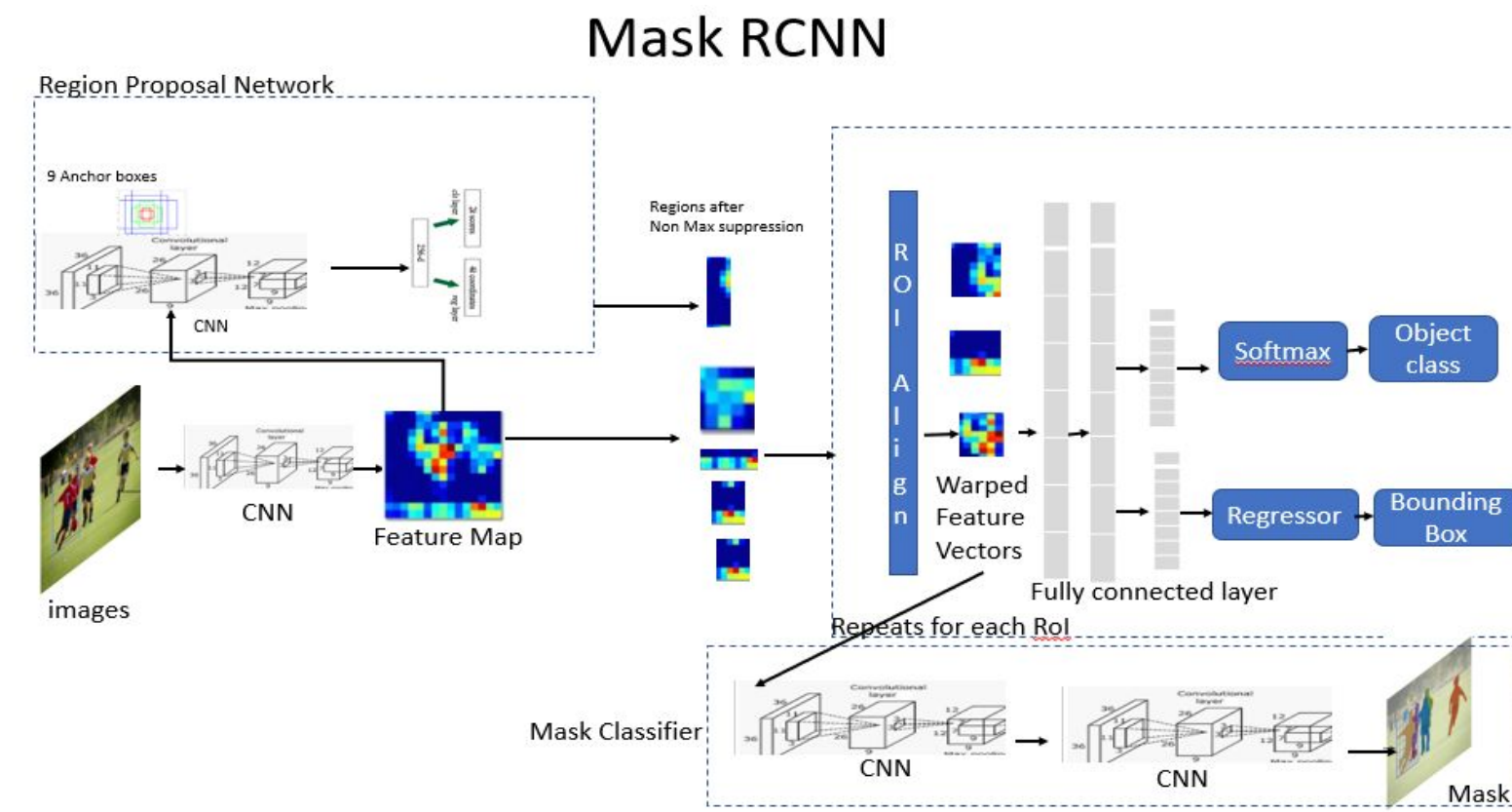
- Only 30%\* of recyclable materials actually get recycled.
- Automated system needed to improve efficiency and create a sustainable process to manage waste.
- Instance segmentation is challenging as it requires the correct detection of all objects in an image while also precisely segmenting each instance.
- We aim to mitigate this issue by developing a model that automatically detects different types of waste products into predefined classes.



\* **source** - Recycling rate of municipal solid waste in the United States 1960-2018. Published by [Ian Tiseo](#), Mar 30, 2022

# Task

- Implement **Faster R-CNN** model.
- Implement **Mask R-CNN** for image segmentation to detect the type of waste.
- Measured using **Region of Interest (RoI)**.



\* **source** - Kaiming He, Georgia Gkioxari, Piotr Dollar, Ross Girshick, 'Mask R-CNN' <https://arxiv.org/pdf/1703.06870.pdf>

# Dataset

- The primary dataset used to train the model is inspired from the resources curated by Jay et.al <sup>[1]</sup>.
- The data for other classes like Medical waste was scraped from Google Images using the Simple Image Downloader library <sup>[2]</sup>.
- The images are broadly classified into 6 classes such as **Metal, Glass, Paper, Organic, E-Waste** and **Medical**.
- We have: **856** examples, **685** are training and **171** testing. (80-20 split)

\* **sources** - [1] <https://drive.google.com/drive/folders/1CTvTgnTvwlcKwJ8yz4jUOs0JYTKrplA>  
- [2] <https://libraries.io/pypi/simple-image-downloader>

# Sample Images



Glass



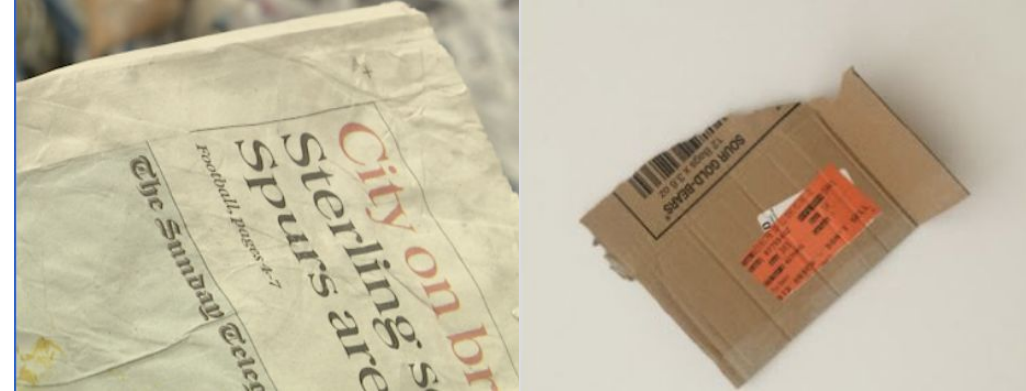
Medical



Organic



Metal



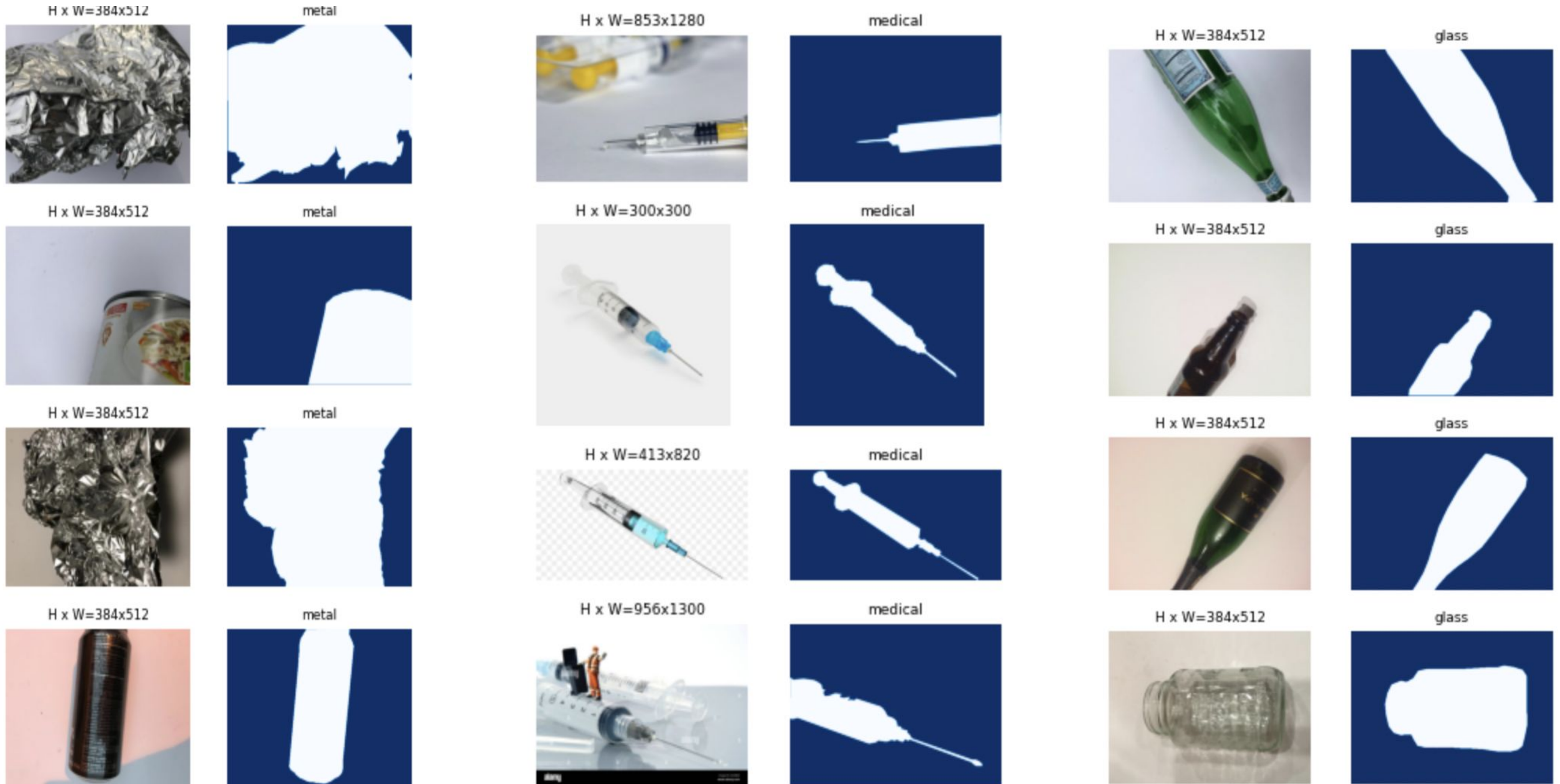
Paper



E-waste

# Annotations

- The six classes were annotated for the actual masked segments to be found



# Methodology - Faster RCNN

- **Faster R-CNN** consists of two stages:
  1. Region Proposal Network (RPN)
  2. Fast R-CNN
- During training<sup>[1]</sup>, the model expects input tensors and targets containing:
  - **boxes (FloatTensor[N, 4])**: the ground-truth boxes in [x1, y1, x2, y2] format, with  $0 \leq x1 < x2 \leq W$  and  $0 \leq y1 < y2 \leq H$
  - **labels (Int64Tensor[N])**: the class label for each ground-truth box
- The model returns a Dict[Tensor] during training, containing the classification and regression losses for both the RPN and the R-CNN.

\* sources - [1] [https://pytorch.org/vision/stable/generated/torchvision.models.detection.fasterrcnn\\_resnet50\\_fpn.html](https://pytorch.org/vision/stable/generated/torchvision.models.detection.fasterrcnn_resnet50_fpn.html)

# Baseline Performance

IoU metric: bbox

Average Precision (AP) @[ IoU=0.50:0.95	area= all	maxDets=100	] = 0.001
Average Precision (AP) @[ IoU=0.50	area= all	maxDets=100	] = 0.010
Average Precision (AP) @[ IoU=0.75	area= all	maxDets=100	] = 0.000
Average Precision (AP) @[ IoU=0.50:0.95	area= small	maxDets=100	] = -1.000
Average Precision (AP) @[ IoU=0.50:0.95	area=medium	maxDets=100	] = -1.000
Average Precision (AP) @[ IoU=0.50:0.95	area= large	maxDets=100	] = 0.001
Average Recall (AR) @[ IoU=0.50:0.95	area= all	maxDets= 1	] = 0.002
Average Recall (AR) @[ IoU=0.50:0.95	area= all	maxDets= 10	] = 0.009
Average Recall (AR) @[ IoU=0.50:0.95	area= all	maxDets=100	] = 0.009
Average Recall (AR) @[ IoU=0.50:0.95	area= small	maxDets=100	] = -1.000
Average Recall (AR) @[ IoU=0.50:0.95	area=medium	maxDets=100	] = -1.000
Average Recall (AR) @[ IoU=0.50:0.95	area= large	maxDets=100	] = 0.009

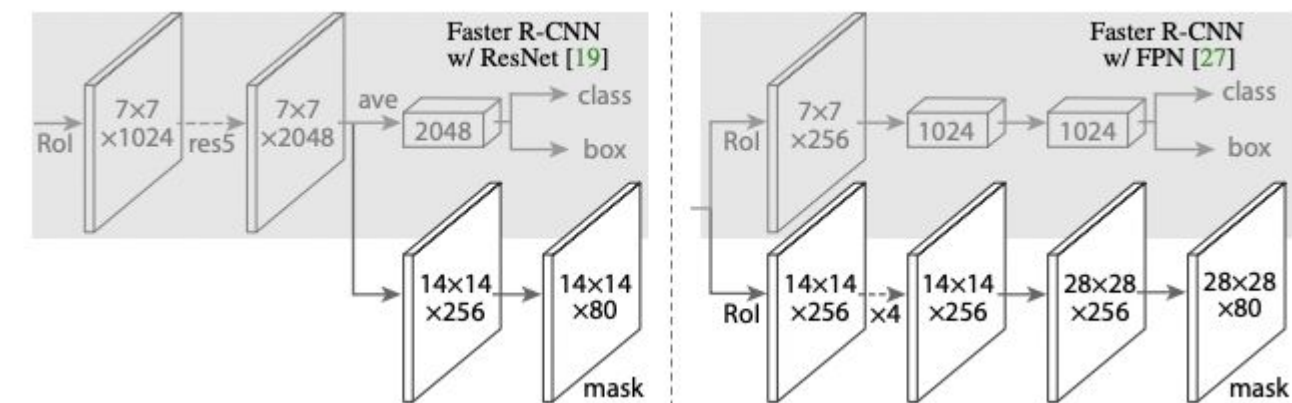




# Methodology - Mask RCNN

- **Extends Faster R-CNN** by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition
- **Mask R-CNN is simple to train** on Faster R-CNN, running at **5 fps**.
- Two level architecture
  - Convolutional **backbone** architecture used for feature extraction over an entire image.
  - The network **head** for bounding-box recognition (classification and regression) and mask prediction that is applied separately to each RoI.
- A multi-task loss on each sampled RoI is defined as  $L = L_{cls} + L_{box} + L_{mask}$
- $L_{mask}$  is defined only on positive Rols.

\* **sources** - [1] arXiv:1703.06870 [cs.CV]



# Proposed Model: Mask R-CNN

```
def detect(self, images, verbose=0):
    assert self.mode == "inference", "Create model in inference mode."
    assert len(
        images) == self.config.BATCH_SIZE, "len(images) must be equal to BATCH_SIZE"

    if verbose:
        log("Processing {} images".format(len(images)))
        for image in images:
            log("image", image)

    # Mold inputs to format expected by the neural network
    molded_images, image_metas, windows = self.mold_inputs(images)

    # Validate image sizes
    # All images in a batch MUST be of the same size
    image_shape = molded_images[0].shape
    for g in molded_images[1:]:
        assert g.shape == image_shape, \
            "After resizing, all images must have the same size. Check IMAGE_RESIZE_MODE and image sizes."

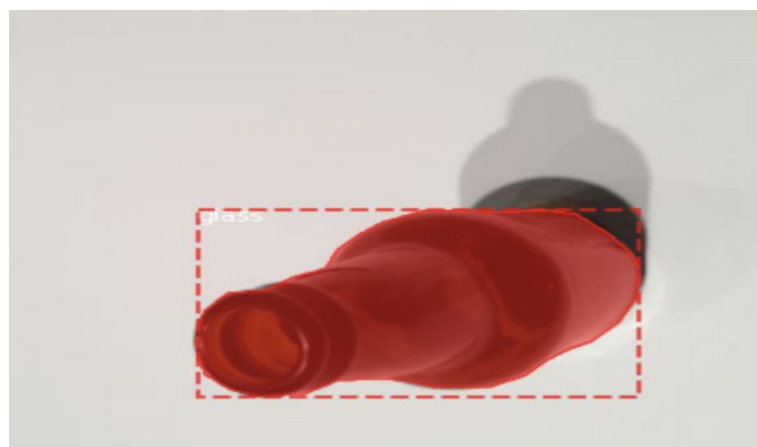
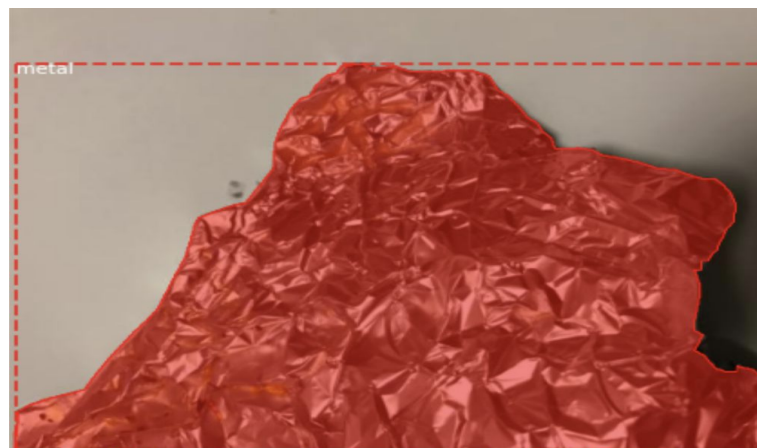
    # Anchors
    anchors = self.get_anchors(image_shape)
    # Duplicate across the batch dimension because Keras requires it
    # TODO: can this be optimized to avoid duplicating the anchors?
    anchors = np.broadcast_to(anchors, (self.config.BATCH_SIZE,) + anchors.shape)

    if verbose:
        log("molded_images", molded_images)
        log("image_metas", image_metas)
        log("anchors", anchors)
    # Run object detection
    detections, _, _, mrcnn_mask, _, _, _ = \
        self.keras_model.predict([molded_images, image_metas, anchors], verbose=0)
    # Process detections
    results = []
    for i, image in enumerate(images):
        final_rois, final_class_ids, final_scores, final_masks = \
            self.unmold_detections(detections[i], mrcnn_mask[i],
                                  image.shape, molded_images[i].shape,
                                  windows[i])
        results.append({
            "rois": final_rois,
            "class_ids": final_class_ids,
            "scores": final_scores,
            "masks": final_masks,
        })
    return results
```



# Predictions

Input Image



Class Detection



**THANK YOU**