

Street2Sat: A Machine Learning Pipeline for Generating Ground-truthGeo-referenced Labeled Datasets from Street-Level Images

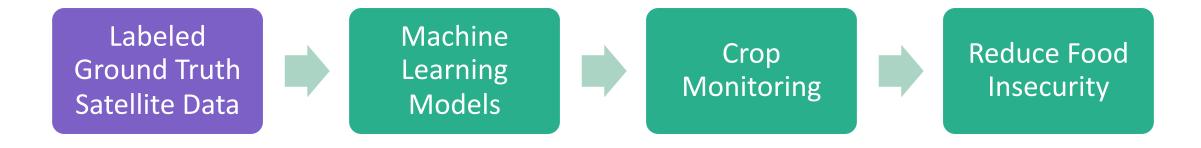
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Motivation

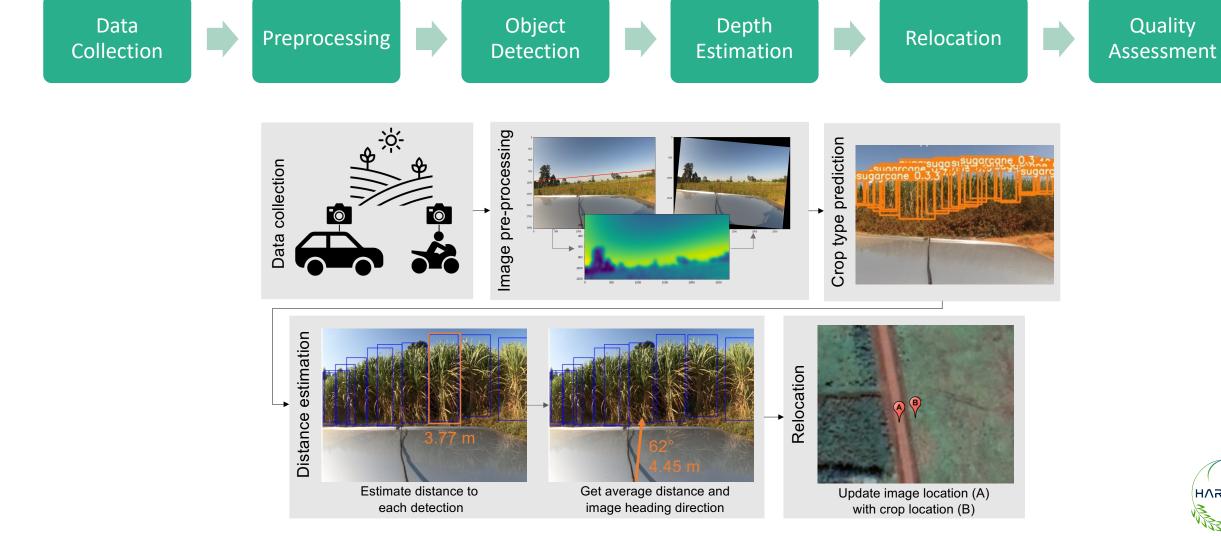


Difficult to obtain and scarce in many areas of the world

Street2sat provides a solution to create large datasets of geo-referenced labels to be used in machine learning and other applications.



Approach



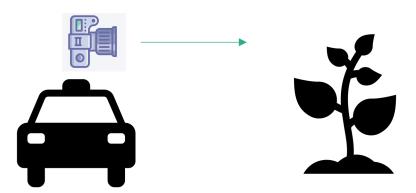


Quality

Data Collection



- Images from initial study collected in Western Kenya
- GoPro Max 360 cameras pointing orthogonal to the side of the car closest to the crops
- Routes mapped to ensure maximal coverage of crops

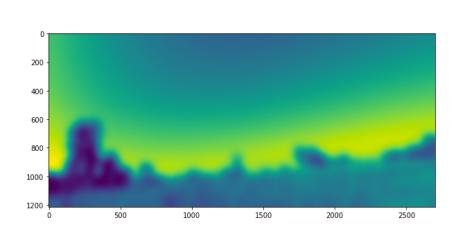


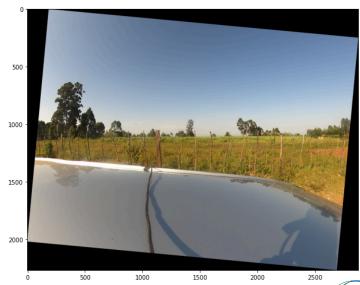


Preprocessing

- Images were straightened using Otsu's method to create training and validation sets
- Straightening was needed so that the predicted bounding boxes would have accurate height representation

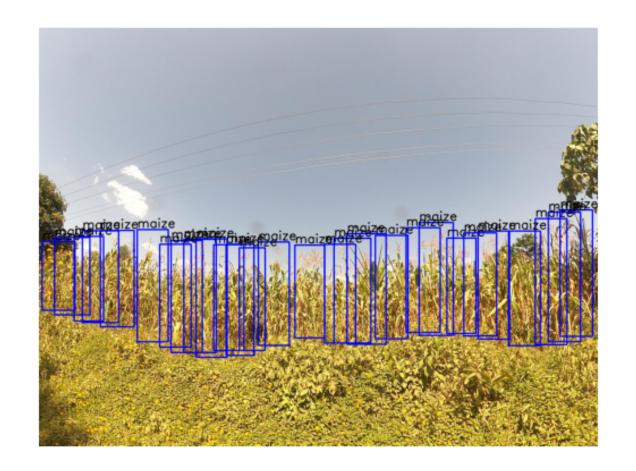






Object Detection

- A custom Yolov5 model was trained using hand labeled data
- Initialized using pretrained weights from COCO
- Fine-tuned using hand labeled data





Depth Estimation

$$d = \frac{(l_{focal} * h_{crop} * h_{image})}{(h_{bbox} * h_{sensor})}$$

- I_focal: focal length of camera
- h_crop: height of crop based on lookup table
- h_image: image height in pixels
- h_bbox: detected bounding box height in pixels
- h_sensor: sensor height obtained from GoPro website
- d: distance to crop

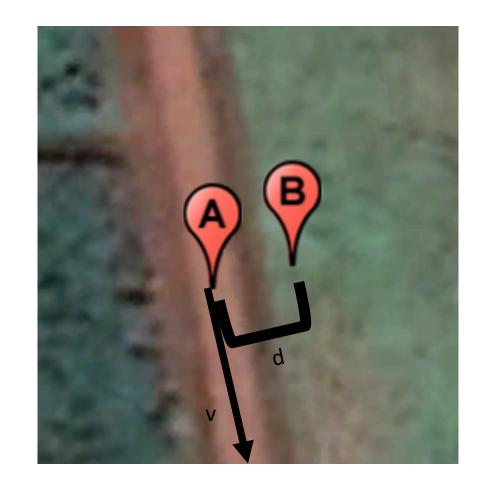
In a given image, all predicted distances were averaged to get one distance per crop per image.



Relocation

 Once distance (d) is known, create a velocity vector based on the closest other image in time

 Since cameras are placed orthogonal to the drive direction, translate the image coordinates d meters 90 degrees west of the velocity vector





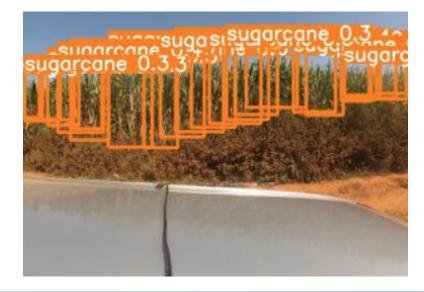
Experiment Setup

- Labeled 296 training images and 53 test images with expert guidance
- 755 instances of maize and 1795 instances of sugarcane in training set
- 253 maize and 229 sugarcane in test set
- Precision: 0.41, Recall: 0.59, mAP @ 0.5: 0.45, and mAP@.5-.95: 0.13
- Often more bounding boxes were predicted than labeled, which affected precision but is good for accurate crop distance.

Labels



Predictions





Quality Assessment/Quality Checks

- We did not have ground truth labels for the test set so we compared our predicted points with a 10 m/pixel crop/no crop map of Kenya
- 73/85 (86%) predicted crop points were also classified as crop on the map.
- In the future we hope to test on thousands of points in several locations
- Additional quality checks will be implemented in future work





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