Prioritizing Aid From Above

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Introduction

Fruit trees such as coconuts and bananas are an important source of food and income for many communities in the South Pacific. These same communities are at high risk for natural disasters such as hurricanes, tsunamis, and volcanic eruptions[1].

Currently, aid organizations collect and manually analyze aerial imagery to assess damage to affected areas. This analysis helps guide efficient distribution of aid, prioritizing communities whose food sources have been most affected by disaster.

However, manual analysis of this data can take days to complete, a significant amount of time following major disasters. This delay hinders organizations from responding to crises in the most efficient manner possible.

In response, WeRobotics is hosting an Open AI Challenge, focused on accelerating aerial image analysis surrounding humanitarian disasters.

Goal

Develop a tool to automatically identify and count coconut and banana trees in aerial imagery, thereby providing a tool for aid organizations to deliver aid efficiently.

Data Science Pipeline

Import
Convert shapefiles to GeoJSON and extract single image layer.

Clean
Map label's coordinate values from latitude and longitude to pixels.

Tile & Annotate
Split image into 1260 tiles and generate ground truth for each.

Model
Train YOLO[2] models on 1000 tiles to detect coconut and banana trees using darknet[3].

Evaluate
Compare models using mean average precision (mAP) across all classes (Figure 2).

Final Product
Select model and implement automated identification and counting of fruit trees.

Figure 1. Comparing predictions (dashed boxes) with the ground truth (solid boxes) for banana and coconut trees in six validation images.

Results

Model performance was evaluated using mAP across classes and average precision for each individual class (Figure 2).

The YOLOv2 model trained from scratch was chosen for use in our user-facing product. Figure 1 shows the predictions made by this model on six of the 200 validation images.

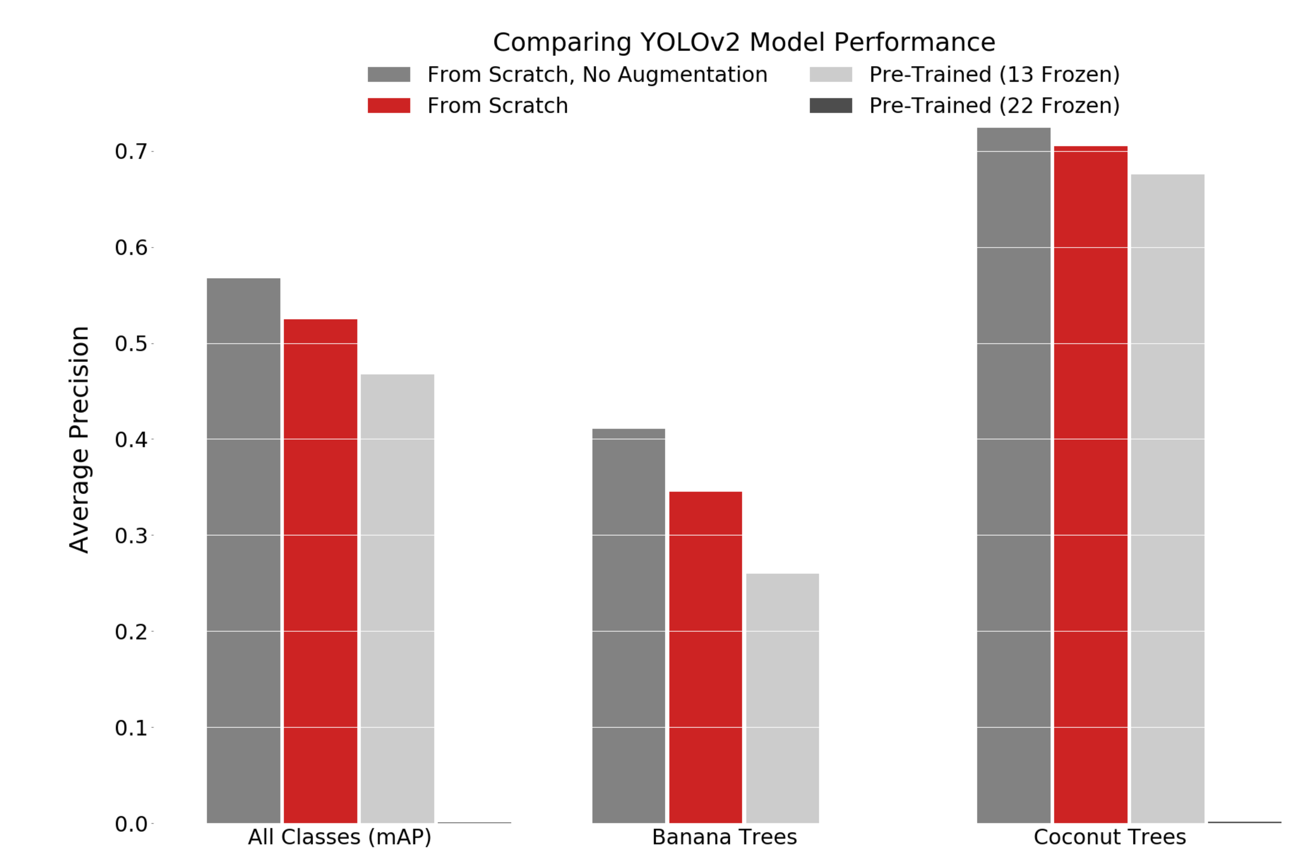

Figure 2. Comparing model performance using average precision.

Recommendations

We recommend further work on this project focus on the following three tasks:

1. Improving the dataset (e.g. variation & accuracy)
2. Using models pre-trained on aerial imagery
3. Implementing YOLOv3 models

Acknowledgements

Thank you to WeRobotics, OpenAerialMap, and World Bank for supporting and sponsoring this challenge. Thank you to Nelson Nauata for sharing his expertise on computer vision. Thank you to Dr. Jiannan Wang and Dr. Steven Bergner for their support throughout CMPT 733.

References

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