CS230

Building a Deep Learning Model for Satellite Image Segmentation

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1 Background and Problem Statement

Satellite data has long been used as a way to observe the Earth at a spatial and temporal scale. Earth observation via satellites has been increasingly used across the public and private sectors with agriculture, military, commercial, and other goals for the past several decades. In recent years, the availability of high quality, temporally regular, and public satellite image data has coincided with the rise of Machine Learning and Computer Vision. Advancements in image segmentation technology have been applied to satellite imagery to map landslides and waterways, analyze poverty within cities, and more, as in related literature [1] [2] [3]. Only recently has deep learning been used to segment images [4] [5]. Last spring, I was tasked with building a random forest model that could identify pineapple plantations in Costa Rica for years which the government had no data for (2020-present). This work was done through CS 131: Computer Vision, as well as through my job in the Mordecai Lab at Stanford. Although the models worked, the resulting datasets were not accurate enough to be used (roughly 80 percent accuracy with lots of noise). Further literature reviews revealed that the state of the art for satellite image segmentation is via deep learning. Thus, this project aims to build a deep learning model that can identify pineapple plantations across the entirety of Costa Rica for the years 2020-2024.

2 Challenges

The primary challenges in this project are data related. There is plenty of available data through both Google Earth Engine and Planet Labs, but very little documentation or available packages for integrating satellite imagery with deep learning frameworks. The second major challenge will be evaluative, as prediction maps for 2020-2023 have no ground-truthing data available, so I will have to be creative about using the 2019 dataset as both training and testing data without creating a model that is over-fitting or misleading in its results. I plan to rely on the expertise of several research contacts at Stanford and NASA for help addressing these challenges.

3 Dataset

This project will rely on Sentinel 2 10m resolution data available via Google Earth Engine. The project will also use 2019 pineapple plantation data for Costa Rica provided through researchers in the Mordecai Lab as a training basis.

4 Learning Methods

The anticipated learning methods will involved building and changing a Convolutional Neural Net (CNN) for image segmentation. More specifically, the current research frontiers in the realm of satellite segmentation specifically are using models similar to an attention U-Net model [5]. This is likely where the project will jump off from, but other models of similar architecture will be explored.

5 Evaluation

I plan to evaluate the model using accuracy assessments on 2019 ground-truth test data to compare the predicted segmentation directly to the ground-truth. Additionally, I will use standard measure of model performance such as F1 score, confusion matrices, and kappa coefficient. Finally, I will visually inspect the resulting maps and overlay the maps for different years to observe whether there is logically visible change in the shapes and distributions of plantations over 2020-2023 based on research on the pineapple industry in Costa Rica over that time. This will serve as a visual check to complement the computational evaluation methods.

References

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