USING NAIP IMAGERY TO ENHANCE AN INDIVIDUAL TREE CROWN DETECTION MODEL FOR VIRGINIA, USA

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Abstract

The National Agricultural Imagery Program (NAIP) imagery provides a unique opportunity to detect individual tree crowns routinely across the United States with sub-meter resolution. In this study, we will use NAIP imagery from 2021 with a convolutional neural network architecture (CNN) called U-Net-ID that performs an instance segmentation to identify and calculate crown area for dominant and co-dominant canopy crowns over Virginia, USA. We will use the methodology and results from a preliminary analysis completed in the Lake Tahoe Basin of California, USA, to adapt the crown segmentation model to the Commonwealth of Virginia and compare sample areas of forest cover to lidar-detected crowns. Identified trees in the sample area will be validated using equivalence tests on the calculated total crown area where we will assume that the NAIP and lidar-detected tree crown areas will not be equal. It is expected that adjustments to the original crown segmentation model will be necessary so that a crown delineation map of the sample area can be produced to estimate crown area with an accuracy greater than or equal to 85%.

1. Introduction

1.1 Motivation

The National Agricultural Imagery Program (NAIP) is an airborne imagery program by the United States Department of Agriculture's (USDA) Farm Service Agency (FSA). This program routinely collects imagery every 2 to 3 years across the continental United States during the agricultural growing season. Research has shown that the coarse resolution and point clouds of NAIP (or other digital aerial photogrammetry) are great predictors at forest measurements, including height (e.g., *Prior et al., 2022; Ritz et al., 2022*), basal area (e.g., *Noordermeer et al., 2019*; *White et al., 2015*), and tree detection (e.g., *Noordermeer et al., 2019*; *Strunk et al., 2020*). Other research has used Norway's International Climate and Forest Initiative (NICFI) Planet imagery to map tree cover at the 5 m spatial resolution, showing high accuracy of individual tree detection (*Wagner et al., 2023*).

Individual tree crown area and mapping using remote sensing has provided researchers with a vast new collection of information that would otherwise only be available from field measurements, which is not practical at large-scale assessments (*Kumar and Mutanga, 2017*). Although field measurements are considered highly accurate at measuring most tree metrics, such as diameter at breast height (DBH) and total height, NAIP and other optical imagery have shown high correlations with crown area estimations (*Jing et al., 2012*). With sub-meter spatial resolution and RGB and NIR bands, NAIP imagery has the potential to identify individual trees in the dominant and co-dominant canopy. The combination of NAIP imagery with the individual tree detection methods described in Wagner et al.'s research provides an opportunity to map trees across an entire state at the sub-meter resolution.

1.2 Research Objectives

1. Utilize one sided equivalence tests to determine if NAIP imagery is equivalent to lidar at calculating individual tree crown area.
2. Iterate the U-Net-ID model parameters to the tree crown segmentation model such that 85% accuracy is achieved.

1.3 Preliminary Results

This study expands on recent analysis in which I participated that investigated the ability for NAIP imagery to detect and separate individual tree crowns in California, US. This pilot study started in the Lake Tahoe Basin with fifty-three overlapping images between California and Nevada. We used a combination of the U-Net-ID instance segmentation model described in Wagner et al. (2020) and the deep learning models used in Mugabowindekwe et al. (2022) to develop an approach with NAIP imagery to detect the individual crowns. The process includes three interconnected paths to predict crown borders, crown segments, and the crown inner segment (Figure 1). The predicted inner segment is calculated by adding the ID attribution to the crown buffer to recover the original size of the crown. The training samples were segmented or manually edited from the model results. There were 3,291 images of 128 x 128 pixels (76.8 x 76.8 m, ~0.6 ha), of which 2,597 contained trees and covered different view angles, forest types, and camera orientation.

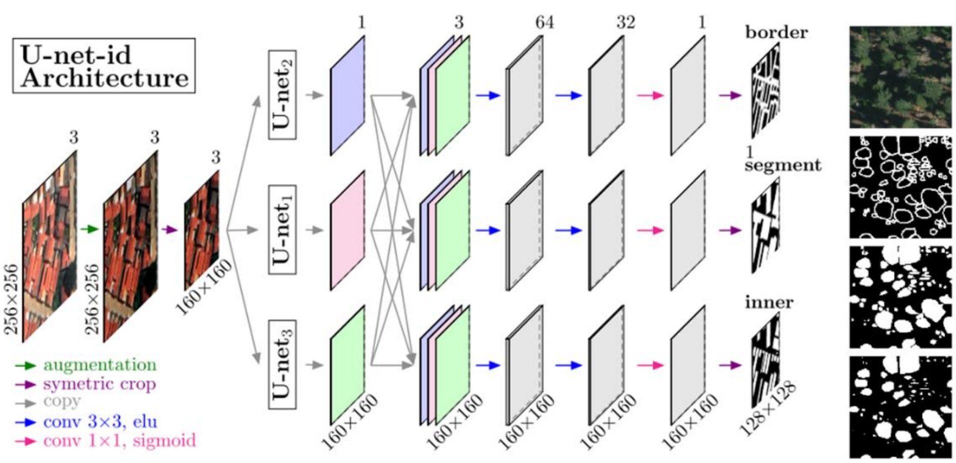

Figure 1. Instance segmentation flow chart

Samples were split into 80% training and 20% validation with crown area accuracy of 99.7% and 77.8%, respectively. Our intersection over union (IoU = Area of Overlap ÷ Area of Union) had a value of 0.64 and our final model that included all the data had a crown area accuracy of 99.8%. A section of the model output of the crown segmentation in the Lake Tahoe Basin can be seen in Figure 2. As a result of our pilot study, the model was deemed suitable for semantic segmentation across tree crown sizes as well as over various slope orientations and was tested over the entire state of California this past fall. Some problems we have already encountered include trees with the same color foliage and texture or with no visible separation, image distortion that removes some of the crown features, and shade.

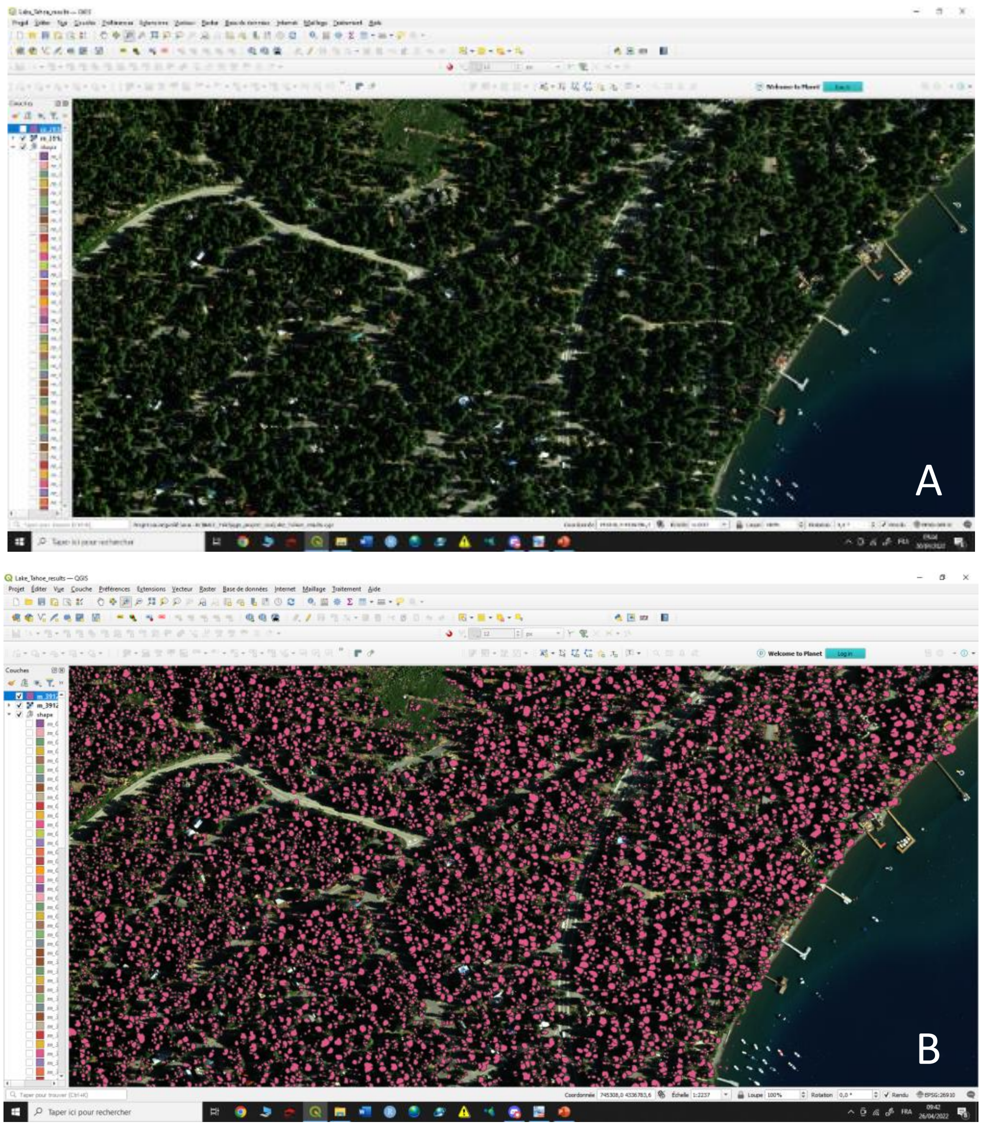

Figure 2. Tree crown segmentation over a section of the Lake Tahoe Basin where a) is the original NAIP image and b) shows the final crown segmentation polygon in pink.

2. Methods

2.1 Study Area

The application area of this study includes the entirety of the state of Virginia, USA. The state will be divided into two sections, pine plantation, and non-plantation forests using a 2019 active plantation map (*Thomas et al., in progress*). This separation will allow for different modeling techniques for the crown delineation to be utilized to account for the differences in crown structure between pine plantations and natural forests. The pine plantation study area will be at the Reynolds Homestead (RH) plantation, part of the Forest Productivity Cooperative's (FPC) Region Wide 20 study, in southwest Virginia (*Sumnall et al. 2023*). The non-plantation forest measurements are part of National Ecological Observatory Network (NEON) field site at Mountain Lake Biological Station (MLBS) in southwest Virginia.

2.2 Data

2.2.1 Lidar

The lidar data from the MLBS site was collected on June 13, 2021, with the ALTM Gemini Lidar sensor (*NEON, Discrete return LiDAR point cloud*). Acquisition parameters include a scan angle of 18°, pulse repetition frequency of 250 kHz, scan frequency between 59 Hz and 62 Hz, and a beam division of 0.25 mRad. (*Goulden & Hass, 2021*). For the RH, lidar was collected in July of 2021 using the DJI M600 hexacopter platform with a Riegl MiniVux1 Lidar scanner *(Sumnall et al., 2023)*. The specifications include a ≤85° scan angle, pulse repetition frequency of 100 kHz, and an 80% overlap between flight lines *(Sumnall et al., 2023)*.

2.2.2 NAIP

The NAIP imagery was acquired with the Leica ADS-100 sensor with 27% side overlap and 0.6 m ground sampling distance *(Surdex Corporation, 2021)*. Collection was done with a combination of twin-engine aircraft flying at 27,100 ft above mean terrain. NAIP imagery is formatted to the UTM coordinate zone and may have up to 10% cloud cover. Imagery includes bands red (R), green (G), blue (B), and near-infrared (NIR) and has 8-bit pixel depth.

2.3 Tree Crown Delineation

Lidar data were used to map tree crowns at the pine plantation and natural forest sample sites to establish an expected crown delineation shape and area. This process took place in R where the lidR package was used to create shapefiles of the crowns, following the steps of *(Roussel et al., 2022)*. The final product for each tree crown is a .shp file which can be exported for comparison with the NAIP imagery segmentation. Since NAIP imagery will not be able to detect trees under the overstory canopy, only dominant and co-dominant crowns captured by the lidar were kept for the analysis. The lidar crown segmentation served as the true crown area and shape to compare the NAIP imagery segmentation against.

The NAIP training samples will be segmented over the same regions as the lidar samples for direct comparison of model accuracy. We will use the NAIP imagery with the U-Net-ID machine learning techniques to identify and segment crowns in the image raster file, following the method of Wagner et al. (in progress). Then, individual tree polygons will be created in R from the raster segmentation which will allow for the calculation of the area of each crown. Once the NAIP crown area shapefile has been created for each study area with lidar, we will use the equivalence tests for differences between two independent means found in Lakens 2017. Assuming equal variances, the model is based on:

$$t_L = \frac{\bar{M}_1 - \bar{M}_2 - \Delta_L}{\sigma\sqrt{\frac{1}{n_1}+\frac{1}{n_1}}} \text{ and } t_U = \frac{\bar{M}_1 - \bar{M}_2 - \Delta_U}{\sigma\sqrt{\frac{1}{n_1}+\frac{1}{n_1}}}, \qquad (1)$$

and will be used to validate the model's ability to calculate approximately the same crown area as the lidar on a 5 m gridded basis. After assessing the accuracy of the crown area, adjustments to the model will be made as necessary, and the sample areas will be tested again. Then we will apply the machine learning algorithm to all NAIP files across the state of Virginia. The final product will be a crown map for the state of Virginia at 0.6m resolution with a crown area value in square meters for each tree.

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