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DEEP LEARNING ANALYSIS OF UAV LIDAR POINT CLOUD FOR INDIVIDUAL TREE DETECTING

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ABSTRACT

In this paper, we address the important task of Individual Tree Detection (ITD) in forest environments for enabling tree parameter estimation including tree count, height, volume, and crown dimensions. Recent advances in high-resolution multispectral and LiDAR data collected by Unmanned Aerial Vehicles (UAVs) show a promising solution for ITD. We introduce a novel ITD method using the YOLO V7-tiny deep learning framework on UAV LiDAR data. First, we rasterize point clouds into Vertical Density (VD) and Canopy Height Models (CHM), and then we utilize the modified YOLO V7-tiny algorithm to detect the boundary of the trees. The accuracy, precision, recall, and F1-score results of YOLO V7 compared to YOLO3 showed a significant improvement. The proposed method demonstrates promising results for urban and forest tree inventory updates and contributes to large-scale satellite-based forest structure and biomass estimation.

Index Terms**—** UAV, LiDAR, Photogrammetry, Tree Detection, Deep Learning, Object Detector, YOLO.

1. INTRODUCTION

Forested areas cover one-third of the earth's land and serve as biodiversity hotspots by absorbing carbon dioxide, producing oxygen, and mitigating climate change [1]. Thus, monitoring and management of forested areas, known as forest management, is essential. Effective forest management relies on accurate forest inventory metrics derived from individual tree attributes such as tree count, location, height, volume, crown size, and species. Therefore, Individual Tree Detection (ITD) is the primary step to enable comprehensive tree parameter estimations [2]. Traditional tree detection and parameter estimation rely on field measurements including plot surveys and Terrestrial Laser Scanning (TLS) which are expensive, time-consuming, and labor-intensive [3]. In contrast, utilizing high spatial resolution remotely sensed data such as LiDAR and multispectral data provides a cost-effective and efficient solution for comprehensive tree parameter estimations [4], [5]. Although spaceborne and airborne remote sensing data are effective for large-scale forest inventory, they have spatial resolution limitations for studying individual trees [6]. On the other hand, Unmanned Aerial Vehicles (UAVs) offer high spatial resolution data in a cost-effective way that makes them a powerful tool for tree detection and parameter estimation [6]–[8]. Individual Tree Detection (ITD) methods can be categorized into 2-dimensional (2D) and 3-dimensional (3D) methods. 2D methods utilize image processing, machine learning, and deep learning-based techniques such as DeepForest on 2D multispectral images for ITD [9]. However, 2D methods have limitations including over-segmentation, inefficiency in dense canopies, and the absence of tree structural and vertical information attributes such as height and volume. On the other hand, 3D methods provide tree structures and vertical information that can be categorized as point-based and raster-based [10]. Point-based methods rely on spatial relationships in 3D point clouds, while raster-based methods rasterized point clouds into various image channels and utilize traditional 2D ITD methods and AI methods such as Deep Learning to detect individual trees [11].

Recent studies on rasterized point clouds focus on filtering methods such as Local Maximum (LM) utilized on Canopy Height Models (CHMs) and deep learning methods. Filtering-based methods face challenges in accurately detecting individual trees, especially in complex and dense forest structures, such as overestimation, dependency on window size, and sensitivity to noise and tree crown shapes [12]. However, utilizing deep learning algorithms for ITD on rasterized LiDAR point clouds demonstrated a promising solution for existing limitations, particularly in its early stages of development. Previous studies utilized deep learning models such as Mask R-CNN and You Only Look Once V3-V5 (YOLO) for ITD on rasterized point clouds, achieving F1 detection scores between 64% and 93%. However, challenges still exist in accurately detecting dense deciduous trees and mixed forests on UAV-dense point clouds [13]. To explore the capabilities and limitations of deep learning object detectors for advancing tree detection over dense pine, deciduous, and mixed trees forested areas using high-resolution UAV LiDAR data, we introduce an innovative data-driven methodology for ITD utilizing the YOLO V7 object detector on rasterized UAV LiDAR point clouds. YOLO V7, known for its superiority in accuracy and inference speed, addresses re-parameterized module issues and dynamic label assignment compared to other object detectors and YOLO versions [14]. The geometric models derived from our method for individual trees can be directly applied to detect the individual trees and estimate various forest parameters including biomass, volume, crown area, etc.

Our contributions are as follows:

- Introduction and assessment of the usability and performance of the YOLO V7 model for tree detection using UAV LiDAR data on various tree types and densities.
- Comparison of the performance of the YOLO V7 versus other baseline methods, i.e., YOLO V3.

2. STUDY AREA AND DATA COLLECTION

The study area is a section of SUNY ESF Heiberg Forest in Tully, New York. The study area consists of diverse tree types and varying tree densities, covering approximately 40 hectares (Fig 1). Data collection is done using the DJI Matrice 300 RTK drone platform equipped with the Zenmuse L1 LiDAR sensor designed for precise forest 3D modeling. The Zenmuse L1 captures accurate elevation data with a range of up to 450 meters and a point cloud density of 240,000 points per second.

Fig 1: Study area

3. METHODOLOGY

The basic idea focuses on utilizing the YOLO V7 deep learning object detector on rasterized LiDAR data to detect and locate individual trees enabling tree structural attributes estimation such as location and height. The proposed method involves ground points detection and removal, rasterizing non-ground points into Vertical Density (VD) and Canopy Height Model (CHM), utilizing YOLO V7 object detector to detect tree boundaries, and overlaying the detected boundaries with point cloud. Fig 2 provides an overview of this comprehensive workflow.

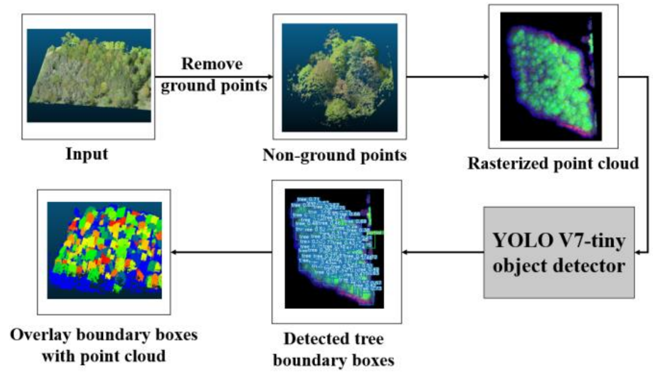


Fig 2: workflow overview

3.1. Ground points detection and removal

To detect and remove the ground points, first, the point cloud is subdivided into 2x2 meter grid cells, then the Digital Terrain Model (DTM) is generated using the K-nearest neighbors (KNN) search algorithm by picking the lowest elevation (Z) in each cell and averaging the heights of the four nearest points weighted by distance to the lowest elevation point. Finally, to select the non-ground points, points exceeding a height threshold above the DTM are included. This enhances the accuracy of tree detection by eliminating false positives from ground-based vegetation.

3.2. Rasterization

Rasterization is the process of projecting a 3D point cloud into the xy-plane that generates a 2D, three-channel image. Once non-ground points are excluded from ground points, they rasterize into VD and CHM. Vertical density is captured by counting the number of occupied voxels by point along the vertical direction of each cell divided by the total number of voxels that represents point concentration in each cell. CHM is derived by subtraction of the DTM- Digital Terrain Model from the DSM- Digital Surface Model that provides tree height. We are exploring the effectiveness of the YOLO V7 on rasterized point clouds into an image composed of VD and CHM. Fig 3 shows a sample of rasterized channels.

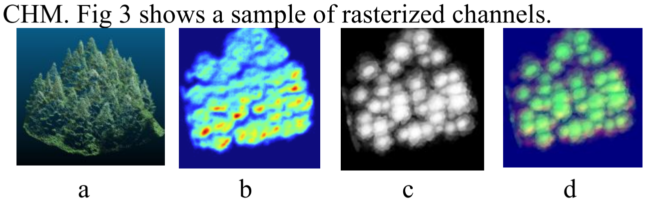
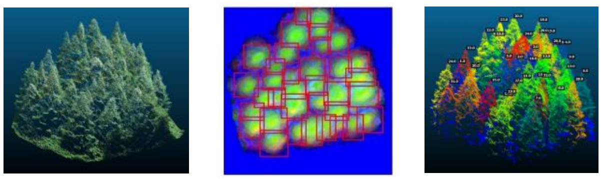


Fig 3: Sample of rasterized channel, (a) point cloud, (b) VD, (c) CHM, and (d) composed VD and CHM

3.3. Individual Tree Detection (ITD) using YOLO V7

To detect the individual tree on rasterized point clouds, we employ a simplified variant of basic YOLO V7 called YOLO V7-tiny with just over 6 million parameters [14]. YOLO V7-tiny's efficiency and speed make it suitable for tree bounding box detections. For training, a 600×600×1000 m grid with a 10 cm resolution is used to rasterize point clouds into VD and

CHM. Trees in each image are annotated with bounding boxes and pre-trained YOLO V7-tiny weight is updated using the new datasets. About 30% and 10% of the image dataset is used for validation and testing. After updating, the new YOLO V7-tiny weight is used to detect each tree boundary boxes on rasterized point clouds. Then, the points associated with each tree are delineated by projecting the detected 2D bounding boxes from an image into a 3D point cloud (Fig 4).

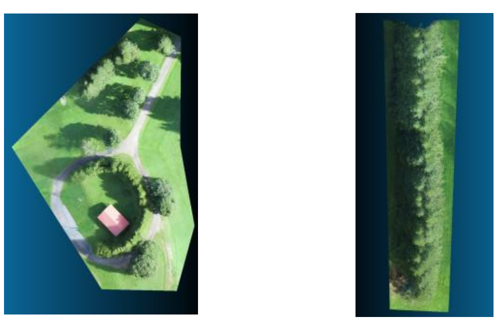


a b c

Fig 4: Detected tree bounding boxes on a rasterized point cloud, (a) point cloud, (b) detected boundary boxes, and (c) classified point cloud.

4. EXPREMENT AND EVALUATION

Two plots with varying tree densities and types were selected for experiment evaluation (Fig 5) due to differences in forest composition. The first plot encompasses 52 semi-dense coniferous and deciduous trees. The second plot encompasses 36 dense coniferous trees. The experiment evaluation is done in two parts. The first part assesses YOLO V7-tiny network performance for tree detection, and the second part compares results with YOLO V3-tiny trained by Windrim [15].



Plot I Plot II

Fig 5: Sample plots used for experiment evaluation.

4.1. Evaluation

Our performance evaluation of tree detection uses the Intersection over Union (IoU)-based method. A True Positive (TP) is determined if the IoU exceeds 50%, otherwise, it's considered a misdetection (categorized into False Positive (FP) and False Negative (FN)). Subsequently, accuracy, recall, precision, and F1 score metrics were computed for each plot where recall is the producer's accuracy, and precision is the user's accuracy. These metrics are defined as follows:

Accuracy = TP / (TP + FP + FN)
Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1-score = (2 × Precision × Recall) / (Precision + Recall)

4.2. YOLO V7-tiny network performance assessment

Our results indicate that the YOLO V7-tiny model consistently and accurately detects individual trees in addition to adaptability to different tree densities and types. The training network results reached an overall accuracy of X%, precision of X%, recall of X%, and F1-score of X%. The results of test plots reveal that our YOLO V7-tiny model successfully detected 42 of 52 trees in Plot I and 34 of 36 in Plot II. Our model successfully detected trees with an overall accuracy of 70% and 91% for Plot I and II respectively. Our method achieves precision, recall, and F1 score values of 0.95 and 0.97, 0.8 and 0.94, 0.86 and 0.95 for Plot I and II respectively (Fig 6). Lower accuracy in the first plot may be due to variability in the shape of deciduous trees. Another reason could be that the train dataset contains more coniferous trees than deciduous ones. Performance metrics assessments show the model's effectiveness. These results suggest the generalization potential to similar forest types with density.

4.2. Comparison with YOLO V3-tiny assessment

Comparative assessment of our proposed method (i.e., YOLO V7-tiny) outperforms YOLO V3-tiny trained by Windrim et al. Our method achieves accuracy of 0.7 and 0.91, while YOLO V3-tiny shows significantly lower accuracy of 0.2 and 0.15 for Plot I and II, respectively (Fig 6). Further analysis suggests higher, precision, recall, and F1 scores in both plots. The inefficiency of YOLO V3-tiny may be attributed to its training on sparse and coniferous trees and its network architecture.

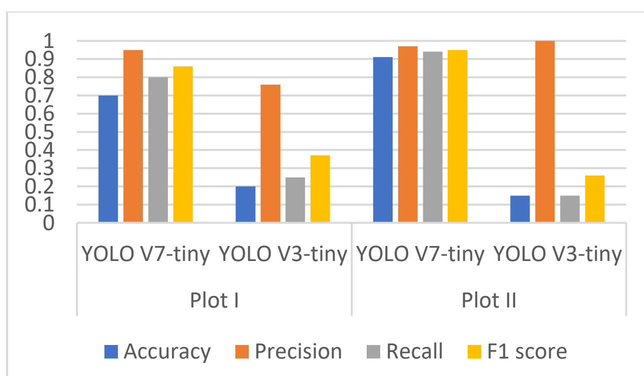


Fig 6: A comprehensive metrics overview of YOLO V7-tiny tree detection performance versus YOLO V3-tiny

5. CONCLUSION

Utilizing the YOLO V7-tiny object detector demonstrates high accuracy and precision in automating tree detection using UAV LiDAR point clouds. Due to the deep learning object detector, our method can be adapted to various tree shapes and point cloud sources. The results outperform previous studies in terms of accuracy, precision, recall, and F1-score metrics. These results can be used for applications such as biomass estimation and forest inventory by extracting essential tree structural parameters.

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