Evaluating of Tree Branch Recognition Algorithm in Pruning Robots under Augmented Environmental Conditions.

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Abstract

Integrating service robots has revolutionized several sectors, by enhancing accuracy, efficiency, and scalability. Those robots are crucial in automating labor-intensive processes such as tree pruning, where accurate branch detection is vital. This research evaluates the performance of YOLOv8-seg model for recognizing tree branches as a step towards fully autonomous pruning. To address the challenges posed by diverse and complex real-world conditions, video sequences are augmented using techniques that simulate environmental variations, such as changes in brightness, contrast, and Gaussian noise. The evaluation metrics including the number of true detections, number of false detections, and precision, demonstrate robust and accurate branch perception under real-world conditions. These results highlight the potential of YOLOv8-seg to improve pruning systems, paving the way for scalable, efficient, and accurate robotic solutions in tree maintenance.

Keywords: Tree Pruning, Automation, Branch, YOLOv8, Recognition.

1. Introduction:

Integrating service robots across various applications has significantly improved operational capabilities, accuracy, efficiency, and scalability [1]. Among these diverse applications, one area that is expected to benefit greatly is the automation of labor-intensive arboricultural operations, such as tree pruning [2].

Tree pruning is a critical maintenance operation that requires precision and accurate branch recognition for pruning to promote healthy growth, and improve overall appearance [3]. Automating this process presents opportunities to boost productivity while reducing the demand for human labor, especially in large-scale operations. Despite its benefits, automated tree pruning remains a challenge due to the need for accuracy, especially for diverse real environments. In this context, advanced machine vision techniques have become essential in enabling robots to accurately identify branches and then perform pruning operations. This research investigates the use of YOLOv8-seg, a state-of-the-art object detection algorithm [4][5], to recognize tree branches as part of a fully autonomous pruning system. Detecting tree branches is difficult due to the complexities of natural environments, which may vary greatly in brightness, contrast, and Gaussian noise conditions, making it necessary to evaluate the performance of the detection model under these dynamic scenarios in the real environment. The findings of this study aim to demonstrate the feasibility of using YOLOv8-seg in practical arboricultural environments, which could lead to significant advances in autonomous tree maintenance.

2. Architecture of YOLOv8 – Segmentation Model:

Segmentation models provide a precise definition of branch boundaries [6], which helps determine their exact shape and contributes to separating them from overlapping branches and performing post-segmentation analysis such as measuring branch thickness and angle, which may facilitate the pruning process. As shown in Figure 1, the segmentation model uses the training image to process it through a convolutional backbone to extract features. These features are fed into two parallel heads: the segmentation head, which predicts segmentation masks among the pixel level, and the detection head, which outputs bounding boxes and confidence scores. This dual output allows for accurate object detection and segmentation, making it particularly effective in applications of overlapping environments such as the recognition of tree branches.

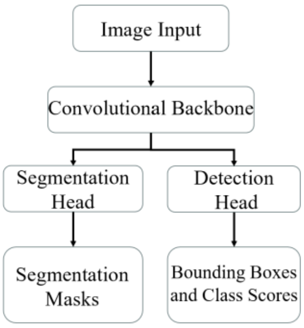

Fig. 1: Simple architecture of the YOLO segmentation.

3. Methodology:

3.1. *Data Collection and Training:*

The YOLOv8-seg model was trained on a dataset of 1973 images taken at different periods to account for seasonal variations in foliage density and scene conditions [7]. Different scenarios were considered, including branches surrounded by dense foliage, varying branch spacing, and diverse environmental backgrounds. This diversity ensures that the model is robust and capable of detecting branches under real-world conditions. Table 1 shows the dataset statistics and training parameters.

Table 1: Dataset statistics and training parameters.

Parameter	Value
Training Images	1,973
# of branches	37,146
Preprocessing	Stretched into 640 × 640 Pixels
Training Model	YOLOv8m-seg
# of Epochs	500
Batch Size	16

Figure 2 shows the decline in the main loss components over 500 epochs. The box loss refers to the error in determining the predicted coordinates of the specified box compared to the training data, while the classification loss measures the error in classifying objects into their correct classes. Finally, the segmentation loss measures the error in predicting the segmentation masks, which estimate the pixels that include the branches. The continuous decline in the loss of components indicates the ability of the model to learn and improve its performance on detection and segmentation tasks.

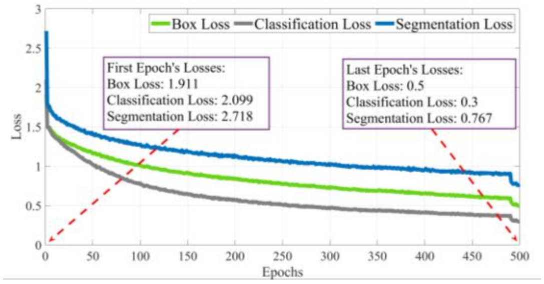

Fig. 2: Training loss reduction across 500 epochs.

The figure shows that the improvement in loss exceeds 1.4 for the box loss, 1.7 for the classification loss, and 1.9 for the segmentation loss. This demonstrates the robustness of the training process and the closeness of the dataset used.

3.2. *Experiment Setup:*

The experiment aims to investigate the detection behavior, for video sequences that initially captured the movement of the pruning robot as it steadily advances towards the branch.
As shown in Figure 3, a mechanical arrangement is utilized to simulate the effect of distance on branch detection, which is interesting to the pruning process. This experiment uses an iPhone mounted on a stick controlled by a DC motor to capture branches of the tree species while changing the distance. The stick advances gradually up to 1 m toward the tree to simulate the effect of distance on branch detection performance.

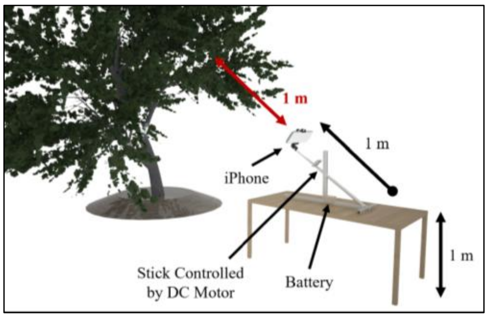

Fig. 3: Experiment setup.

The evaluation data consists of 1352 frames, captured for 3 trees. Figure 4 illustrates a sample of branch recognition for the three captured videos.

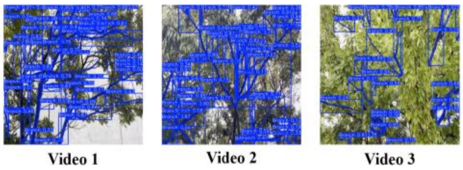

Fig. 4: A sample of branch recognition for evaluation data.

4. Results and Discussion:

4.1. *False Positives and True Positives vs Confidence Threshold:*

As an evaluation of the model, the focus was on the total of true positives (true detections), false positives (false detections), and precision as performance metrics. A true positive (TP) result occurs when the model correctly predicts the positive class. A false positive (FP) result occurs when the model incorrectly predicts the positive class. Precision measures the accuracy of positive detections and is calculated as the ratio of true positives to all predicted positives as the following equation:

$$Precision = TP/TP + FP \qquad (1)$$

Figure 5 shows the variation in the number of TP and FP with different confidence thresholds, providing valuable insight into the model's behavior.

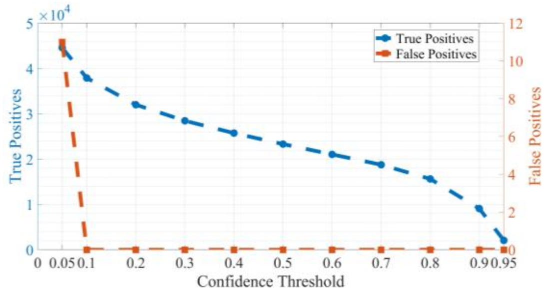

Fig. 5: Impact of confidence threshold on true positives and false positives.

At very low confidence thresholds (0.05), the model detects many cases as TP, at the existence of a few false positives. The precision in this case is 0.999, this value indicates that the model is not lenient in its predictions, even at very low thresholds. As the confidence threshold increases, false positives disappear, indicating a perfect performance in precision; however, this disappearance is accompanied by a decrease in true positives, indicating that the model is becoming more conservative and may miss valid detections. To ensure that there are no false positives, with a satisfied number of true positives, the model can operate with confidence thresholds ranging from 0.1 to 0.3.

Figure 6 shows the true positive detections of tree branches across the video of evaluation data for confidence thresholds 0.1, 0.2, and 0.3.

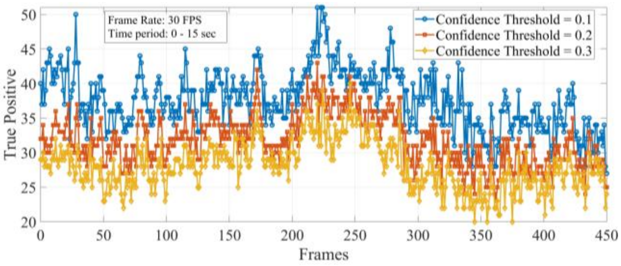

Fig. 6: Analyzing true positives across frames.

The figure shows that the number of TP tends to decrease with time. This decrease may explicate by some branches falling out of the frame range. On the other hand, the fluctuation in the number of TP over close times suggests that scene complexity may affect detection performance.

In the next section, the effect of some real-world environmental conditions like brightness, contrast, and Gaussian noise will be simulated by augmenting the evaluation videos with Python's computer vision libraries, according to the general equation:

$$Output\ (x, y) = \alpha \times Input(x, y) + \beta + N(x, y) \qquad (2)$$

Where; Output (x, y) is the pixel intensity in the output image at position (x, y), Input (x, y) is the pixel intensity in the input image at position (x, y), α is the contrast adjustment factor, β is the brightness adjustment factor, and N(x, y) is the Gaussian noise at position (x, y).
The adjustment parameters α, β, and N values are applied to the RGB domain images.

4.2. *True Positives and Average of Confidence Scores for Simulated Brightness Conditions:*

Evaluating brightness conditions enhances the reliability of the pruning system in dealing with different brightness conditions across the day, season, and different scene conditions. Figure 7 shows the effect of different brightness conditions on TP.

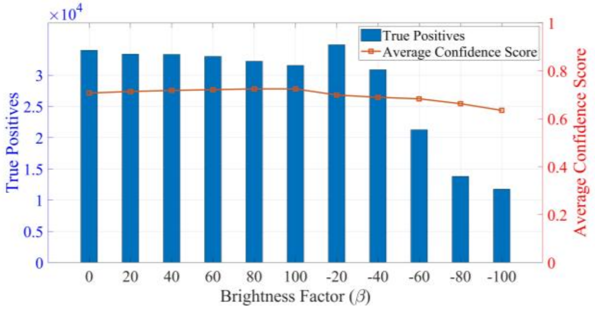

Fig. 7: TP vs. brightness conditions.

The number of TP remains relatively stable across a wide range of brightness levels. This suggests that the model is robust to different brightness conditions. For extremely low lighting levels, significant decreases in TP occur, indicating that very dark conditions negatively affect detection performance. The model generally maintains stable confidence performance across a wide range of brightness conditions.

4.3. *True Positives and Average of Confidence Scores for Simulated Contrast Conditions:*

Contrast refers to the difference in brightness between branches and their background, such as foliage, sky, and other overlapping branches. In our case, shadows and scene conditions can create areas of low contrast, making it difficult to detect branches. Figure 8 shows the detection performance for different contrast levels.

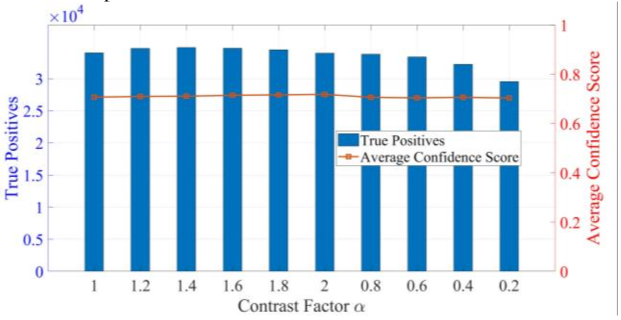

Fig. 8: TP vs. contrast conditions.

From Figure 8, the model demonstrates a high degree of robustness to different contrast levels within a moderate range. The number of TP remains relatively stable across these contrast levels. This indicates that the model is well-trained to handle variations in contrast that might occur due to changes in lighting, shadows, or weather conditions. In addition, the average confidence score remains relatively stable across all contrast levels.

4.4. *True Positives and Average of Confidence Scores for Simulated Gaussian Noise:*

Gaussian noise reflects real-world noise that may be generated by cameras or environmental factors. according to this equation:

$$noise \sim \mathcal{N}(\mu = 0, \sigma^2) \qquad (3)$$

Where: $\mathcal{N}$ is the Normal (gaussian) distribution, μ is the mean, σ is the standard deviation, and σ^2 is the variance.

The noise distribution is symmetric around zero ($\mu = 0$), therefore, there is no systematic increase or decrease in brightness or intensity. Figure 9 illustrates the effect of Gaussian noise on detection performance.

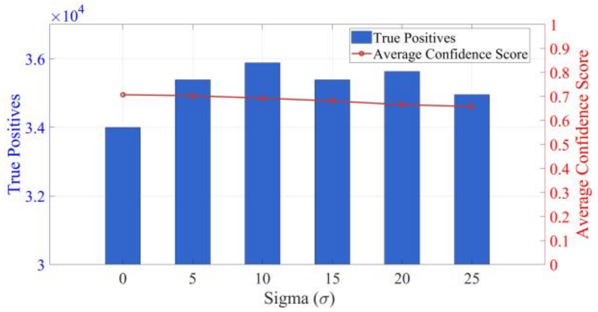

Fig. 9: TP vs. Gaussian noise conditions.

The model maintains a close number of detections under Gaussian noise $\mathcal{N}(0, \sigma^2)$, indicating high robustness, the average confidence scores decrease slightly as noise levels increase. suggesting reduced prediction certainty in noisy conditions.

5. Conclusion:

This research demonstrates the robustness of the Yolov8-seg model in detecting tree branches under very low confidence thresholds with very few false positives and high precision. To investigate the robustness of the model in the real world, different brightness, contrast, and normal Gaussian noise conditions were simulated using computer vision's Python libraries. The results showed that the model maintains a stable number of detections under most conditions. A slight decrease in confidence scores was observed for extreme environmental conditions, indicating a decrease in certainty while maintaining detection ability. This stability indicates that the model is effective and reliable in terms of precision for low thresholds and different environmental conditions.

As a future of this research, we will investigate expanding the evaluation scope to include additional environmental factors, such as blur noise, the effect of the distance between the robot and branches, and the camera angles. The YOLO model could also be integrated into an autonomous real-time pruning system and evaluated in field environments.

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Authors Introduction

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