

Research Article

An Adaptive 2D–3D Approach for Urban Tree Pruning Using Computer Vision and Quantitative Structure Modeling

Mohammad Albaroudi^{1*}, Abdullah Alraee¹, Hussam Alraie², Raji Alahmad¹, Kazuo Ishii¹

¹Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu-ku, Kitakyushu, 808-0196, Japan

²Electrical and Electronic Engineering Program, Middle East Technical University Northern Cyprus Campus, Güzelyurt, 99750, Mersin 10, Türkiye

Emails: albaroudi.mohammad344@mail.kyutech.jp, mohammadmalbaroudi@gmail.com, alraee.abdullah-abdul648@mail.kyutech.jp, hussam@metu.edu.tr, raji@brain.kyutech.ac.jp, ishii@brain.kyutech.ac.jp

*Corresponding Author

ARTICLE INFO

Article History

Received 21 November 2025

Accepted 1 June 2026

Keywords

Urban tree pruning
YOLO-OB
Computer vision
Quantitative Structure Model (QSM)
2D–3D modeling
Decision support

ABSTRACT

Urban trees provide significant ecological and aesthetic benefits in urban environments; however, ensuring their safe maintenance requires regular pruning to prevent conflicts with surrounding infrastructure. Traditional pruning practices rely heavily on manual labor and expert judgment, making them time-consuming, potentially hazardous, and highly dependent on experience. This study proposes a computer vision–based decision-support system for urban tree pruning that integrates two-dimensional (2D) perception with three-dimensional (3D) structural modeling. For trees with relatively simple crown structures, pruning decisions are derived from image-space coordinates. Tree trunks and branches are detected from RGB images using a YOLOv8-OB model, enabling the extraction of branch positions to identify candidate branches for two common pruning strategies: crown raising and crown reduction, based on operator-defined height thresholds. For trees with dense or overlapping crowns, a Quantitative Structure Model (QSM) is constructed from point cloud data to provide a more complete representation of tree geometry. For the proposed 2D system, experimental results demonstrate reliable tree structure analysis using a large-scale dataset collected in this study, where the detection accuracy exceeds 90%. While pruning simulations for both the proposed 2D and 3D systems confirm stable and controllable crown raising and reduction under varying threshold conditions. These systems provide an efficient and scalable decision-support for safe, consistent, and interpretable urban tree management.

© 2026 The Author(s). Published by The Society of Artificial Life and Robotics.
This is an open access article distributed under the CC BY-NC 4.0 license
(<http://creativecommons.org/licenses/by-nc/4.0/>).

1. Introduction

Urban trees provide several environmental, aesthetic, and social benefits [1], [2]. To ensure the safety of the public and urban infrastructure, urban trees require regular pruning [3]. Appropriate pruning helps reduce potential risks by minimizing the chance of tree branches interfering with surrounding infrastructure, such as overhead power lines, transportation routes, and surrounding buildings [4]. Conventional manual pruning is robust but requires significant manual effort [5], time-consuming, and risk-exposed for laborers [6]. With the continued expansion of urban areas, the scale and frequency of pruning activities have grown considerably, increasing the demand for municipal resources and labor.

Automation can reduce labor requirements, operational risks, and human error while enhancing the consistency and efficiency of pruning operations [7]. As a result, automated and semi-automated pruning systems have attracted growing attention as sustainable solutions for variable tree management [8], [9], [10], [11], [12].

While significant progress has been made in automated pruning systems, prior research has largely emphasized execution-related aspects, including robotic manipulation [13], cutting strategies [14], and path planning [15]. In contrast, the decision-making stage, specifically identifying which branches are candidates to be pruned, remains underexplored. Most existing methods often rely on implicit or manually defined rules, limiting adaptability and interpretability. In addition, some approaches focus primarily on branch detection, leaving the final pruning decision to human experts [16].

In this work, we shift the focus toward pruning decision-making by proposing an interpretable approach that selects pruning candidates based on height-based criteria. In particular, branches are evaluated according to their spatial position relative to surrounding urban constraints, where pruning priority is assigned to branches that pose potential conflicts with the environment. By decoupling decision-making from execution, the proposed approach enhances flexibility and supports more transparent and scalable pruning strategies.

Tree pruning includes two common approaches: crown raising and crown reduction [17]. As shown in Figure 1, crown raising involves removing lower branches that may obstruct pedestrian movement or vehicle passage. In contrast, crown reduction focuses on pruning upper branches that may interfere with overhead infrastructure, such as power lines [4], [18].

The selection of an appropriate pruning strategy depends on multiple factors, including tree structure, surrounding infrastructure, and functional requirements of the urban environment. However, this study specifically focuses on the importance of branch removal based on its potential impact on the surrounding environment. In particular, branches are prioritized for pruning when their spatial position may interfere with or pose risks to nearby infrastructure. Both approaches contribute significantly to urban safety by addressing hazards associated with branch position and infrastructure proximity.

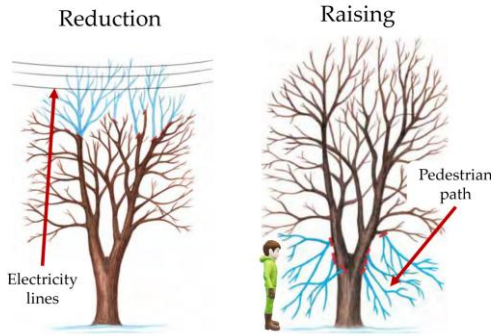


Figure 1 Conceptual Illustration of Crown Reduction and Crown Raising for Urban Safety (Adapted from [17])

Automated pruning systems must begin with a reliable vision technique that recognizes the tree and its main components, such as the trunk and branches [16]. The trunk represents the primary vertical axis that supports the tree, while branches extend from it and may potentially interfere with surrounding urban infrastructure. Accurate perception of these structural elements is therefore essential for identifying pruning candidates and ensuring safe tree management.

It is important to note that tree structures vary significantly depending on species, age, and growth conditions, leading to diverse crown geometries and branch distributions that directly affect vision requirements.

Three-dimensional visualization techniques, particularly those based on LiDAR sensing, provide highly detailed representations of tree geometry and enable precise reconstruction of branch structures [19], [20]. Such approaches are particularly beneficial for analyzing trees with dense or overlapping crowns where structural visibility is limited.

In this context, tree perception can be broadly categorized into two-dimensional (2D) and three-dimensional (3D) approaches. However, the primary objective in many urban pruning tasks is to determine the

vertical position of branches relative to surrounding infrastructure. From this perspective, full three-dimensional reconstruction is often unnecessary, as it introduces higher computational cost without providing additional benefits for height-based decision-making. In many urban scenarios involving minimally occluded trees, pruning decisions such as crown raising and crown reduction rely mainly on the vertical distribution of branches. Therefore, two-dimensional vision analysis can provide sufficient structural information for identifying pruning candidates while significantly reducing computational complexity.

2. Methodology

Motivated by previous observations, this study proposes an adaptive pruning decision-support system. For trees with relatively simple crown structures, pruning decisions are derived using a two-dimensional vision pipeline, in which branches and trunks are detected from RGB images using an Oriented Bounding Box (OBB) model, and candidate branches are selected based on operator-defined height criteria. For trees with dense or complex crowns, a three-dimensional structural analysis is employed to provide a more comprehensive representation of tree geometry.

In practical deployment, the selection between the 2D and 3D pipelines can be determined in advance through a preliminary inspection stage, such as a drone-based or mobile sensing system. This initial assessment evaluates the level of crown complexity and occlusion, enabling the system to select the most appropriate processing pipeline prior to detailed data acquisition and pruning analysis. Algorithm 1 simplifies the proposed adaptive system methodology.

Algorithm 1: Adaptive Selection of Pruning Analysis Pipeline

Input: Preliminary inspection data P

Output: Selected pipeline M

Process:

1. Evaluate crown complexity and occlusion from P .
 2. If the crown is simple and clearly visible, then set $M = 2D$ vision pipeline.
 3. Otherwise, set $M = 3D$ structural analysis pipeline.
 4. Return M .
-

This study does not explicitly evaluate crown complexity or occlusion. Instead, it presents both the 2D and 3D pipelines as alternative approaches for pruning decision support.

This paper is organized as follows. Section 1 presents the introduction and reviews related work in urban tree pruning and computer vision-based approaches. Section 2 describes the proposed methodology, including both the 2D vision-based pipeline and the 3D QSM-based pipeline, along with the experimental setup used for performance evaluation. Section 3 presents the experimental results and provides a detailed discussion of the findings. Finally,

Section 4 concludes the paper and outlines directions for future work.

The following sections introduce the proposed 2D and 3D pipelines. Trees with relatively clear crown structures are referred to as open crown trees, while those with dense or occluded structures are referred to as overlapping crown trees.

2.1. 2D Pipeline for Open Crown Trees

Figure 2 clarifies the proposed methodology for the 2D pipeline, which consists of four main stages: first, isolating the tree and identifying its structural components (branches and trunk); second, extracting branch positions within the image coordinate space from the detection outputs; third, defining operator-specified pruning thresholds; and finally, determining pruning decisions by selecting branches that exceed these thresholds. Notably, this decision-making process relies exclusively on two-dimensional image information, as three-dimensional reconstruction or additional sensing is not required for branch selection, although it may be incorporated in later stages for pruning execution.

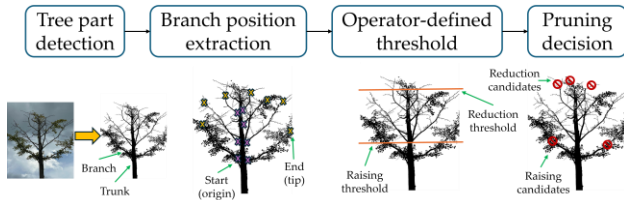


Figure 2 Proposed 2D Vision-Based Pipeline for Pruning Decision-Making

2.1.1. Tree Part Detection

To initiate the pruning decision process, a deep learning-based object detection model (YOLOv8-OB) was trained to detect objects using oriented bounding boxes, enabling the basic identification phase of tree branches and trunk. Unlike pixel-level segmentation methods, which generally require higher computational resources, oriented bounding box detection provides a compact geometric representation of objects, which is sufficient for estimating branch position, a critical factor in raising and reduction pruning decisions. In addition, compared to axis-aligned bounding boxes, OBs capture elongated and tilted branch structures more accurately, thereby reducing localization ambiguity [21].

The OB model was trained on a large and diverse collection of urban tree images, captured in Fukuoka, Japan, covering different tree species and environmental scenarios. The output of the training stage is a set of optimized model weights, which are then used during inference to predict oriented bounding boxes corresponding to detected tree branches. Figure 3 illustrates the training workflow of the custom YOLOv8-OB model. The architecture includes three main components: a backbone for extracting visual features, a neck for multi-scale feature fusion, and a head that predicts

oriented bounding boxes together with class labels and confidence scores.

Table 1 summarizes the statistics of the training data set used. Image augmentation was performed using cropping operations in Roboflow to address variations in tree scale, branch spatial distribution, and camera perspective, which naturally occur under real-world data acquisition conditions. Cropping exposes the model to both full-tree and partial-structure views, improving scale robustness and branch localization reliability when robot accessibility limitations or environmental obstacles prevent capturing trees at consistent distances or viewpoints. From Table 1, the crop augmentation ratio of 1:3 indicates that for each original image, three additional cropped samples were generated during training.

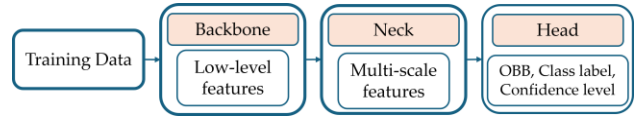


Figure 3 Training Workflow of the YOLOv8-OB Model for Trunk and Branch Detection in Urban Tree Images

Table 1 Statistics of the Urban Tree Dataset used for Training the YOLOv8-OB Model

Feature	Value
Number of images	~ 7,500
Number of objects	~ 150,000
Image size	640 × 640 pixels
Augmentation ratio	1:3
Training epochs	1,000
Batch size	16

Figure 4 illustrates the convergence behavior of the YOLOv8-OB model during the learning process. Both the bounding box regression loss and classification loss decrease steadily across epochs, indicating stable optimization of the network parameters. The gradual reduction and smooth trends of the losses demonstrate effective learning and reliable model convergence for trunk and branch detection. In the final ten epochs, a relatively sharper decline in loss is observed. This behavior is consistent with the standard convergence dynamics of model trained with cosine annealing learning rate schedules and progressive data augmentation decay, both of which are default settings in YOLOv8. Such a pattern does not indicate overfitting or training instability.

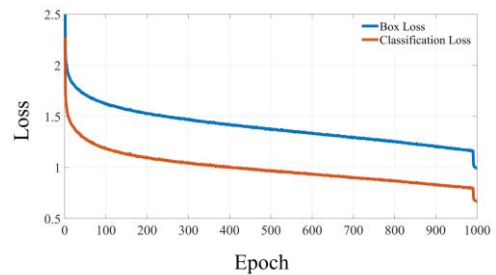


Figure 4 Training Loss Curves of the YOLOv8-OB Model

2.1.2. Branch Position Extraction

Detection outputs of machine learning based models, such as YOLO, are frequently used to infer object locations and spatial relationships in diverse application domains [22], [23]. In the case of this study, once the YOLO-OBB model predicts the branches and trunk, the following step is to determine the position of each branch relative to the tree trunk.

The derived spatial coordinates serve as the foundation for the candidate pruning decision stage, where branch positions are evaluated primarily based on their vertical location. This information is then utilized to determine whether branches pose potential conflicts with surrounding urban elements, including roads, buildings, and utility lines, according to predefined operator-specified thresholds. The complete OBB-based branch position estimation is outlined in Algorithm 2.

Algorithm 2: OBB-based branch position estimation

Input: Branch corner coordinates $B = \{p_1, p_2, p_3, p_4\}$,

Trunk corner coordinates $q = \{q_1, q_2, q_3, q_4\}$

Output: Branch start point S , branch end point E

Process:

1. Compute the trunk center from the trunk OBB:

$$T = (x_t, y_t), x_t = \frac{1}{4} \sum_{j=1}^4 x_j^{(t)}, y_t = \frac{1}{4} \sum_{j=1}^4 y_j^{(t)}$$

2. Compute the midpoints of the OBB edges:

$$m_i = \frac{p_i + p_{i+1}}{2}, \quad i = 1, \dots, 4 \text{ (with } p_5 = p_1)$$

3. Compute the Euclidean distance to the trunk center:

$$d_i = \|m_i - T\|$$

4. Assign the closest midpoint to the trunk as the branch start point:

$$k = \arg \min \{d_i\}, i \in \{1, 2, 3, 4\}, S = m_k$$

5. Assign the farthest midpoint from the trunk as the branch end point:

$$l = \arg \max \{d_i\}, i \in \{1, 2, 3, 4\}, E = m_l$$

6. Return S, E .

The trunk center is computed from the corner coordinates of the detected trunk OBB and is used as the reference point for estimating the branch origin and tip positions. The extracted S and E points provide a compact representation of the branch geometry and are subsequently used for height-based threshold evaluation in the pruning decision stage.

2.1.3. Operator-Defined Threshold

After the branch positions were derived, spatial thresholds will be defined to determine whether a branch lies within restricted regions of the tree structure. In this study, thresholds were defined along the vertical axis, as branch height is a key indicator for safety-related pruning decisions in urban environments.

Instead of using fixed height thresholds, the proposed approach allows the operator to interactively define threshold lines, accounting for variations in urban infrastructure, where clearance requirements depend on

the specific context, such as pedestrian zones, roadways, and overhead utilities. This flexibility facilitates adaptation to diverse urban scenarios without relying on rigid, scenario-specific constraints.

Two operator-defined reference lines are introduced: a lower threshold H_{min} or an upper threshold H_{max} . These thresholds partition the tree into height-based zones and enable identification of branches that fall below or exceed acceptable vertical limits. Figure 5 illustrates how to select candidate branches for crown raising and reduction, respectively. Branches whose vertical positions violate operator-defined thresholds are flagged as pruning candidates, as detailed in Section 2.1.4. By incorporating operator-defined height thresholds, the proposed system preserves human expertise within the decision-making loop while enabling flexible adaptation to different urban conditions. This approach allows pruning decisions to reflect specific infrastructure clearance requirements, such as pedestrian pathways, roadways, and overhead utilities, without imposing rigid constraints.

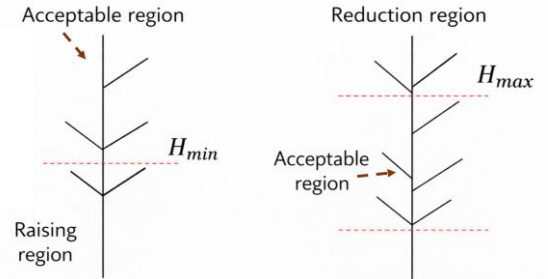


Figure 5 Illustration of Height-Based Threshold Regions for Crown Raising and Crown Reduction

2.1.4. Pruning Decision Set

A branch b is selected as a pruning candidate when its vertical position violates a predefined height threshold. Let y_b denote the vertical coordinate of the branch b , obtained from the extracted branch position. The candidate pruning decisions are defined as follows.

A. Raising decision, expressed as (1):

$$y_b \leq H_{min} \Rightarrow b \in C_r \quad (1)$$

B. Reduction decision, expressed as (2):

$$y_b \geq H_{max} \Rightarrow b \in C_d \quad (2)$$

where:

H_{min}	lower threshold for crown raising
H_{max}	upper threshold for crown reduction
C_r	set of raising candidates
C_d	set of reduction candidates

These criteria enable efficient and interpretable selection of pruning candidates based on vertical positioning. However, in trees with highly overlapping crown structures, the visibility of branches becomes limited in two-dimensional images. To address this

limitation, a three-dimensional analysis approach is introduced.

2.2. 3D Pipeline for Overlapping Crown Trees

For the proposed 3D pipeline, Terrestrial Laser Scanning (TLS) provides dense point cloud data that enables accurate reconstruction of tree structures, even under complex crown conditions (Figure 6).

After acquiring the TLS point cloud, the tree's geometric structure is reconstructed using a Quantitative Structure Model (QSM). The QSM represents the tree as a set of connected cylinders that approximate the trunk and branches. This representation enables the extraction of structural attributes such as branch orientation, connectivity, and height.

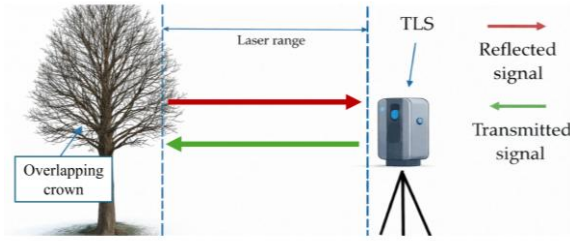


Figure 6 TLS Captures Overlapping Tree Crowns to Reconstruct a 3D Point Cloud of the Tree Structure

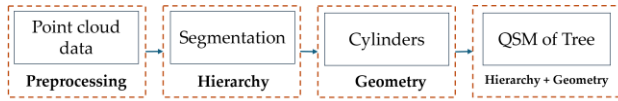


Figure 7 Processing Stages for Generating a Tree's QSM from TLS Point Clouds

Figure 7 summarizes the simplified procedure of QSM. In the QSM representation, the tree structure is modeled as a set of connected cylindrical segments, where each cylinder corresponds to a branch element. Each segment is defined by its radius r_i (m) and length l_i (m). The volume of the i -th branch segment is computed as Eq. (3).

$$V_i = \pi r_i^2 l_i \quad (3)$$

where V_i (m^3) denotes the volume of the branch segment, r_i is the cylinder radius, and l_i is its length. The spatial configuration of each segment is described using its starting point $P_0 = (x_0, y_0, z_0)$, and a unit direction vector $a = (a_x, a_y, a_z)$. where (x_0, y_0, z_0) represent the 3D coordinates of the starting point P_0 . The endpoint of the segment is then computed as Eq. (4).

$$P_1 = P_0 + a \cdot l_i \quad (4)$$

where $P_1 = (x_1, y_1, z_1)$ represents the endpoint coordinates of the branch segment. This parametric representation enables accurate extraction of branch position, orientation, and height, which are essential for threshold-based pruning decision-making. In particular,

the vertical coordinate (z) of the segment endpoints is used to evaluate pruning conditions based on height thresholds.

This study utilizes the QSM reconstruction method proposed in [24] and implements the software package available on [25] to evaluate pruning decision support. The resulting QSM is then used to inform pruning decisions by analyzing branch geometry and identifying candidate branches for pruning. The same decision logic and height threshold criteria used in the 2D pipeline are applied in the 3D analysis. However, in contrast to the image-based approach, the thresholds are defined in real-world metric units, enabling more physically accurate and interpretable pruning decisions.

3. Experimental Setup

Experiments were conducted on urban trees with different structural characteristics to evaluate the proposed pruning decision-making system for 2D vision and for 3D vision (including QSM-based reconstruction).

3.1. 2D Vision-Based Evaluation

For the 2D vision-based approach, experiments were conducted on open crown urban trees. The detection performance of the custom YOLO-OBb model was evaluated using images from five trees, comprising approximately 200 annotated tree components (branches and trunks). These images were not seen in the training phase. The detailed detection setup is summarized in Table 2. For detection evaluation, standard performance metrics including accuracy, precision, recall, and F1-score were used to assess the reliability of branch and trunk detection. These metrics provide a balanced evaluation of detection correctness and completeness [26].

For pruning behavior analysis, ten trees were used to evaluate the effect of height-based thresholds on pruning decisions. Both crown-raising and crown-reduction scenarios were simulated to analyze how pruning behavior varies with threshold selection. Pruning thresholds were defined as percentages of the relative crown height, enabling normalized comparison across trees of different sizes. In addition, the computational time required for the prediction of branches and trunk, in addition to the time for pruning decision-making, was analyzed to assess the efficiency of the proposed system.

Table 2 Description of Experimental Data and Setup for Evaluation of the 2D Pipeline Pruning Decision

Item	Detection	Pruning Decision
purpose	detection evaluation	pruning behavior
Tree type	Open crown, Fukuoka, Japan	Same as detection
# trees	5	10
# objects	200	500
Metrics	Accuracy, F1 score	Avg. of $\Delta H, I_p$
Threshold	-	% of H_c

where H_c denotes the crown height. In the pruning decision analysis, Crown height change (ΔH) was used to estimate the pruning effect, where positive values correspond to crown raising and negative values correspond to crown reduction, while Pruning intensity (I_p) was approximated as the ratio between the projected area of candidate pruning branches and the total projected branch area, providing a relative measure of pruning extent. Furthermore, pruning intensity can serve as an indicator of pruning severity, which should be carefully controlled to maintain tree health [17].

3.2. 3D QSM-Based Evaluation

To evaluate the system under overlapping structural conditions, additional experiments were conducted using a QSM-based 3D pipeline. Two trees with dense and overlapping crown structures were selected, and their point cloud data were obtained from [27], [28]. These trees were used to assess the robustness of the proposed method in scenarios where 2D visibility is limited.

Table 3. Description of experimental data and setup for evaluation of the 3D pipeline pruning decision.

Item	3D Pruning Decision (QSM-based)
purpose	- Computational efficiency - visualization of pruning decisions
Tree Species	- Oak [27] - Liriodendron tulipifera [28]
Trees Height	12.64 m - 36.48 m
Number of branches	172 - 1720
Pruning Threshold	% of H_c

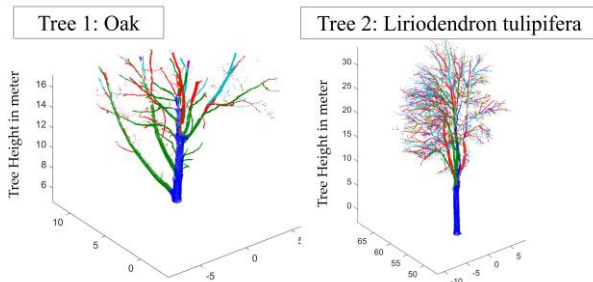


Figure 8 Point Cloud Visualization of Experimental Data for the 3D Pipeline Pruning Decision System (Left: [27], Right: [28])

The geometric structure of each tree was reconstructed using the QSM approach proposed in [25], enabling detailed analysis of branch connectivity, spatial distribution, and overall tree architecture.

Like the 2D approach, pruning decisions in the 3D pipeline were evaluated based on height thresholds defined relative to the crown height. However, due to the structural completeness provided by the QSM representation, the focus of the 3D analysis shifts toward computational

efficiency and the identification of candidate branches based on threshold criteria, rather than crown-level metrics.

Unlike the 2D pipeline, where pruning behavior is evaluated in terms of crown height change and pruning intensity, the 3D evaluation emphasizes processing time and its comparison with the 2D approach. The experimental setup is summarized in Table 3, and examples of point cloud visualizations and reconstructed QSM models are presented in Figure 8.

4. Results and Discussion

4.1. 2D Vision-Based Results

As illustrated in Figure 9, the prediction results demonstrate accurate detection of tree trunks and branches under realistic conditions. The detection results presented in Table 4 indicate that the trained YOLO-OBB model achieved high performance in recognizing urban tree components, with an average accuracy exceeding 90%. The high precision value (98%) indicates reliable detection with few false positives, whereas the strong recall (91.5%) emphasizes the model's ability to identify the most relevant branches and trunks. The obtained F1 score of 94.8% indicates a well-balanced trade-off between precision and recall, confirming the reliability of the model for downstream pruning decision tasks.



Figure 9 YOLO-OBB Prediction Results for Trunk and Branch Detection (Red boxes denote trunks, and green boxes denote branches)

Table 4 Detection Performance of the Custom YOLO-OBB Model for Trunk and Branch Recognition

Metric	Value [%]
Accuracy	90.1
Precision	98
Recall	91.5
F1-score	94.8

Once branch positions were extracted by Algorithm 2, candidate branches for raising and reduction were determined based on operator-defined pruning height thresholds. Figure 10 illustrates the selected pruning

candidates for thresholds ranging from 5% to 15% of the crown height H_c .

Adjusting the threshold resulted in significant differences in both the number and positioning of the selected branches, emphasizing the sensitivity of pruning decisions to threshold selection. This confirms that the proposed method offers a straightforward and controllable approach to pruning based on branch height.

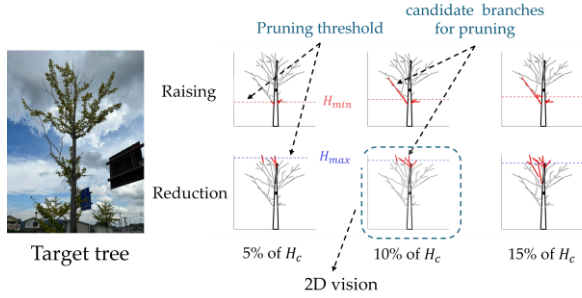


Figure 10 Effect of Height Threshold Variation on Pruning Candidate Selection

Furthermore, the gradual variation in candidate selection highlights the sensitivity of the system to threshold adjustment, allowing fine-grained control over pruning outcomes. This behavior supports adaptive decision-making across different urban scenarios with varying clearance requirements.

Table 5 summarizes the effect of pruning height threshold on crown height change (ΔH) and pruning intensity (I_p) for both crown-raising and crown-reduction scenarios. As the threshold increases from 5% to 25% of the crown height (H_c), crown raising results in a gradual increase in ΔH , while crown reduction leads to a corresponding decrease, indicating consistent structural response to threshold variation.

In addition, pruning intensity (I_p) increases monotonically with the threshold in both cases, reflecting a higher proportion of selected pruning branches. These results demonstrate that threshold adjustment provides a controllable mechanism for regulating pruning extent while maintaining predictable structural modifications.

Table 5 Variation of Crown Height Change and Pruning Intensity with Respect to Pruning Threshold

Pruning Threshold	Reduction		Raising	
	ΔH	I_p	ΔH	I_p
5	-0.08	0.06	0.06	0.12
10	-0.10	0.09	0.11	0.18
15	-0.13	0.13	0.14	0.23
20	-0.16	0.17	0.17	0.29
25	-0.20	0.30	0.24	0.38

The computational analysis demonstrates that the proposed pruning decision stage achieves efficient performance, with an average runtime of approximately 0.03 ms per branch and around 1.42 ms per tree, based on an average of 48 branches per tree. In addition, the branch detection stage requires approximately 1 ms per object,

while the image acquisition time is negligible within the overall pipeline. These results highlight the capability of the system for fast and scalable decision-making in real-world scenarios.

4.2. 3D QSM-Based Results

By utilizing QSM reconstruction, a complete representation of the tree geometry was obtained, enabling accurate extraction of branch positions, connectivity, and hierarchical structure. In this study, pruning decisions are evaluated along the vertical axis (Z-axis), following the same mechanism described for the 2D pipeline in Section 2.1.4. Figure 11 illustrates the pruning decision process based on height thresholds. Specifically, for crown raising, branches located below the lower height threshold (along the Z-axis) are identified as pruning candidates, while crown reduction targets branches exceeding the upper height threshold.

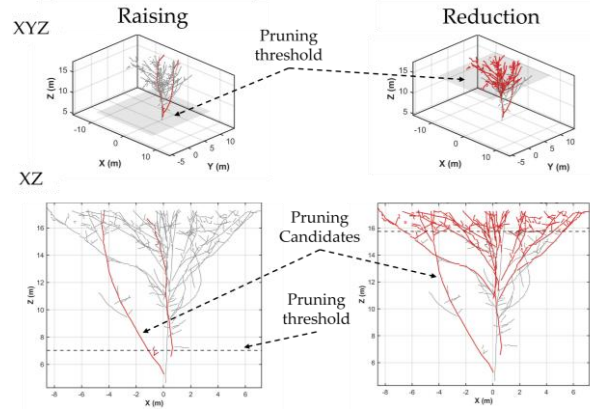


Figure 11 Visualization of Threshold-Based Pruning Decisions using QSM Reconstruction

As shown in Figure 11, some branches are removed even if only a portion of the branch intersects the defined threshold. This behavior follows the pruning rule described earlier, where a branch is considered a candidate if any part of it violates the height constraint. The objective is to ensure a clean and continuous pruning zone rather than allowing partially retained branches within the target region. This strategy improves the consistency and interpretability of pruning decisions, particularly in maintaining clear crown boundaries. Overall, the 3D pipeline provides robust and reliable pruning decisions under overlapping crown conditions. In addition, the observed pruning behavior follows trends similar to the 2D approach, where increasing the threshold results in a higher number of selected branches, ensuring controllability and interpretability of the pruning process.

Table 6 provides a quantitative comparison between the 2D and 3D (QSM-based) pruning pipelines, highlighting the distribution of computational cost across different processing stages. In the 2D approach, the total runtime per tree is approximately 0.051 s, where the dominant component is branch detection (~1 ms per branch for ~50 branches), while the pruning decision stage itself requires only 0.03 ms per branch. In contrast, the 3D pipeline

exhibits a significantly higher total runtime, averaging around 60 s per tree, primarily due to QSM reconstruction. Within this stage, cylinder fitting alone accounts for approximately 45.4 s, confirming that geometric modeling is the main computational bottleneck. Despite the large difference in total runtime, the pruning decision stage remains negligible in both approaches, requiring only ~1.42 ms per tree in 2D and ~0.005 ms per tree in 3D, indicating that decision-making itself introduces minimal computational overhead regardless of the representation.

From a practical perspective, these values should be interpreted together with the data acquisition time. In the 2D pipeline, image capture using a standard RGB camera is fast and can be considered negligible relative to processing time. In contrast, the 3D pipeline requires additional non-negligible time for LiDAR scanning, sensor setup, and field data collection, which further increases the total operational cost beyond the reported reconstruction time. Therefore, the observed performance difference is not solely due to algorithmic complexity but also reflects fundamental differences in sensing modalities and processing frameworks. Overall, the results demonstrate that while the 3D QSM-based approach provides detailed structural information, its computational and operational cost is dominated by data acquisition and reconstruction, whereas the 2D approach offers a lightweight and near real-time alternative for pruning decision support.

Table 6 Numerical Comparison between 2D and 3D Pruning Decision Pipelines

Metric	2D	3D
Branches per tree	~ 50	~ 925
Det. time/branch (ms)	~ 1	-
Reconstruction time (s)	-	~ 60.15
Cylinder fitting (s)	-	~ 45.4
Dec. time/branch (ms)	0.03	~0.000011
Decision time/tree (ms)	~1.42	~0.005
Total time/tree (s)	~0.051	~60
Data acquisition time	negligible	considerable

Despite differences in processing libraries, pruning decision time is negligible in both pipelines, while total runtime is dominated by detection in 2D and reconstruction in 3D, with additional overhead from LiDAR data acquisition. These results emphasize the need for an adaptive mechanism, where 3D processing is avoided for simple trees due to its high cost, and 2D methods are not solely relied upon in complex structures due to potential reliability limitations.

5. Conclusion

This study presented a pruning decision-support hybrid system utilizing 2D vision-based analysis and 3D QSM reconstruction. The 2D pipeline enables fast and scalable processing with negligible acquisition cost, making it suitable for real-time applications in simple tree structures. In contrast, the 3D pipeline provides a detailed geometric

representation, allowing reliable pruning decisions in complex and occluded crowns.

The results show that pruning decision-making introduces negligible computational cost in both approaches, while total runtime is dominated by detection in 2D and reconstruction in 3D, including non-trivial LiDAR data acquisition overhead. This reveals a trade-off between efficiency and structural accuracy. Accordingly, an adaptive strategy is required, where 3D processing is avoided for simple trees due to its high cost, and 2D methods are not solely relied upon in complex conditions due to reduced reliability.

Future work will focus on developing a tree structure classification mechanism to automatically assess crown complexity and select the most appropriate processing pipeline for each scenario. In addition, the pruning decision system will be extended to incorporate a wider range of pruning strategies and biologically informed criteria, aiming to better align automated decisions with arboricultural best practices.

References

1. Song, X. P., Tan, P. Y., Edwards, P., & Richards, D. (2018). The economic benefits and costs of trees in urban forest stewardship: A systematic review. *Urban forestry & urban greening*, 29, 162-170.
2. Tyrväinen, L., Pauleit, S., Seeland, K., & De Vries, S. (2005). Benefits and uses of urban forests and trees. In *Urban forests and trees: A reference book* (pp. 81-114). Berlin, Heidelberg: Springer Berlin Heidelberg.
3. Muscas, D., Orlandi, F., Petrucci, R., Proietti, C., Ruga, L., & Fornaciari, M. (2024). Effects of urban tree pruning on ecosystem services performance. *Trees, Forests and People*, 15, 100503.
4. Most, W. B., & Weissman, S. (2012). Trees and power lines: Minimizing conflicts between electric power infrastructure and the urban forest.
5. He, L., & Schupp, J. (2018). Sensing and automation in pruning of apple trees: A review. *Agronomy*, 8(10), 211.
6. Hauer, R. J., & Johnson, G. R. (2003). Tree risk management. *Urban tree risk management: A community guide to pro-gram design and implementation*, 5-10.
7. Botterill, T., Paulin, S., Green, R., Williams, S., Lin, J., Saxton, V., ... & Corbett-Davies, S. (2017). A robot system for pruning grape vines. *Journal of field robotics*, 34(6), 1100-1122.
8. Zahid, A., He, L., Zeng, L., Choi, D., Schupp, J., & Heinemann, P. (2020). Development of a robotic end-effector for apple tree pruning. *Transactions of the ASABE*, 63(4), 847-856.
9. Devang, P. S., Gokul, N. A., Ranjana, M., Swaminathan, S., & Binoy, B. N. (2010, December). Autonomous arecanut tree climbing and pruning robot. In *INTERACT-2010* (pp. 278-282). IEEE.
10. Fu, G. H., Liu, X. M., Chen, Y. F., & Yuan, J. (2015). Fast-growing forest pruning robot structure design and climbing control. *Advances in Manufacturing*, 3(2), 166-172.
11. Albaroudi, M., Alahmad, R., Alraie, H., Alraee, A., Puwei, S., Inniyaka, I. R., & Ishii, K. (2026). Estimation of Branch Geometry and Hierarchy in Orchard Trees for Robotic Pruning. *Journal of Robotics and Mechatronics*, 38(2), 495-512.

12. Mohammad, A., Abdullah, A., Raji, A., Hussam, A., & Kazuo, I. (2026, January). Semi-Automated Urban Tree Pruning Using a Rule-Based 2D Vision Approach. In 人工生命とロボットに関する国際会議予稿集 (Vol. 31, pp. 139-144). 株式会社 ALife Robotics.
13. Megalingam, R. K., Vignesh, N., Sivanantham, V., Elamon, N., Sharathkumar, M. S., & Rajith, V. (2016, January). Low cost robotic arm design for pruning and fruit harvesting in developing nations. In 2016 10th International conference on intelligent systems and control (ISCO) (pp. 1-5). IEEE.
14. Fujinaga, T. (2024). Strawberries recognition and cutting point detection for fruit harvesting and truss pruning. *Precision Agriculture*, 25(3), 1262-1283.
15. Wang, J., Li, B., & Meng, M. Q. H. (2021). Kinematic Constrained Bi-directional RRT with Efficient Branch Pruning for robot path planning. *Expert Systems with Applications*, 170, 114541.
16. Mohammad, A., Raji, A., Kazuo, I., & Abdullah, A. (2025, February). Evaluating of Tree Branch Recognition Algorithm in Pruning Robots under Augmented Environmental Conditions. In 人工生命とロボットに関する国際会議予稿集 (Vol. 30, pp. 356-360). 株式会社 ALife Robotics.
17. Bedker, P. J. (2016). How to prune trees (Vol. 95, No. 1). Government Printing Office.
18. Bahreini, F., & Hammad, A. (2025). Detection of vegetation proximity to power lines: Critical review and research roadmap. *Forests*, 16(11), 1658.
19. Yazdi, H., Shu, Q., Rötzer, T., Petzold, F., & Ludwig, F. (2024). A multilayered urban tree dataset of point clouds, quantitative structure and graph models. *Scientific Data*, 11(1), 28.
20. Zhu, W., Bai, X., Xu, D., & Li, W. (2025). Pruning branch recognition and pruning point localization for walnut (*Juglans regia* L.) trees based on point cloud semantic segmentation. *Agriculture*, 15(8), 817.
21. Ye, L., Ma, J., Lv, Y., Guo, Z., Lai, Z., Ou, C., ... & Wu, F. (2025). The YOLO-ORB-Based Approach for Citrus Fruit Stem Pose Estimation and Robot Picking. *Agriculture*, 15(22), 2330.
22. Lim, B., Jeong, S., & Yoo, Y. (2024). A methodology for estimating the assembly position of the process based on yolo and regression of operator hand position and time information. *Applied Sciences*, 14(9), 3611.
23. Abdullah, A., Mohammad, A., Hussam, A., Raji, A., & Kazuo, I. (2025, February). Efficient Ball Position Estimation for Tennis Court Robot Assistants using DualCamera System. In 人工生命とロボットに関する国際会議予稿集 (Vol. 30, pp. 378-381). 株式会社 ALife Robotics.
24. Raunonen, P., Casella, E., Calders, K., Murphy, S., Åkerblom, M., & Kaasalainen, M. (2015). Massive-scale tree modelling from TLS data. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2, 189-196.
25. P. Raunonen et al., "TreeQSM: Quantitative structure models of trees from point cloud data," GitHub repository, 2022. [Online]. Available: <https://github.com/InverseTampere/TreeQSM>
26. Kıvrak, E., Simav, O. E., Şahin, A., Alraee, A., Albaroudi, M., Alahmad, R., ALRAIE, H., & NESİMOĞLU, T. (2026 0). Comparative Performance Analysis of YOLOv5 and YOLOv8 for Tomato Detection in Agricultural Robotics. 31st International Conference on Artificial Life and Robotics, ICAROB 2026, Oita, Japan.
27. oliverm06, "One Oak Tree - Central Section," Sketchfab, licensed under CC BY 4.0, [Online]. Available: <https://skfb.ly/6ToG6>
28. astovall, "Large Yellow Poplar (*Liriodendron tulipifera*)," Sketchfab, licensed under CC BY 4.0, [Online]. Available: <https://skfb.ly/6URZR>

Authors Introduction

Mr. Mohammad Albaroudi



He obtained his B.Sc. degree in Telecommunication Engineering from Al-Wataniya Private University (WPU), Syria, in 2018, and his M.Sc. degree in Radio and Mobile Telecommunication Systems from the Higher Institute for Applied Sciences and Technology, Syria, in 2021. He is currently a Ph.D. candidate at Kyushu Institute of Technology, Japan, with an expected graduation in March 2026. His research interests include machine learning, image processing, and antenna design, with a focus on developing advanced computational methods for engineering applications.

Mr. Abdullah Alraee



He obtained his B.Sc. degree in Telecommunication Engineering from Al-Wataniya Private University (WPU), Syria, in 2018, and his M.Sc. degree from Kyushu Institute of Technology, Japan, in 2024. He is currently a Ph.D. candidate at Kyushu Institute of Technology. His research focuses on robotics, artificial intelligence, image processing, and automation.

Dr. Hussam Alraie



He obtained his Master's degree in Telecommunication Engineering from Homs University, Syria, and completed his Ph.D. at Kyushu Institute of Technology, Japan, in 2024. He is currently working as a postdoctoral researcher at Middle East Technical University, Northern Cyprus Campus (METU-NCC), Türkiye. His academic interests span underwater communication, image analysis, and machine learning, with an emphasis on intelligent and data-oriented approaches.

Dr. Raji Alahmad



He is a researcher in the Department of Human Intelligence Systems at Kyushu Institute of Technology, Japan. He earned his M.Eng. degree in 2018 and his Doctor of Engineering (D.Eng.) degree in 2022 from Kyushu Institute of Technology. His research interests encompass artificial intelligence, underwater communication systems, image processing, and machine learning, with an emphasis on intelligent sensing and the development of data-driven solutions for real-world applications.

Prof. Kazuo Ishii



He is currently a Professor at the Department of Human Intelligence Systems of Kyushu Institute of Technology, Japan. He obtained his M. S. degree in 1993 and his D. Eng. degree in 1996 at the University of Tokyo. His research interests are in the fields of Underwater Robotics, Field Robotics, Neural Networks, and Intelligent Systems.