

|                                                                                   |                                                                                                                                                               |                                                                         |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
|  | <p style="text-align: center;">AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br/>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br/>IMAGERY</p> | <p style="text-align: right;">COMPUTER<br/>TECHNOLOGY  <br/>3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p style="text-align: center;">Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                           | <p style="text-align: right;">Digital computers</p>                     |

# AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV IMAGERY

Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui y Manuel A. Aguilar  
Universidad de Almería. Departamento de Ingeniería. Carretera de Sacramento, s/n – 04120 La Cañada de San Urbano, Almería (España).

DOI: <https://doi.org/10.52152/D11497> | Recibido: 18/jul/2025 • Inicio Evaluación: 23/jul/2025 • Aceptado: 05/nov/2025

To cite this article: AGUILAR, Fernando J.; ALCAYDE, Alfredo; VALVERDE, Marcos E.; NEMMAOUI, Abderrahim; AGUILAR, Manuel A. AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES

BASED ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV IMAGERY. DYNA January February 2026. Vol. 101, n.1, pp. 81-86 | DOI: <https://doi.org/10.52152/D11497>

## ABSTRACT:

*The control, supervision and monitoring of trees, both in terms of their location and height, is of vital importance in teak plantations (Tectona grandis L.f.). This allows planning silvicultural work related to thinning, replanting, irrigation and phytosanitary treatments, estimating production and harvesting. It is also crucial for determining their carbon sequestration capacity to contribute to climate change mitigation. In this work, three different size versions of the anchor-free and single-stage detector YOLOX deep learning network, pre-trained on the COCO dataset, were specifically trained for automatic localization of teak trees in large and dense plantations from UAV imagery. This study used two teak plantations located in Ecuador. "La Marina" plantation (456 ha) served as the training and validation area, while "La Selena" (195 ha), was reserved for testing and accuracy evaluation, constituting a true holdout dataset to assess the generalization capabilities of the developed model. Very high-resolution RGB images were taken in both plantations using a RTK Phantom 4 drone at a flight altitud of 120 m above ground. Regarding the results obtained, they showed that the "small" version of the YOLOX deep learning network performed significantly better than the other two versions tested ("medium" and "large" size YOLOX), presenting notably good average metrics of Precision (94.74%), Recall (82.40%) and F1-score (87.91%). In this sense, the trained model proved to be a suitable solution to address complex visual recognition challenges in very high-resolution UAV images.*

*Keywords: UAV Images, YOLOX, Tree Detection, Teak Plantations, Deep Learning*

## FUNDING

This work was supported by the research project "Sophisticated pavement inspection based on VHR satellite imagery and artificial intelligence (SOTER)", funded by the Andalusian Technology Corporation (Corporación Tecnológica de Andalucía; CTA) through the consortium formed by CONACON S.A., 3D Geospace and University of Almería. The authors would like to thank also to the INGEGRAF association (<https://ingegraf.es/>).

## 1. - INTRODUCTION

Although natural forests are of much greater value for biodiversity conservation, the inherent value of planted forests has been recently confirmed (e.g., [1]). Thus, despite considering teak plantations (*Tectona grandis* L.f.) as an exotic and invasive species in many Central and South American countries from a strictly ecological perspective, teak plantations paradoxically appear quite promising for biodiversity conservation compared to other land-use alternatives because they provide forest cover and, in addition, generate

|                                                                                   |                                                                                                                                                               |                                                                         |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
|  | <p style="text-align: center;">AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br/>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br/>IMAGERY</p> | <p style="text-align: right;">COMPUTER<br/>TECHNOLOGY  <br/>3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p style="text-align: center;">Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                           | <p style="text-align: right;">Digital computers</p>                     |

sustainable livelihoods and economic returns for farmers [2]. In this regard, the control, supervision and monitoring of trees, both in terms of their location and height, is of vital importance in teak plantations. This allows planning silvicultural work related to thinning, replanting, irrigation and phytosanitary treatments, estimating production and harvesting [3].

Overall, knowledge of the number of plants, spatial location and estimation of their height is crucial for the management of large tree plantations, as well as for determining their carbon fixation capacity and their contribution to climate change mitigation [4]. Until a few years ago, this work was carried out through costly field inventories consisting of counting or estimating the number of trees in plots previously defined for the management of teak plantations. Height estimates were made using hypsometers or allometric equations relating tree height and diameter measured at breast height [5]. More recently, statistical inference methods have also been employed based on inventories conducted using terrestrial laser scanning [6] or angle sampling method [7]. In any case, these methods are costly in terms of time and human resources. On the other hand, statistical inference is a method that is unsuitable for the precise location of the plantation trees, being more suitable for obtaining dasometric estimates such as basal area or average Lorey height [8].

The emergence of the possibility of capturing high spatial and spectral resolution data using unmanned aerial vehicles (UAVs), together with improvements in image and point cloud data processing, have widened the horizons of remote sensing applications in forest management to limits unimaginable just a few years ago [9], [10]. Furthermore, there has recently been a huge interest in the scientific community in developing and validating deep learning networks with convolutional neural networks (CNNs) for tree detection in aerial, UAV, or even satellite images [11], [12]. Ultimately, the goal is to find a way to facilitate the collection of the desired data automatically and with greater accuracy. This can be addressed by training and validating new computer vision technologies for object detection in RGB images, such as the well-known deep learning object detector implemented in the YOLO (You Only Look Once) series (e.g., [12]), especially suitable to be applied in small objects detection (SOD). It should be noted that SOD represents a distinct subdomain of object detection that focuses on detecting small-sized objects which is gaining increasing interest in recent years [13]. For example, the single-stage anchorless deep learning object detector YOLOX was designed to improve the detection and accuracy of small objects while maintaining real-time inference speed [14].

The first goal of this study is to test YOLOX for the automatic localization of teak trees in large plantations from UAV RGB images. Three different size versions of the YOLOX deep learning network, pre-trained on the COCO dataset, were specifically trained and tested for automatic localization of teak trees in large and dense plantations from RGB UAV images. Note that models pre-trained on very large-scale datasets have clearly demonstrated their invaluable contribution in many applications and improvements related to the field of computer vision [15].

## 2. - MATERIAL & METHODS

### 2.1.- STUDY SITE AND IMAGE DATASET

The two teak plantations used in this study are located in Ecuador. "La Marina" plantation, totaling 456 hectares, served as the training and validation area, while "La Selena", with 195 hectares, was reserved for testing and accuracy evaluation, constituting a true holdout dataset to assess the generalization capabilities of the developed deep learning model. Both plantations are located very close to each other, with a geographic coordinate of 1.02052°S and 79.80579°W (Figures 1 and 2).

Very high-resolution RGB images were taken in both plantations using a Phantom 4 drone with RTK positioning. The flight height above ground was 120 m, which meant a ground sample distance from 3.7 cm (La Marina) to 3.8 cm (La Selena). The captured images presented a longitudinal and transverse overlap of 80% and 60%, respectively. These flight parameters were selected because they meet the usual operating conditions in Ecuador.

The RGB orthoimage of "La Marina" training plantation was divided into 1024x1024 pixel square tiles (approximately 37.9x37.9 m ground size) to facilitate labeling of the teak trees. This process was performed semi-manually on the mosaicked images using the open-source software Label Studio [16]. Only 300 randomly selected images were ultimately labeled, representing a total of 4,485 labeled teak trees. These initial labels, configured as rectangular bounding boxes, were filtered using the typical average canopy dimensions of a teak tree in the region to avoid incorrectly labeled trees.

|                                                                                   |                                                                                                                           |                                      |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|--------------------------------------|
|  | <p>AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV IMAGERY</p> | <p>COMPUTER TECHNOLOGY   3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p>Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                   | <p>Digital computers</p>             |

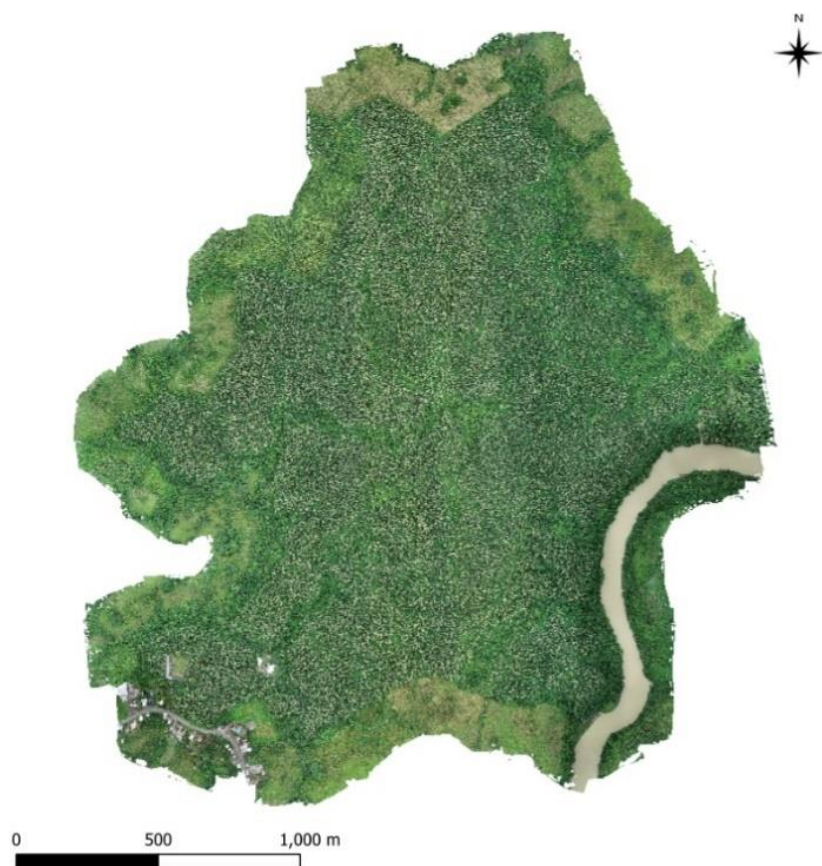


Fig. 1. Nadir view of the teak plantation “La Marina” used for training and validation.



Fig. 2. Nadir view of the teak plantation “La Selena” used for testing and accuracy evaluation. The eight test plots used for accuracy evaluation are represented as red rectangles.

|                                                                                   |                                                                                                                                                               |                                                                          |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------|
|  | <p style="text-align: center;">AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br/>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br/>IMAGERY</p> | <p style="text-align: center;">COMPUTER<br/>TECHNOLOGY  <br/>3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p style="text-align: center;">Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                           | <p>Digital computers</p>                                                 |

## 2.2.- DEEP LEARNING NETWORK AND EXPERIMENTAL SETUP

In this work, the YOLOX version of the YOLO series was used as a reference network to train teak tree detection in UAV RGB images. YOLOX is a single-stage, anchor-free deep learning object detection model specifically devised to reduce the model size and computational burden typically associated with previous YOLO models [14]. It has proved to be a good choice to deal with detecting fine details and small objects (in this case trees on UAV imagery) [17]. Thus, YOLOX was selected over other object detector alternatives because it offers high detection accuracy with the computational efficiency needed for real-time, cost-effective deployment on edge hardware, making it the optimal solution for a scalable, high-speed automated inventory system using UAV imagery. Regarding inference speed (i.e., real-time capability), the single-stage detector YOLOX processes images much faster than two-stage detectors (like Faster R-CNN or Mask R-CNN), which first propose regions and then classify/refine them. For inventory scanning from UAV imagery, which requires processing a continuous stream of images or video frames from a moving aerial platform, YOLOX's high frame rate capability is indispensable for real-time operation and minimizing overall scanning time. Furthermore, YOLOX offers various model scales (from YOLOX-Tiny to YOLOX-X), allowing for flexible computational trade-offs. Note that models of small parameter sizes (e.g., YOLOX-Small) allow efficient inference to run on relatively affordable edge-computing hardware (e.g., an NVIDIA Jetson or lower-end GPU), keeping hardware acquisition costs and power consumption low.

YOLOX uses a backbone network consisting of a COCO dataset pre-trained convolutional neural network based on CSP-DarkNet-53 with cross stage partial connections (the same as YOLOv8). This backbone is used to compute feature maps from the input images, being specifically designed for object detection tasks because it can extract richer features from up to three different scales (multi-scale approach [18]). In this way, YOLOX pretrains an implicit knowledge component based on the COCO dataset to sketch a general representation of the target to be detected. Explicit knowledge (e.g., the detection of teak in UAV images) is learned using another set of parameters specifically trained to extract the fine-tuned feature vector needed to detect the target. Both knowledge components will then be used for inference.

The neck of the network connecting the backbone and the head relies on a Feature Pyramid Network (FPN) that can generate initial grids and feature maps at three different scales. This model component functions as a path aggregation network to meaningfully fuse low- and high-level feature information.

Finally, the concatenated information from the backbone layers is fed into the head of the network at the three different scales. The usual coupled head of YOLO is replaced in YOLOX by a decoupled one that processes the aggregated features in three feature pipelines related to: i) classification scores, ii) regression scores (position and shape of the bounding boxes), and iii) objectness scores (probability that each bounding contains the target object).

It should be noted that the three scale grids computed during the YOLOX pipeline can be reconfigured depending on image size. This feature allows to train the full network on patches and later predict the location of objects by performing inference on full-size images. This is how this network is used in this work to automatically infer the geolocation of teak trees in the orthoimage of "La Selena" test plantation, once it has been properly trained on "La Marina" plantation.

Both the network training and its accuracy evaluation were coded in MATLAB® (R2024b) with support from Deep Learning Toolbox™ and the Computer Vision Toolbox™ Automated Visual Inspection Library package.

Three different versions of the YOLOX deep learning network were tested, termed "Small", "Medium" and "Large" size. The training of these three versions was carried out in a HP Z2 Tower Workstation with an Intel(R) Xeon(R) E-2126G CPU (3.30 GHz and 32 GB RAM) and an NVIDIA Quadro P2000 GPU (5 GB RAM and 8 multiprocessors).

Regarding the training phase, the available labeled data extracted from the 300 mosaic images of the "La Marina" teak plantation were randomly divided into 90% for training and 10% for validation. Notably, the validation dataset provides an unbiased assessment of the model's fit to the training dataset by tuning the model's hyperparameters. Training began with a learning rate of 0.0005, being optimized using stochastic gradient descent (SGDM) with a momentum of 0.9 and a weight decay of 0.0005. The learn rate schedule applied was piecewise, also setting a gradient decay factor of 0.9, a learn drop period of 1 (i.e., number of epochs to reduce the learning rate) and a factor for L<sub>2</sub> regularization of 0.0005. The option of shuffle every-epoch was selected to allow changing the order of the training data before each training epoch and changing the order of the validation data before each validation of the neural network. To enhance the model's efficacy while preventing overfitting, we conducted 50 training epochs, adjusting the hyperparameters progressively based on experimental outcomes. In this sense, no early stopping criteria were established. With respect to the application of augmentation techniques, no augmentation methods (e.g., rotation, scaling, or jitter) were applied to the original labeled dataset because the nadir view of the teak plantation produced uniform, non-occluded, and geometrically stable canopies, making these forms of geometric augmentation unnecessary.



|                                                                                   |                                                                                                                          |                                     |
|-----------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------|-------------------------------------|
|  | AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br>IMAGERY | COMPUTER<br>TECHNOLOGY  <br>3304.14 |
| RESEARCH ARTICLE                                                                  | Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar                         | Digital computers                   |

### 2.3.- METRICS USED FOR ACCURACY ASSESSMENT

Regarding the testing phase, up to eight evenly distributed plots with areas ranging from 4,330 m<sup>2</sup> to 19,580 m<sup>2</sup> within the test plantation "La Selena" were used as field reference (see Figure 2). These test plots were carefully selected to address the diversity of tests needed to assess the generalization capabilities of the trained models in scenarios ranging from very dense stands to areas where teak is mixed with other tree or shrub species, to plots where teak trees are evenly distributed, or even plots with teak trees of different sizes. All teak trees within these reference plots were manually digitized on-screen in QGIS environment as "points geometry", constituting the ground truth for accuracy assessment.

In this work, Precision, Recall and F1-Score accuracy metrics [19] were calculated. Precision (P) measures the number of rightly detected teak trees with respect to the total number of teak trees detected by the model, thus estimating the over-detection error (related to commission error). Recall (R) measures the number of rightly detected teak trees with respect to the total number of teak trees present in the ground truth data, thus giving an approximation to the under-detection error (i.e., omission error). Finally, F1-Score is computed as the harmonic mean of P and R, thus providing an overall performance metric capable of jointly balancing commission and omission error. The calculation of these three metrics is shown in Eq. (1).

$$P = \frac{TP}{TP+FP}; R = \frac{TP}{TP+FN}; F1 - Score = 2 \times \frac{P \times R}{P+R} \quad (1)$$

Where TP represents true positives (an object that is actually a teak tree and is correctly classified by the model as a teak tree), TN means true negatives (an object that is actually not a teak tree and is correctly classified by the model as not a teak tree), FP refers to false positives (incorrectly detected teak trees), and FN refers to false negatives (teak trees that were not detected).

Finally, the mAP50 metric (mean Average Precision at 50% threshold) was also calculated during the process of training/validation. This metric measures the model's average teak tree detection accuracy when the intersection-over-union (IoU) threshold is set to 0.5. This means that the detection of object *i* is considered correct if the overlap between the ground truth bounding box for this object *i* and the predicted bounding box is greater or equal to 50%.

## 3. – RESULTS & DISCUSSION

### 3.1.- MODEL LEARNING. TRAINING AND VALIDATION LOSS CURVES.

Training and validation loss curves for the representative case of YOLOX-small network (same behavior was observed for medium and large versions) is displayed in Figure 3 over 50 epochs. Loss curve shows the training loss (blue) and validation loss (red) curves that represent the progress of the model in predicting the coordinates of the bounding boxes during training. Both curves reach very low values after relatively few epochs, demonstrating a rapid convergence and clear stability of the predicted bounding box coordinates around the teak trees. In addition, both curves appear reasonably flat at the end, which avoids an underfitting scenario. This implies that the model cannot generate a sufficiently low error rate on the training set. It can also mean that the training loss curve continues to trend downward at the end of training, indicating that training has not been sufficient and the number of epochs needs to be increased [20]. It is worth noting that the training loss at the end of the training phase is clearly lower than the validation loss, which could indicate a certain level of overfitting that compromises the model's generalization. However, considering that the validation loss curve is calculated from a holdout validation dataset, we can assume that the proposed model appears capable of generalizing adequately. In any case, this point is positively confirmed by the results presented and analyzed in Section 3.2, where validation is performed under real-world conditions using a test dataset collected and compiled from another teak plantation called "La Selena," which had not been previously seen in the training phase (holdout data). This test dataset is used to evaluate the generalization capability of the developed model.

The values over iterations of the mAP50 metric are shown in Figure 4. This metric is frequently used in object detection tasks when applying binary classifiers on imbalanced datasets because it incorporates the trade-off between Precision and Recall by considering both false positives and false negatives [21]. In this way, mAP50 shows stable and reasonably good value above 0.80 after a few

|                                                                                   |                                                                                                                                                               |                                                                         |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
|  | <p style="text-align: center;">AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br/>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br/>IMAGERY</p> | <p style="text-align: right;">COMPUTER<br/>TECHNOLOGY  <br/>3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p style="text-align: center;">Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                           | <p style="text-align: right;">Digital computers</p>                     |

training iterations, which points to a very promising model in terms of teak trees detection accuracy and reinforces that the training process was effective after 50 epochs.

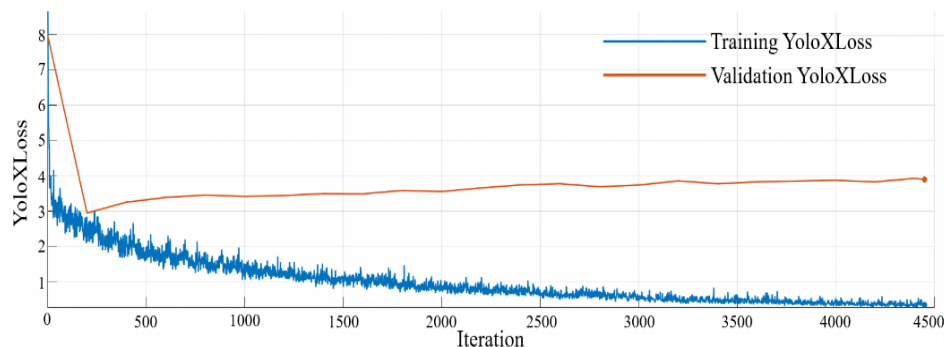


Fig. 3. Loss curve during training of the YOLOX-small deep learning network. Blue line represents the training loss, while red line indicates the validation loss.

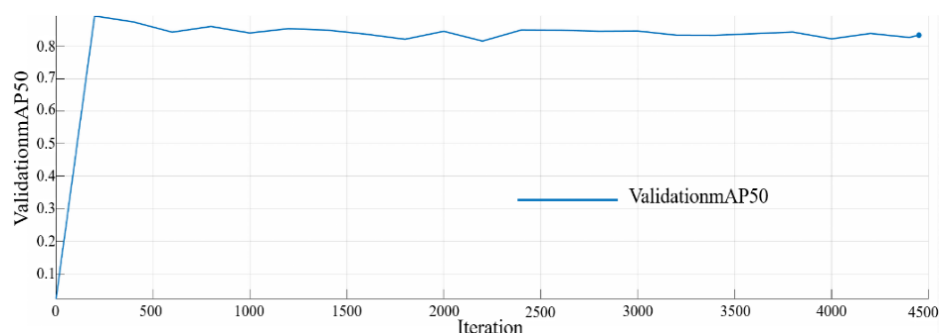


Fig. 4. Evolution of the mAP50 metric along training calculated on the validation dataset.

### 3.2.- ACCURACY ASSESMENT OF THE TEST PLANTATION DATASET.

Figures 5 and 6 show the geolocation of teak trees automatically predicted by the YOLOX-small model in the test plots 4 and 1 of "La Selena" plantation. Note that incomplete trees (i.e., partially rendered canopy trees located at the edge of the image) were not considered for the accuracy assessment stage because the detector requires a full canopy to make a correct inference. All models were trained in "La Marina" plantation, meaning that the model never saw the data from the test plantation. In this way, a "true validation" process was performed to test the generalization capabilities of the models trained in "La Marina" plantation.

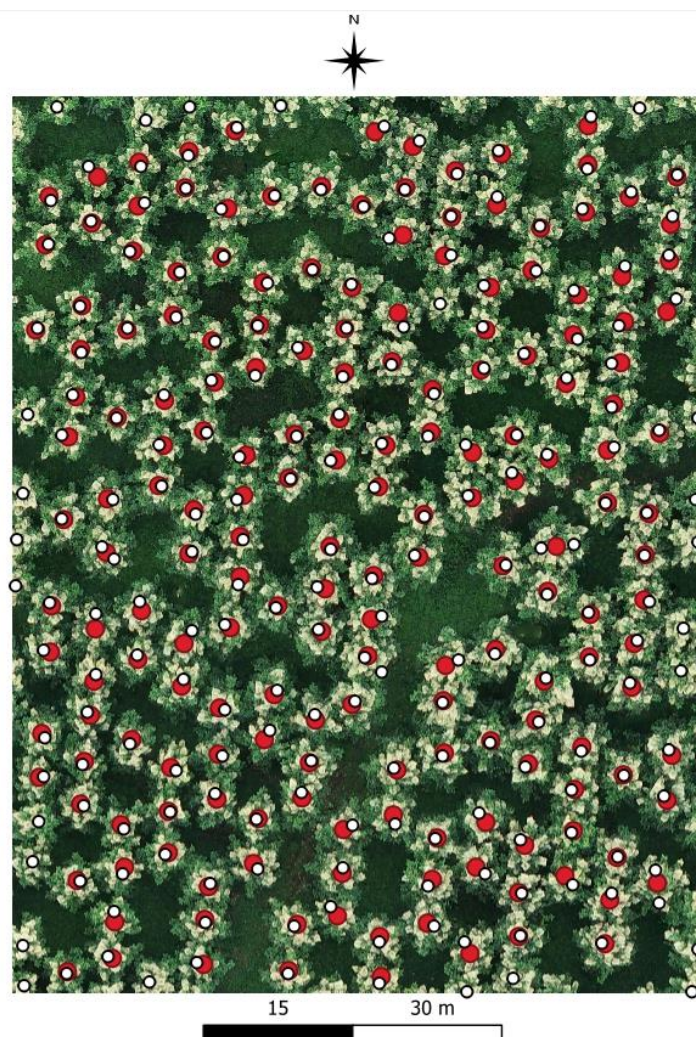
|                                                                                   |                                                                                                                           |                                      |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|--------------------------------------|
|  | <p>AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV IMAGERY</p> | <p>COMPUTER TECHNOLOGY   3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p>Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                   | <p>Digital computers</p>             |



*Fig. 5. Test plot number 4 at the “La Selena” teak plantation. The red dots superimposed on the orthoimage represent the geolocation of the teak trees predicted by the YOLOX-small model, while the white dots represent the manually digitized teak trees (ground truth).*



|                                                                                   |                                                                                                                                                               |                                                                         |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
|  | <p style="text-align: center;">AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br/>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br/>IMAGERY</p> | <p style="text-align: right;">COMPUTER<br/>TECHNOLOGY  <br/>3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p style="text-align: center;">Fernando J. Aguilar, Alfredo Alcaide, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                           | <p style="text-align: right;">Digital computers</p>                     |



*Fig. 6. Test plot number 1 at the “La Selena” teak plantation. The red dots superimposed on the orthoimage represent the geolocation of the teak trees predicted by the YOLOX-small model, while the white dots represent the manually digitized teak trees (ground truth).*

These two figures allow us to appreciate that the trained model based on the small YOLOX network managed to produce visually outstanding results. In fact, the predicted teak trees overlaid on test plot number 4 (Figure 5) proves that the model was able to accurately discriminate teak trees from other tree species. Furthermore, the results shown in test plot number 1 (Figure 6) indicate the good performance of the model in detecting teak trees even in dense stands. In this regard, it is necessary to underline YOLO models predict bounding boxes and class probabilities directly from the full image in a single pass, making them exceptionally efficient as compared to traditional methods based on region proposals or sliding windows [22].

Table 1 outlines the quantitative results in terms of three accuracy metrics corresponding to the 8 reference plots for the three trained models based on the YOLOX network (small, medium and large versions) and a threshold score for inference of 0.1. Overall, the YOLOX-small model performed much better than heavier models like the YOLOX-medium and YOLOX-large networks. Keeping in mind that precision is related to the accuracy of positive predictions, while recall is focused on addressing how well the model is able to detect all the target objects in the image [23], it is important to underline that the final average Precision metric achieved (94.74%, 92.41%, and 92.91% for small, medium and large sizes, respectively) is clearly higher than that of Recall (82.40%, 68.04%, and 65.47% for small, medium and large sizes, respectively), which points to a model more prone to under-detection error (omission error). This fact is especially notable in the case of models that involve more parameters to be calculated in the network (i.e., medium and



large sizes), where the drop in Recall is especially pronounced. That is, the model behaves cautiously simply to avoid providing an excessive number of incorrectly detected teak trees (false positives). These figures could be slightly modified if the threshold score for accepting a teak tree predicted by the model were lower than 0.1, which would increase Recall at the cost of decreasing Precision ([19], [21]).

The performance metrics achieved on the unseen "La Selena" test plantation confirm the model's ability to generalize effectively. For example, the trained model based on YOLOX-small deep learning network achieved notably good average metrics across the eight test plots located in "La Selena": Precision = 94.74%, Recall = 82.40%, and F1-score = 87.91%. These results, derived from a test dataset the model had not encountered during training, indicate that the training data, despite its limited size (300 images of 1024x1024 pixels), provided sufficient representation for the network to adequately generalize and prove itself to be a suitable solution to address complex visual recognition challenges in very high-resolution UAV images across different areas.

| Plot           | YOLOX-small  |              |              | YOLOX-medium |        |          | YOLOX-large  |        |          |
|----------------|--------------|--------------|--------------|--------------|--------|----------|--------------|--------|----------|
|                | Precision    | Recall       | F1-score     | Precision    | Recall | F1-score | Precision    | Recall | F1-score |
| Number 1       | 98.40        | <b>97.35</b> | <b>97.87</b> | <b>100</b>   | 86.77  | 92.92    | 99.40        | 87.83  | 93.26    |
| Number 2       | <b>89.02</b> | <b>70.87</b> | <b>78.92</b> | 88.89        | 62.14  | 73.14    | 88.06        | 57.28  | 69.41    |
| Number 3       | <b>98.75</b> | <b>73.83</b> | <b>84.49</b> | 93.44        | 53.27  | 67.86    | 91.07        | 47.66  | 62.58    |
| Number 4       | <b>92.28</b> | <b>81.20</b> | <b>86.39</b> | 83.15        | 60.57  | 70.09    | 90.46        | 61.88  | 73.49    |
| Number 5       | <b>92.86</b> | <b>91.41</b> | <b>92.13</b> | 88.57        | 72.66  | 79.83    | 89.69        | 66.97  | 77.33    |
| Number 6       | 94.08        | <b>77.18</b> | <b>84.80</b> | 95.45        | 71.36  | 81.67    | <b>96.50</b> | 66.99  | 79.08    |
| Number 7       | <b>97.22</b> | <b>92.11</b> | <b>94.59</b> | 96.74        | 78.16  | 86.46    | 94.44        | 80.53  | 86.93    |
| Number 8       | <b>95.33</b> | <b>75.28</b> | <b>84.12</b> | 93.06        | 59.41  | 72.52    | 93.67        | 54.61  | 69.00    |
| <b>Average</b> | <b>94.74</b> | <b>82.40</b> | <b>87.91</b> | 92.41        | 68.04  | 78.06    | 92.91        | 65.47  | 76.39    |

Table 1. Accuracy assessment of each ground truth plot in the test teak plantation "La Selena". Threshold score for inference = 0.1. The figures in bold refer to the maximum value of Precision, Recall, and F1-score in each reference plot.

The results indicate that YOLOX-small consistently outperforms the medium and large versions across diverse teak tree distributions within plots, ranging from very dense stands to areas where teak is mixed with other tree species or shrubs, to evenly distributed teak trees and plots with teak trees of varying sizes. This finding may be attributed to the fact that the target teak tree in the dataset might be relatively small compared to the image size and, in addition, teak trees are densely distributed within it. In this type of scenario, the receptive field size of the small version of the YOLO series might be more appropriate (e.g., [24]). In this regard, YOLOX-small has proven to be the most versatile option for tree detection, as well as being faster to train and infer thanks to its reduced number of parameters to calculate. Note that the height of each teak tree could be easily estimated, once the tree position has been automatically geolocated, by using standardized digital canopy models generated from photogrammetrically derived point clouds obtained through the same UAV flight [25].

To the authors' knowledge, there are no similar studies on detecting teak trees from UAV images by applying deep learning networks. However, we can refer to works carried out on other planted tree species such as banana or palm. For example, Neupane et al [26] reported average recall rates of 78.8% working on banana plantations with UAV RGB images taken at low altitude (40, 50 and 60 m) and applying a Faster R-CNN model pretrained on the COCO dataset. They increased the model's performance by transforming the original RGB data using three methods to enhance feature maps extraction such as Linear Contrast Stretch (LCS), Synthetic Color Transform (SCT), and Triangular Greenness Index (TGI). The lowest flight altitude variant (40 m) yielded the best results using TGI-transformed data, achieving an impressive recall of 88%. In any case, the accuracy results were quite poor for the 60 m flight height, reaching only 60% recall for the SCT-transformed data (only 45.7% for the original RGB data). Regarding palm tree plantations, Hajjaji et al [27] achieved a recall of 86% in detecting palm trees from RGB UAV images taken at 65 m above ground using the YOLOv8 deep learning network. In this case, the palm trees presented a clear plantation pattern and showed virtually no overlap between trees.

It is worth underlining that the UAV images used in our study were taken at 120 m above ground to achieve maximum data capture efficiency. This is the maximum permitted limit for UAV flight in Ecuador (and most other countries). The results obtained would likely have been significantly better if we had reduced the flight altitude, although at the expense of scale and mapping efficiency.

|                                                                                   |                                                                                                                          |                                     |
|-----------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------|-------------------------------------|
|  | AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br>IMAGERY | COMPUTER<br>TECHNOLOGY  <br>3304.14 |
| RESEARCH ARTICLE                                                                  | Fernando J. Aguilar, Alfredo Alcaide, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar                         | Digital computers                   |

In summary, the primary factor driving the success of YOLOX-small is the nature of the target objects (i.e., individual teak tree canopies) as captured by the UAV imagery. In fact, the teak trees are relatively small compared to the overall image size (which is common in high-altitude, very-high-resolution UAV imagery) and are densely distributed. When facing scenarios involving dense, small objects, YOLO models with fewer parameters and smaller receptive fields can effectively focus on the fine details of individual small objects, avoiding feature confusion when objects are clustered closely together, a critical problem in dense SOD. In addition, deep learning models with an excessively large number of parameters (like YOLOX-large) can be too complex to optimize effectively when training data is limited relative to the model's capacity. In this sense, a larger model architecture can easily overfit the nuances of the training dataset ("La Marina" plantation), resulting in poor generalization to unseen data ("La Selena" test plantation). The quantitative results confirm this, showing a particularly pronounced drop in Recall for the medium and large models compared to the small model, suggesting these models failed to detect a significantly higher number of true objects (omission error) on the test data. In conclusion, the YOLOX-small version demonstrated the most versatile option for tree detection, requiring fewer parameters to calculate, which made it faster to train and infer while maintaining superior generalization capability.

#### 4. – CONCLUSIONS

The results obtained in terms of teak tree detection can be qualified as very good for the trained model based on the YOLOX-small network. In fact, Precision metric, i.e. the ratio between correctly detected teak trees and the total number of teak trees detected by the model, took average values of 94.74% in the test plantation, which implies a very low rate of false positives or over-detection (very low commission error). On the other hand, Recall metric, which measures the number of correctly detected teak trees with respect to the number of teak trees present in the ground truth data, yielded average values of 82.40%, thus achieving a reasonably low rate of false negatives or under-detection (low omission error). Finally, F1-score metric, which provides an overall performance of the tested model, showed an impressive average value of 87.91%.

These excellent model performance results are based on YOLOX-small's remarkable ability to efficiently learn and extract teak tree features from vertical RGB images taken by UAVs flying at high altitudes of up to 120 m above ground (i.e., operational conditions). In this sense, the trained model has proven to be a very efficient solution to address complex visual recognition challenges in very high-resolution RGB UAV images.

This approach could also be applied in the management and handling of other planted species that have great economic importance in Ecuador. In this regard, the research team is currently working on developing and training similar models to detect banana and balsa trees from drone images in large plantations in Ecuador. In this way, this UAV-based detection models could also be adapted to map individual trees in natural forest ecosystems such as the Ecuadorian Amazon, although the results would likely be inferior to those obtained in planted forests due to the loss of homogeneity related to the presence of several tree species of different ages and phenological stages, in addition to the lack of clear location patterns that are characteristic of commercial tree plantations.

#### REFERENCES

- [1] S. L. Mang and J. F. Brodie, "Impacts of non-oil tree plantations on biodiversity in Southeast Asia," *Biodivers Conserv*, vol. 24, no. 14, pp. 3431–3447, Dec. 2015, doi: 10.1007/S10531-015-1022-5/METRICS.
- [2] J. T. Hallett, J. Díaz-Calvo, J. Villa-Castillo, and M. R. Wagner, "Teak Plantations: Economic Bonanza or Environmental Disaster?," *J For*, vol. 109, no. 5, pp. 288–292, Jul. 2011, doi: 10.1093/JOF/109.5.288.
- [3] A. N. A. Pachas, S. Sakanphet, S. Midgley, and M. Dieters, "Teak (*Tectona grandis*) silviculture and research: applications for smallholders in Lao PDR," *Aust For*, vol. 82, no. sup1, pp. 94–105, May 2019, doi: 10.1080/00049158.2019.1610215.
- [4] A. Nölte, H. Meilby, and R. Yousefpour, "Multi-purpose forest management in the tropics: Incorporating values of carbon, biodiversity and timber in managing *Tectona grandis* (teak) plantations in Costa Rica," *For Ecol Manage*, vol. 422, pp. 345–357, Aug. 2018, doi: 10.1016/J.FORECO.2018.04.036.
- [5] J. A. Kershaw, M. J. Ducey, T. W. Beers, and B. Hush, *Forest mensuration*, 5th edit. Chichester: John Wiley & Sons, 2016.
- [6] A. Peñalver *et al.*, "Precisión y eficiencia del inventario de plantaciones de teca en Ecuador mediante escáner láser terrestre," *Madera y Bosques*, vol. 27(1), no. 1, p. e2712097, Jul. 2021, doi: 10.21829/MYB.2021.2712097.
- [7] J. A. Mora-Espinoza, A. Peñalver-Romeo, F. J. Aguilar-Torres, J. R. Rivas-Barzola, and Á. Triana-Tomalá, "Método de muestreo angular para el inventario de plantaciones forestales de teca (*Tectona grandis* L. f.)," *Revista Chapingo serie ciencias forestales y del ambiente*, vol. 26, no. 3, pp. 419–432, Dec. 2020, doi: 10.5154/R.RCHSCFA.2019.11.081.
- [8] D. dos Santos Vieira, M. L. Romarco de Oliveira, J. R. Vasconcelos Gama, E. L. Mendonça Machado, B. Lafetá Oliveira, and A. Simões Figueiredo, "Loirey height for vertical stratification of an Alluvial Ombrophilous Forest," *Bosque (Valdivia)*, vol. 41, no. 3, pp. 321–331, 2020, doi: 10.4067/S0717-92002020000300321.
- [9] F. J. Aguilar, A. Nemmaoui, M. A. Aguilar, and R. Jiménez-Lao, "Aleppo pine allometric modeling through integrating UAV image-based point clouds and ground-based data," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. V-3-2022, no. 3, pp. 353–360, May 2022, doi: 10.5194/ISPRS-ANNALS-V-3-2022-353-2022.
- [10] C. Torresan *et al.*, "Forestry applications of UAVs in Europe: a review," *Int J Remote Sens*, vol. 38, no. 8–10, 2017, doi: 10.1080/01431161.2016.1252477.

|                                                                                   |                                                                                                                                                               |                                                                          |
|-----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------|
|  | <p style="text-align: center;">AUTOMATED DETECTION AND GEOLOCATION OF TEAK TREES BASED<br/>ON DEEP LEARNING FROM VERY-HIGH-RESOLUTION RGB UAV<br/>IMAGERY</p> | <p style="text-align: center;">COMPUTER<br/>TECHNOLOGY  <br/>3304.14</p> |
| <p>RESEARCH ARTICLE</p>                                                           | <p style="text-align: center;">Fernando J. Aguilar, Alfredo Alcayde, Marcos E. Valverde, Abderrahim Nemmaoui, Manuel A. Aguilar</p>                           | <p>Digital computers</p>                                                 |

- [11] M. Onishi and T. Ise, "Explainable identification and mapping of trees using UAV RGB image and deep learning," *Scientific Reports* 2021 11:1, vol. 11, no. 1, pp. 1–15, Jan. 2021, doi: 10.1038/s41598-020-79653-9.
- [12] Ş. N. Topgöl, E. Sertel, S. Aksoy, C. Ünsalan, and J. E. S. Fransson, "VHRTrees: a new benchmark dataset for tree detection in satellite imagery and performance evaluation with YOLO-based models," *Frontiers in Forests and Global Change*, vol. 7, p. 1495544, Jan. 2024, doi: 10.3389/FFGC.2024.1495544/BIBTEX.
- [13] S. Cheng, Y. Zhu, and S. Wu, "Deep learning based efficient ship detection from drone-captured images for maritime surveillance," *Ocean Engineering*, vol. 285, p. 115440, Oct. 2023, doi: 10.1016/J.OCEANENG.2023.115440.
- [14] Z. Ge, S. Liu, F. Wang, Z. Li, and J. Sun, "YOLOX: Exceeding YOLO Series in 2021," *ArXiv*, vol. abs/2107.0, 2021, doi: <https://doi.org/10.48550/arXiv.2107.08430>.
- [15] J. Zhang, F. Lei, and X. Fan, "Parameter-Efficient Fine-Tuning for Individual Tree Crown Detection and Species Classification Using UAV-Acquired Imagery," *Remote Sensing* 2025, Vol. 17, Page 1272, vol. 17, no. 7, p. 1272, Apr. 2025, doi: 10.3390/RS17071272.
- [16] "Label Studio Documentation — Overview of Label Studio." Accessed: Oct. 06, 2025. [Online]. Available: [https://labelstud.io/guide/get\\_started](https://labelstud.io/guide/get_started)
- [17] X. Liu and M. Yang, "The Research of Small Object Detection based on YOLOX in UAV," in *2024 27th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, Tianjin, China: IEEE, 2024, pp. 507–512. doi: 10.1109/CSCWD61410.2024.10580555.
- [18] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature Pyramid Networks for Object Detection," *ArXiv*, no. 1612.03144v2, Dec. 2016, doi: <https://doi.org/10.48550/arXiv.1612.03144>.
- [19] C. Goutte and E. Gaussier, "A Probabilistic Interpretation of Precision, Recall and F-Score, with Implication for Evaluation," in *Advances in Information Retrieval*, D. E. Losada and J. M. Fernández-Luna, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 345–359. doi: [https://doi.org/10.1007/978-3-540-31865-1\\_25](https://doi.org/10.1007/978-3-540-31865-1_25).
- [20] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge: The MIT Press, 2016. Accessed: Oct. 06, 2025. [Online]. Available: <http://www.deeplearningbook.org>
- [21] T. Saito and M. Rehmsmeier, "The Precision-Recall Plot Is More Informative than the ROC Plot When Evaluating Binary Classifiers on Imbalanced Datasets," *PLoS One*, vol. 10, no. 3, p. e0118432, Mar. 2015, doi: 10.1371/JOURNAL.PONE.0118432.
- [22] W. Hua and Q. Chen, "A survey of small object detection based on deep learning in aerial images," *Artif Intell Rev*, vol. 58, no. 6, pp. 1–67, Jun. 2025, doi: 10.1007/S10462-025-11150-9/TABLES/5.
- [23] A. Tharwat, "Classification assessment methods," *Applied Computing and Informatics*, vol. 17, no. 1, pp. 168–192, Jan. 2018, doi: 10.1016/J.ACI.2018.08.003/FULL/PDF.
- [24] Z. Yang, X. Lan, and H. Wang, "Comparative Analysis of YOLO Series Algorithms for UAV-Based Highway Distress Inspection: Performance and Application Insights," *Sensors*, vol. 25(5), no. 1475, p. 1475, Feb. 2025, doi: 10.3390/S25051475.
- [25] F. J. Aguilar, J. R. Rivas, A. Nemmaoui, A. Peñalver, and M. A. Aguilar, "UAV-Based Digital Terrain Model Generation under Leaf-Off Conditions to Support Teak Plantations Inventories in Tropical Dry Forests. A Case of the Coastal Region of Ecuador," *Sensors*, vol. 19(8), no. 1934, p. 1934, Apr. 2019, doi: 10.3390/S19081934.
- [26] B. Neupane, T. Horanont, and N. D. Hung, "Deep learning based banana plant detection and counting using high-resolution red-green-blue (RGB) images collected from unmanned aerial vehicle (UAV)," *PLoS One*, vol. 14, no. 10, p. e0223906, Oct. 2019, doi: 10.1371/JOURNAL.PONE.0223906.
- [27] Y. Hajjaji, W. Bouhila, I. R. Farah, and A. Koubaa, "Enhancing palm precision agriculture: An approach based on deep learning and UAVs for efficient palm tree detection," *Ecol Inform*, vol. 85, no. 102952, Mar. 2025, doi: 10.1016/J.ECOINF.2024.102952.