

Identification of *Araucaria angustifolia* trees in an urban forest fragment using UAV images and YOLOv7 structure

Alan D'Oliveira Correa

Federal University of Paraná (UFPR)

Matheus Kopp Prandini

Federal University of Paraná (UFPR)

Vinicius Costa Cysneiros

Federal University of Santa Catarina - UFSC

Allan Libanio Pelissari

allanpelissari@gmail.com

Federal University of Paraná (UFPR)

Research Article

Keywords: YOLO, tree detection, unmanned aerial vehicles, endangered species, urban ecosystems

Posted Date: April 12th, 2024

DOI: <https://doi.org/10.21203/rs.3.rs-4224004/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

This study addresses the identification of individuals of the *Araucaria angustifolia* species in urban forest fragments, specifically in the Mixed Ombrophilous Forest (FOM) in Curitiba, Paraná, Brazil. The aim of the study is to use UAV images and the computer vision technique of the YOLOv7 model to detect individuals of *A. angustifolia*. The FOM is essential for local biodiversity conservation and human well-being but faces challenges due to urban sprawl and the conversion of land use to agriculture. The species is critically endangered, requiring actions and strategies for its conservation. The study highlights the role of Unmanned Aerial Vehicles (UAVs) and deep learning techniques, such as Convolutional Neural Networks (CNNs), in identifying tree species in urban ecosystems. YOLOv7, an architecture based on CNNs, was chosen because of its detection capacity. YOLOv7 is especially effective at detecting a wide variety of objects, including people, vehicles, animals, household objects, road signs and much more, making it an ideal choice for identifying tree species in urban environments. The data was obtained by a DJI Mavic 3 UAV. Utilizing a UAV, the study area of the urban forest was flown over, generating an orthomosaic that was subsequently divided into 14 parts for training, validation, and testing. The YOLOv7 model was trained with the images to detect *A. angustifolia* trees present in the area. The results show that model achieved a precision of 79.3%, recall of 86.8%, and Mean Average Precision of 87% during training. Comparative analysis with forest inventory data reveals promising performance in detecting *A. angustifolia* trees. The average confidence of the model's classification was $76.18 \pm 12.88\%$, with 80.81% being the most frequent classification for the median result. The present study uses the effective integration of UAV technology, YOLOv7 model with deep learning technique to detect and assess tree species in urban ecosystems. This approach provides an important tool for conservation strategies aimed at assessing and managing the tree biodiversity in urban forest remnants.

1. Introduction

Urban forest fragments are remnants of native forests that have been altered by real estate expansion and human activities (HADDAD et al., 2015). These remnants represent vestiges of the original vegetation and play a crucial role in preserving local biodiversity, constituting the remnants of the native vegetation cover that once dominated the landscape (LINDENMAYER; FISCHER, 2013). The existence of these fragments offers the opportunity to understand how nature can adapt and coexist in urbanized environments, as well as highlighting the importance of conserving these locals for the well-being of communities and environmental sustainability (MULLANEY; LUCKE; TRUEMAN, 2015).

The Mixed Ombrophilous Forest (FOM), also known as the Araucaria Forest, is one of the main formations of the Atlantic Forest biome that has been heavily impacted throughout the 20th century (DE DEUS MEDEIROS, 2005). This forest occupied extensive areas of the plateaus in southern Brazil, representing approximately 200.000 km², 40% of which is located in the state of Paraná (MAACK, 1949; KLEIN, 1960). *Araucaria angustifolia* (Bertol.) Kuntze, popularly known as araucaria, is the dominant tree species in the upper stratum of the FOM and can reach over 30 m in height (SCHEEREN et al., 1999; CHASSOT et al., 2011; FEDRIZZI, 2018).

However, over the last century, *A. angustifolia* has been extensively exploited due to the quality of its wood for construction and its high cellulose content, which is widely used in papermaking (EIRA et al., 1994). It is estimated that between 1930 and 1990, around 100 million *A. angustifolia* trees were logged (BRASIL, 2005). In the state of Paraná, Southern Brazil, an inventory revealed that primary or untouched Araucaria Forests do not exist, with only 0.8% (66,109 hectares) of forested areas in an advanced stage of succession remaining, which are of significant environmental and scientific importance (CASTELLA; BRITZ, 2004). These factors led to the inclusion of *A. angustifolia* on the list of endangered species by the International Union for Conservation of Nature and Natural Resources – IUCN, where it is classified as critically endangered (FARJON, 2006). The species is also on the Official List of Endangered Species of Brazilian Flora (BRASIL, 2008).

Therefore, the accurate diagnosis and continuous monitoring of *A. angustifolia* in forest remnants are crucial for environmental preservation. With technological advances, Unmanned Aerial Vehicles (UAVs), or drones, have increasingly become versatile and accessible tools for research in this field, enabling the mapping and monitoring of trees and forests (SAAD et al., 2021; ECKE et al., 2022; CUNHA NETO et al., 2023). Additionally, computer vision techniques used to analyze images from remote sensors, particularly those based on deep learning, more specifically Convolutional Neural Networks (CNNs), have shown their potential in recognizing tree species in forest regions (KNAUER et al., 2019; SANTOS et al., 2019). These techniques involve applying machine learning models capable of extracting characteristics from images and classifying objects, such as trees, according to their species (ALBUQUERQUE et al., 2022; WAGNER et al., 2022). Such techniques offer the advantage of processing images in real-time and with high precision, outperforming traditional methods based on manual or statistical analysis.

The YOLO (You Only Look Once) is an example of computer vision techniques based on deep learning, which uses a CNN to segment images into smaller regions and estimate bounding boxes, as well as the probabilities of the presence of objects in these boxes and their specific identification (REDMON et al., 2016). YOLO has demonstrated an ability to detect a wide variety of objects in images and video frames, while maintaining a high level of accuracy (REDMON et al., 2016).

Several researchers have applied these techniques to: crown detection and measurement (WU et al., 2020; SUN et al., 2022; CHEN, 2023); tree species classification (KNAUER et al., 2019; SANTOS et al., 2019; WANG et al., 2019; HAMRAZ et al., 2019; CAO; ZHENG; FANG, 2023); tree counting (HANI et al., 2023; PUTRA; WIJAYANTO, 2023); and identification of tree diseases (JEMAA et al., 2023; MAMALIS et al., 2023; WU et al., 2023). These studies represent a wide range of applications and indicate the versatility and usefulness of these techniques for various purposes, contributing to improvement of monitoring and conservation practices in forest ecosystems.

In summary, FOM remnants in urban ecosystems face significant conservation challenges, in which computer vision techniques, such as CNNs and YOLO, are emerging as tools to identify and monitor tree species, contributing to the assessment and management of forest remnants. The integration of Unmanned Aerial Vehicle (UAV) technology with the YOLOv7 identification method presents an innovative approach to conservation, offering promising prospects for protecting biodiversity and promoting environmental sustainability (DÍAZ-DELGADO; MÜCHER, 2019; ZHAO; ZHU, 2023; MOU et al., 2024). In this context, the main aim of this work was to obtain high-resolution images of a FOM in urban forest using a UAV to detect individuals of *A. angustifolia* with the YOLOv7 computer model. This research provides an integration of technological advances with an application that can contribute to broader preservation efforts and the formulation of public plans to guarantee the maintenance of urban forests.

2 Material and methods

2.1 Study area

This study was carried out in a remnant of Mixed Ombrophilous Forest (FOM) located on the urban limits of the municipality of Curitiba, state of Paraná, Brazil, with approximate coordinates of 25°26'50" - 25°27'33" S and 49°14'16" - 49°14'33" O and an altitude of 900 masl. The total area is estimated at 15.24 hectares, of which 12.96 hectares correspond to Montane Mixed Ombrophilous Forest, while 2.28 hectares are occupied by early succession vegetation, with a predominance of bamboos (*Merostachys* spp.). Figure 1 shows the location of the study area.

The local climate is classified as Cfb according to the Köppen classification, with humid subtropical mesothermal, characterized by cool summers, winters with frequent frosts and no dry season. The average annual temperatures during the hot and cold months are below 22°C and 18°C, respectively, with an average annual temperature of 17°C. As for relative humidity and average annual rainfall, values of approximately 85% and 1,300 to 1,500 mm are recorded,

respectively, with a water index ranging from 60 to 100 mm, with no occurrence of water deficiency throughout the year (MAACK, 1981).

Figure 1 – Localization of the study area

2.2 Data collection

The data were collected through aerial images captured using a DJI Mavic 3 UAV, which has the following technical specifications: speed of up to 21 m/s, image resolution of 20 MP, FOV (Field Of View) lenses of 84° (equivalent to 24 mm) f/2.8 to f/11, generating images of 5280 x 3956 pixels, with a weight of 899 g (including battery and propellers) and focus accuracy of 1 meter vertically and horizontally, respectively. The UAV's remote control operates on the 5.725-5.850 GHz frequencies.

The UAV images consist of bands from the visible electromagnetic spectrum, operating in the RGB (Red, Blue, and Green) system for color composition. Data collection was carried out in favorable weather conditions, with a flight close to midday, to minimize shadows due to the solar angle.

Processing was carried out using OpenDroneMap software (WebODM) to generate georeferenced orthomosaics. The orthomosaics were then divided into smaller sections using QGIS software version 3.18, as shown in Figure 2. The cut in orthomosaic was necessary due to its size, since the platform used later to identify the individuals has limitations regarding the number of pixels for processing. The size for the polygons was therefore determined to be approximately 100 m x 100 m. Another approach adopted in the study was to avoid cutting out the treetops, to prevent them from being separated into distinct polygons. Thus, the polygons were adjusted to encircle them, minimizing potential issues in subsequent analysis steps.

Figure 2 – Splitting the orthomosaic into smaller sections in QGIS for processing in Roboflow

The images were processed to train the YOLOv7 model using the Roboflow platform (DWYER et al., 2022), which offers resources for creating customized computer vision models. In the platform, training of the model was conducted, which included the creation of bounding boxes for the identification of *A. angustifolia* individuals using the YOLOv7 model, as well as the assignment of labels to specific categories.

The training and test of the YOLOv7 model used to detect the trees was carried out using Roboflow Train's AutoML (Automated Machine Learning) tool. This AutoML tool enabled not only the efficient training of the model, but also its implementation for the detection of *A. angustifolia* trees (personalized object) in the dataset.

To train the YOLOv7 model in Google Collaboratory, the essential packages were installed, including Roboflow. Roboflow data was accessed and imported from the platform for analysis. The YOLOv7 method was used to identify the images, and the results were stored in spreadsheets for later analysis. This procedure involved setting up the environment, integrating with Roboflow and applying the YOLOv7 model, ensuring the effectiveness of the identification process.

2.3 Model training

We trained the model on the Roboflow platform after loading the images obtained during the field survey. A total of 3,261 araucaria labels for training the model were made referring to the trees present in 300 images, selected from the 848 images covering the mapped area. The labels were distributed as follows: 2,252 for the training set, 687 for validation and 322 for the test set, as illustrated in Figure 3. The model was trained on approximately 160 epochs. Epochs are the The epochs refer to a complete pass of the training data through the YOLOv7 model.

The Box Loss indicates how well the YOLOv7 model can locate the center and bounding box of the *A. angustifolia* in the classification process. Class Loss indicates the classification accuracy of the YOLOv7 model in predicting the classes of araucarias. Object Loss indicates the probability of *A. angustifolia* being in a proposed region of interest.

In addition, the YOLOv7 model's precision, recall, mAP50, and mAP50-95 performance metrics are presented, which are the most important metrics for evaluating the model's performance (Figure 7). The Box Loss, Class Loss, and Object Loss curves showed a similar tendency the training stage, indicating efficient convergence of the model. The curves are expected to decline until they reach a stagnation point (CASAS et al., 2023).

During the pre-processing, we transformed the images to reduce training time. At this stage, we applied the following parameters: automatic orientation of the images in different directions and resizing to 640 x 640 pixels. Automatic orientation disregards the EXIF (Exchangeable Image File Format) data of the images, providing a consistent view regardless of the original orientation determined by the EXIF data. This EXIF data usually indicates the orientation of a specific image. As for resizing, this process adjusts the dimensions of the images while maintaining the proportionality of the annotations. Although this results in square and slightly distorted images, it is important to note that data from the original image were not lost during this procedure.

In the next step, we increased the number of images to improve the model's performance. This was achieved by applying 90° and 180° anticlockwise and clockwise rotations to the existing images. This approach has the potential to improve the model's ability to generalize, resulting in more effective performance when confronted with previously unseen images. During this process, the increments are sequentially chained together with randomization in the settings and values for each setting being applied to each expanded image. Any duplicates identified during this procedure are filtered out of the final version created. In this way, the number of images in the model went from 300 to 659, representing a significant improvement in the model's performance. Figure 3 details the labeling, training, validation, and testing procedure.

Figure 3 – YOLOv7 model labeling, training, validation and testing procedure

2.4 Image georeferencing

After classifying the orthomosaics using the YOLOv7 model, the classification results were generated in the form of bounding boxes. These bounding boxes are polygons that surround the *A. angustifolia* trees identified by the YOLOv7 model, without a coordinate system. To deal this situation, the pixels from image were converted to UTM coordinates using the georeferenced orthomosaic. To perform this transformation, the bounding boxes coordinates were converted into geospatial coordinates (UTM) through conversion operations using the osgeo library (MIARA, 2019) in Python.

2.5 Description of field data and comparison with the model

The database used for comparison with the classification data from the YOLOv7 model comes from a forest inventory carried out in 2021, containing information on 12,836 individuals, 342 of which represent *A. angustifolia*. In turn, specific filtering was carried out for this species, allowing the coordinates of the respective trees to be extracted. These coordinates can be associated with the coordinates of the centroid of the bounding boxes obtained from classifying the images with the *A. angustifolia* individuals identified in the forest inventory.

Since the UAV aerial survey captured images exclusively of the upper canopy of the forest, trees in the lower stratum were not sampled. As a result, the number of individuals detected in the training was lower than that recorded in the

inventory. To adjust for this discrepancy, a Python command was implemented to integrate the inventory data with the geoprocessing data, considering the shortest distance between the coordinates of both sets.

2.6 Model performance metrics

The model performance metrics used and provided by the Roboflow platform were precision, recall, mAP (Mean Average Precision), confusion matrix, and F1 score. The definitions of each of the metrics used are presented below. We also present some additional metrics specific to the YOLOv7 model provided by Roboflow, such as Box Loss, Class Loss, and Object Loss.

mAP can be described as a metric that evaluates the performance of object detection models. The mAP encompasses precision and recall in a single measure, providing a comprehensive view of the model's effectiveness. The annotations mAP50 and mAP50-95 indicate the confidence intervals associated with the metric. mAP50 refers to the average precision considering only detections with a minimum 50% overlap between the predicted bounding box and the reference bounding box. The mAP50-95 expands this analysis to overlap intervals of 50% to 95%.

Accuracy is a metric that assesses the quality of the positive predictions made by a classification model. It is calculated as the ratio between the number of true positives (PV) and the sum of true positives and false positives (FP). Accuracy measures the proportion of instances classified as positive by the model that are positive. A high precision indicates that the model is effective in avoiding misclassification of negative instances as positive. Precision is given by Equation 1.

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \quad (1)$$

Recall is a metric that assesses the model's ability to correctly capture all positive instances. It is calculated as the ratio between the number of true positives (PV) and the sum of true positives and false negatives (FN). Recall measures the proportion of positive instances that were correctly identified by the model in relation to the total number of positive instances in the dataset. A high recall indicates that the model can identify most positive instances. The recall is given by Equation 2.

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)} \quad (2)$$

Both metrics are important, but they can be contradictory to each other. Increasing precision often reduces recall and the other way around. Therefore, when evaluating the performance of a model, it is crucial to consider both metrics. The confusion matrix (Figure 4) provides four crucial pieces of information about the classifier's performance. True Positive (TP) occurs when an image is correctly assigned to its corresponding class. False Positive (FP) occurs when an image is wrongly identified as containing something that is not actually present in the image. True Negative (TN) represents an image correctly identified as not belonging to a particular class. Finally, the False Negative (FN) refers to an image wrongly classified as not belonging to a specific class, when in fact it does belong to that class. However, in the case of object detection, it is not taken into account. Based on the confusion matrix, it is possible to derive essential information for calculating precision and recall.

Figure 4 – Confusion matrix of the YOLOv7 model

The F1 score is a metric that combines the precision and recall measures into a single value, providing a balanced view of the performance of a classification model. It is particularly useful in situations where it is important to consider both false positives and false negatives. F1 ranges from 0 to 1. A score of 1 indicates the best possible performance, indicating an ideal balance between precision and recall. The F1 score is given by Equation 3.

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

The methodological procedure is illustrated in Figure 5, covering everything from obtaining the real data to evaluating the model's performance. This includes flying the UAV, processing the orthomosaics, training the YOLOv7 model and analyzing the performance metrics.

Figure 5 – Flowchart of the work methodology

3. Results

3.1 Model Performance

The training process ended at around 160 epochs. As can be seen in Figure 6, the mAP did not improve from epoch 60 onwards. Training the YOLOv7 model required approximately 24 hours to complete. During the training stage, the model achieved precision of 79.3%, recall of 86.8%, and mAP of 87%. These metrics provide information on the model's performance in detecting araucarias in the images.

Figure 6 – Performance of the YOLOv7 model in relation to the mAP metric during the training periods

Figure 7 illustrates the results of different performance curves for the YOLOv7 model in identifying *A. angustifolia* in the training and validation stages. With a mAP of 87%, the model showed a low rate of false negatives and false positives, indicating precision and recall in its predictions. This score suggests that the model has a robust ability to correctly identify objects of interest, minimizing cases of non-detection and incorrect detection (KUZNETSOVA, 2021; SHI, 2021).

Figure 7 – YOLOv7 model performance curves during the training and validation stages

Figure 8 shows a scatter plot representing the F1 scores for each image in the YOLOv7 model. Each point in the plot corresponds to an image from the test and validation of the model, with semantically similar images (similar characteristics) grouped close together. The coloring of the dots reflects the F1 scores associated with each image. When analyzing the F1 scores, it was observed that around 91.01% of the images achieved a score above 60%, while only 8.99% were below this value. The average F1 score was 77.16%.

This metric provides a clear understanding of the relative performance of the images, highlighting those that showed significant agreement between the true labels and the model's predictions. In addition, this metric makes it easier to identify specific patterns or characteristics that can influence the model's performance on various types of images. This analysis offers valuable insights for improving the effectiveness of the YOLOv7 model in other locations for detecting *A. angustifolia*.

Figure 8 – F1 score of YOLOv7 model for detecting *A. angustifolia*

The minimum deviation refers to the difference between the center point of the bounding box generated by the YOLOv7 model and the actual coordinate identified in the *A. angustifolia* forest inventory. The largest minimum error found was

around 5 m between the actual point and the one estimated by the YOLOv7 model. On average, the error was 1.86 ± 1.18 m. The data obtained from the forest inventory also reveals the crown area (m^2) and the diameter at breast height (DBH, cm).

The graphical representation of the crown area, as well as the descriptive statistics (Figure 9), is shown in Figure 10. The average crown area was $205.52 \pm 69.64 \text{ m}^2$, in a range from 52.81 m^2 to 427.36 m^2 . The APC is presented in a range of colors in Figure 10-A. The average APC of the *A. angustifolia* was $65.20 \pm 11.42 \text{ cm}$, ranging from 34.47 cm to 102.81 cm.

Figure 9 – Descriptive statistics for minimum error, crown area and DBH

The final comparison between the trees of *A. angustifolia* identified in the forest inventory and those classified by the YOLOv7 model is shown in Figure 10. The red dots indicate the actual position of the trees. The squares in Figure 10-A indicate the actual position of the trees with variation in crown size. By comparison, the circles indicate the araucaria identification by the YOLOv7 model, including the variation in crown size.

Figure 10-B shows in color the classification confidence of the YOLOv7 model for identifying the *A. angustifolia* trees. The result obtained from the classification indicates a predominance of confidence, as can be seen in most classifications in red. The average classification confidence of the YOLOv7 model was $76.18 \pm 12.88\%$, with 80.81% being the typical classification for the median.

The classification of the YOLOv7 model proved satisfactory for identifying *A. angustifolia* individuals in an urban forest. The generalization of the model can contribute to public management for conservation and monitoring of endangered species), and their sustainable management (SÜHS; GIEHL; PERONI, 2018; ORELLANA et al., 2021; FINGER et al., 2023).

Against this backdrop, this work significantly expands the applications of computer vision, especially in the context of YOLO, by identifying a tree of critical importance, the species *A. angustifolia*, which appears on lists of endangered species. The approach adopted, inspired by the advances and insights provided by previous studies, stands out as a valuable contribution to the preservation and monitoring of endangered species.

4. Discussion

Our study builds upon the advancements in computer vision techniques, particularly the utilization of YOLOv7, to detect and monitor tree species, with a specific focus on *Araucaria angustifolia* in an urban forest environment. The performance of our model was evaluated using various metrics, demonstrating its effectiveness and reliability in identifying target trees in urban ecosystems

Comparing our results to previous studies employing YOLO for tree species detection, we observed comparable or superior performance. Prasvita et al. (2023) achieved mAP50 and mAP95 values of 85.1% and 45.7%, respectively, in detecting oil palm trees using YOLOv5. In contrast, our model achieved a mAP of 87%, indicating similar levels of accuracy. Similarly, Singh et al. (2023) achieved an F1 score of 81% in detecting cassava stems with YOLOv4, whereas our model achieved an F1 score of 87%. These comparisons highlight the robustness and effectiveness of our approach in identifying tree species.

Furthermore, our analysis of F1 scores revealed that 91.01% of the images achieved a score above 60%, with an average F1 score of 77.16%. This suggests strong agreement between true labels and predicted results for most images, indicating the reliability of our model.

In addition to localization accuracy, our model exhibited satisfactory performance in terms of minimum deviation, with an average error of 1.86 ± 1.18 m between predicted and actual coordinates of the trees. This level of accuracy is crucial for applications requiring precise spatial information, such as forest inventory and management.

Moreover, our study contributes to the growing body of research demonstrating the potential of computer vision techniques in ecological monitoring and conservation efforts. By providing accurate and efficient methods for identifying endangered tree species like *Araucaria angustifolia*, our approach holds promise for enhancing biodiversity conservation and promoting sustainable forest management practices.

Our findings align with those of previous studies that have utilized YOLO for tree species detection. Jemaa et al. (2023) achieved an F1 of 86.24% for detecting apple trees and an overall accuracy of 97.52% for assessing tree health. Similarly, Abeyrathna et al. (2023) obtained mAP50 values of 84%, 86%, 90.5%, and 77.5% for different YOLO algorithms in counting apples. These results collectively underscore the versatility and applicability of YOLO in tree detection tasks across diverse ecological settings.

In summary, our study demonstrates the efficacy of YOLOv7 in identifying *Araucaria angustifolia* trees in an urban forest environment. The robust performance of our model, as evidenced by various metrics, highlights its potential for supporting ecological research, conservation initiatives, and sustainable forest management practices.

Figure 10 – YOLOv7 model classification for *A. angustifolia* trees in the urban forest located in Curitiba, Paraná, Brazil

5. Conclusion

Trees identification in urban forest fragments, particularly *Araucaria angustifolia*, represent a significant challenge to environment management. The scarcity of resources, the time required in the field and the need for trained personnel stand out as major obstacles. However, the importance of accurately identifying *A. angustifolia* for conservation is undeniable, especially considering the threat of extinction hanging over the remnants of the species, which are limited to restricted areas. In this context, the application of advanced computer vision and machine learning techniques, exemplified by the YOLOv7 model, is emerging as a promising solution. These tools not only have the potential to reduce the operational costs associated with identifying species in urban forest fragments, but can also increase the efficiency of the process, providing reliable results within a short timeframe.

The focus of this study involved a novel approach to identifying *A. angustifolia* in an urban forest fragment. The use of aerial images obtained by drone to capture high-resolution georeferenced data, along with the combined utilization of the YOLOv7 model and the Roboflow training platform, proved effective by simplifying the process and eliminating the need for complex pre-processing.

When comparing the results obtained with the data from the forest inventory, there was remarkable consistency in the identification of *A. angustifolia*. Even though some trees recorded in the inventory were in lower forest strata, the YOLOv7 model proved its ability to detect them effectively. It is therefore concluded that the application of advanced technologies, such as aerial images and deep learning, represents a powerful tool not only for assessing and preserving *A. angustifolia*, but also for making a significant contribution to the identification and conservation of other species in urban forests.

Declarations

Conflict of interest statement

All authors have no conflicts of interest.

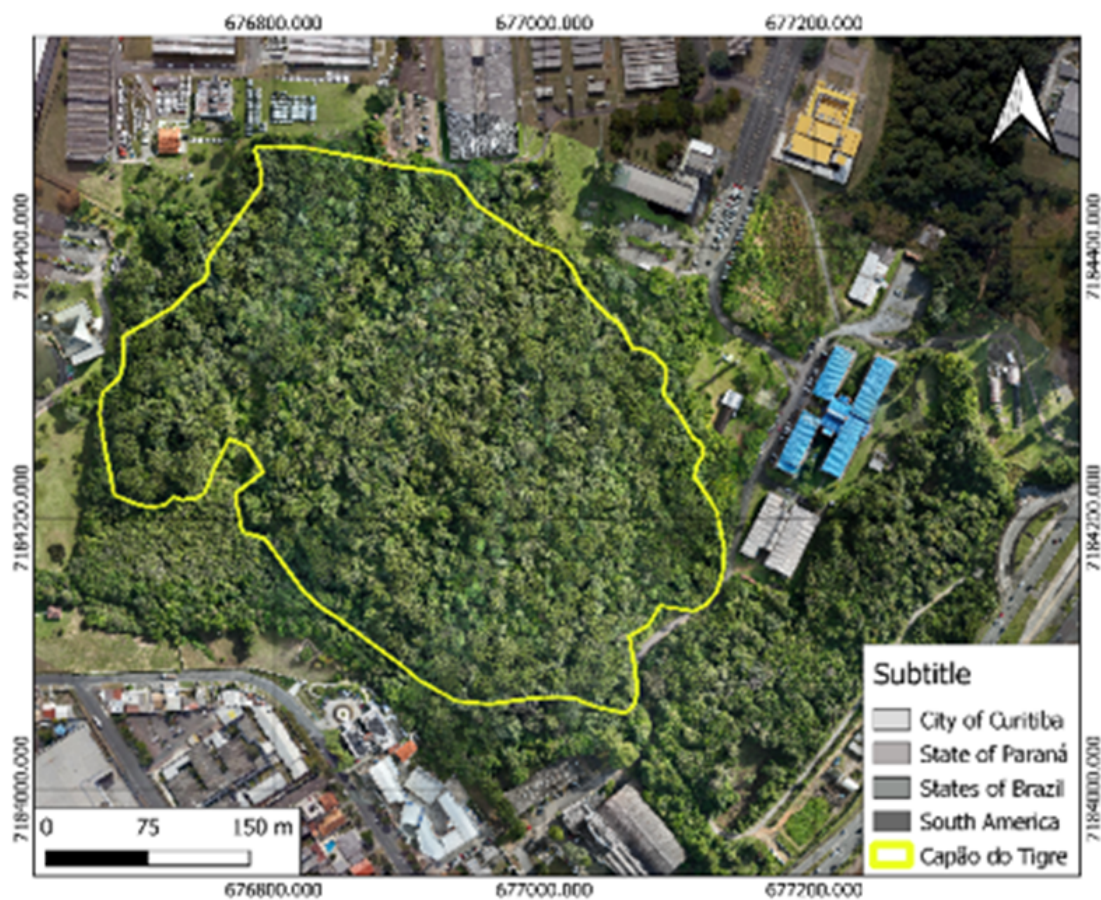
References

1. ABEYRATHNA, RM Rasika D. et al. Recognition and Counting of Apples in a Dynamic State Using a 3D Camera and Deep Learning Algorithms for Robotic Harvesting Systems. *Sensors*, v. 23, n. 8, p. 3810, 2023.
2. ALBUQUERQUE, Rafael Walter et al. Mapping key indicators of forest restoration in the amazon using a low-cost drone and artificial intelligence. *Remote Sensing*, v. 14, n. 4, p. 830, 2022.
3. BARBIZAN SÜHS, Rafael; HETTWER GIEHL, Eduardo Luis; PERONI, Nivaldo. Interaction of land management and araucaria trees in the maintenance of landscape diversity in the highlands of southern Brazil. *Plos one*, v. 13, n. 11, p. e0206805, 2018.
4. BRASIL. Ministério do Meio Ambiente. Instrução Normativa N. 148, de 07 de junho de 2022. Lista Oficial das Espécies da Flora Brasileira Ameaçadas de Extinção, 2008. Disponível em: <https://www.icmbio.gov.br/cepsul/images/stories/legislacao/Portaria/2020/P_mma_148_2022_altera_anexos_P_mma_443_444_445_2014_atualiza_especies_ameacadas_extincao.pdf>. Acesso em: 13 de setembro de 2023.
5. BRASIL. Ministério do Meio Ambiente. Proteção e recuperação da Floresta com Araucárias: Governo propõe novas áreas protegidas para Paraná e Santa Catarina, DF, 2005. Disponível em: <<https://www.gov.br/mma/pt-br/noticias/governo-propoe-novas-areas-protégidas-para-parana-e-santa-catarina>>. Acesso em: 15 setembro de 2023.
6. CAO, Lianjun; ZHENG, Xinyu; FANG, Luming. The Semantic Segmentation of Standing Tree Images Based on the Yolo V7 Deep Learning Algorithm. *Electronics*, v. 12, n. 4, p. 929, 2023.
7. CASAS, G. G. et al. Automatic detection and counting of stacked eucalypt timber using the yolov8 model. *Forests*, MDPI AG, v. 14, n. 12, p. 2369, dez. 2023. ISSN 1999-4907.
8. CASTELLA, P. R.; BRITZ, R. M.; MIKICH, S. B. Áreas prioritárias de Floresta com Araucária para conservação no estado do Paraná. In: Curitiba, Anais do IV Congresso Brasileiro de Unidades de Conservação. 2004. p. 1677-1486.
9. CHASSOT, Tatiane et al. Modelos de crescimento em diâmetro de árvores individuais de *Araucaria angustifolia* (Bertol.) Kuntze em Floresta Ombrófila Mista. *Ciência Florestal*, v. 21, p. 303-313, 2011.
10. CHEN, Youliang et al. An object detection method for bayberry trees based on an improved YOLO algorithm. *International Journal of Digital Earth*, v. 16, n. 1, p. 781-805, 2023.
11. CUNHA NETO, ERNANDES M. DA et al. Combining ALS and UAV to derive the height of *Araucaria angustifolia* in the Brazilian Atlantic Rain Forest. *Anais da Academia Brasileira de Ciências*, v. 95, n. 1, p. e20201503, 2023.
12. DE DEUS MEDEIROS, João; SAVI, Maurício; DE BRITO, Bernardo Ferreira Alves. Seleção de áreas para criação de Unidades de Conservação na Floresta Ombrófila Mista. *Biotemas*, v. 18, n. 2, p. 33-50, 2005.
13. DÍAZ-DELGADO, Ricardo; MÜCHER, Sander (Ed.). *Drones for Biodiversity Conservation and Ecological Monitoring*. MDPI, 2019.
14. DWYER, B. et al. Roboflow (Version 1.0) [Software].
15. ECKE, Simon et al. UAV-based forest health monitoring: A systematic review. *Remote Sensing*, v. 14, n. 13, p. 3205, 2022.
16. EIRA, M. T. S. et al. Efeito do teor de água sobre a germinação de sementes de *Araucaria angustifolia* (Bert.) O. Ktze.-Araucariaceae. *Revista brasileira de sementes*, v. 16, n. 1, p. 71-75, 1994.
17. FARJON, A. 2006. *Araucaria angustifolia*. In: IUCN – International Union for Conservation of Nature and Natural Resources, 2011. IUCN red list of threatened species. Disponível em: <<https://www.iucnredlist.org/es/species/32975/2829141>>. Acesso em: 13 de setembro de 2023.
18. FEDRIZZI, Joice Cristina. Análise da chuva polínica no Parque Nacional das Araucárias–Santa Catarina, Brasil. 2018.

19. FINGER, César Augusto Guimarães et al. Simulating Sustainable Forest Management Practices Using Crown Attributes: Insights for *Araucaria angustifolia* Trees in Southern Brazil. *Forests*, v. 14, n. 7, p. 1285, 2023.
20. HADDAD, Nick M. et al. Fragmentação do habitat e seu impacto duradouro nos ecossistemas da Terra. *A ciência avança*, v. 1, n. 2, pág. e1500052, 2015.
21. HAMRAZ, Hamid et al. Deep learning for conifer/deciduous classification of airborne LiDAR 3D point clouds representing individual trees. *ISPRS Journal of Photogrammetry and Remote Sensing*, v. 158, p. 219-230, 2019.
22. HANI, E. Um et al. Automatic Tree Counting from Satellite Imagery Using YOLO V5, SSD and UNET Models: A case study of a campus in Islamabad, Pakistan. In: 2023 3rd International Conference on Artificial Intelligence (ICAI). IEEE, 2023. p. 88-94.
23. JEMAA, Hela et al. UAV-Based Computer Vision System for Orchard Apple Tree Detection and Health Assessment. *Remote Sensing*, v. 15, n. 14, p. 3558, 2023.
24. KLEIN, Roberto M. O aspecto dinâmico do pinheiro brasileiro. *Sellowia*, v. 12, n. 12, p. 17-44, 1960.
25. KNAUER, Uwe et al. Tree species classification based on hybrid ensembles of a convolutional neural network (CNN) and random forest classifiers. *Remote Sensing*, v. 11, n. 23, p. 2788, 2019.
26. KUZNETSOVA, Anna A. Statistical Precision-Recall Curves for Object Detection Algorithms Performance Measurement. *Cyber-Physical Systems: Modelling and Intelligent Control*, p. 335-348, 2021.
27. LINDENMAYER, David B.; FISCHER, Joern. Habitat fragmentation and landscape change: an ecological and conservation synthesis. Island Press, 2013.
28. MAACK, Reinhard. Geografia física do Estado do Paraná. (No Title), 1981.
29. MAACK, Reinhard. Notas complementares a apresentação preliminar do mapa fitogeográfico do Estado do Paraná (Brasil). *Arquivos do Museu Paranaense*, v. 7, p. 351-361, 1949.
30. MAMALIS, Marios et al. Deep Learning for Detecting Verticillium Fungus in Olive Trees: Using YOLO in UAV Imagery. *Algorithms*, v. 16, n. 7, p. 343, 2023.
31. MIARA, I. A dummy placeholder for the gdal package. 2019.
32. MOU, Chao et al. A novel efficient wildlife detecting method with lightweight deployment on UAVs based on YOLOv7. *IET Image Processing*, 2024.
33. MULLANEY, Jennifer; LUCKE, Terry; TRUEMAN, Stephen J. A review of benefits and challenges in growing street trees in paved urban environments. *Landscape and urban planning*, v. 134, p. 157-166, 2015.
34. ORELLANA, Enrique et al. Predicting the dynamics of a native *Araucaria* forest using a distance-independent individual tree-growth model. *Forest Ecosystems*, v. 3, n. 1, p. 1-11, 2016.
35. PRASVITA, Desta Sandya; ARYMURTHY, Anjani Murni; CHAHYATI, Dina. Deep Learning Model for Automatic Detection of Oil Palm Trees in Indonesia with YOLO-V5. In: Proceedings of the 8th International Conference on Sustainable Information Engineering and Technology. 2023. p. 39-44.
36. PUTRA, Yoga Cahya; WIJAYANTO, Arie Wahyu. Automatic detection and counting of oil palm trees using remote sensing and object-based deep learning. *Remote Sensing Applications: Society and Environment*, v. 29, p. 100914, 2023.
37. REDMON, Joseph et al. You only look once: Unified, real-time object detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2016. p. 779-788.
38. SAAD, Felipe et al. Detectability of the Critically Endangered *Araucaria Angustifolia* Tree Using Worldview-2 Images, Google Earth Engine and UAV-LiDAR. **Land**, v. 10, n. 12, p. 1316, 2021.
39. SANTOS, Anderson Aparecido dos et al. Assessment of CNN-based methods for individual tree detection on images captured by RGB cameras attached to UAVs. *Sensors*, v. 19, n. 16, p. 3595, 2019.

40. SCHEEREN, Luciano Weber et al. Crescimento em altura de *Araucaria angustifolia* (Bert.) O. Ktze. Em três sítios naturais, na região de Canela-RS. *Ciência Florestal*, v. 9, p. 23-40, 1999.
41. SHI, Zihong. Object detection models and research directions. In: 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE). IEEE, 2021. p. 546-550.
42. ZHAO, LiangLiang; ZHU, MinLing. MS-YOLOv7: YOLOv7 Based on Multi-Scale for Object Detection on UAV Aerial Photography. *Drones*, v. 7, n. 3, p. 188, 2023.
43. WAGNER, Fabien H. et al. Regional mapping and spatial distribution analysis of canopy palms in an amazon forest using deep learning and VHR images. *Remote Sensing*, v. 12, n. 14, p. 2225, 2020.
44. WANG, Jiamin et al. Individual rubber tree segmentation based on ground-based LiDAR data and faster R-CNN of deep learning. *Forests*, v. 10, n. 9, p. 793, 2019.
45. WU, Kunjie et al. An improved YOLO model for detecting trees suffering from pine wilt disease at different stages of infection. *Remote Sensing Letters*, v. 14, n. 2, p. 114-123, 2023.
46. WU, Jintao et al. Extracting apple tree crown information from remote imagery using deep learning. *Computers and electronics in agriculture*, v. 174, p. 105504, 2020.

Figures



Flat Coordinate System, UTM Projection Zone 22 S, SIRGAS2000 Datum.
 Source: territorial boundaries (IBGE, 2021)
 Date: 01/26/2024

Figure 1

Localization of the study area

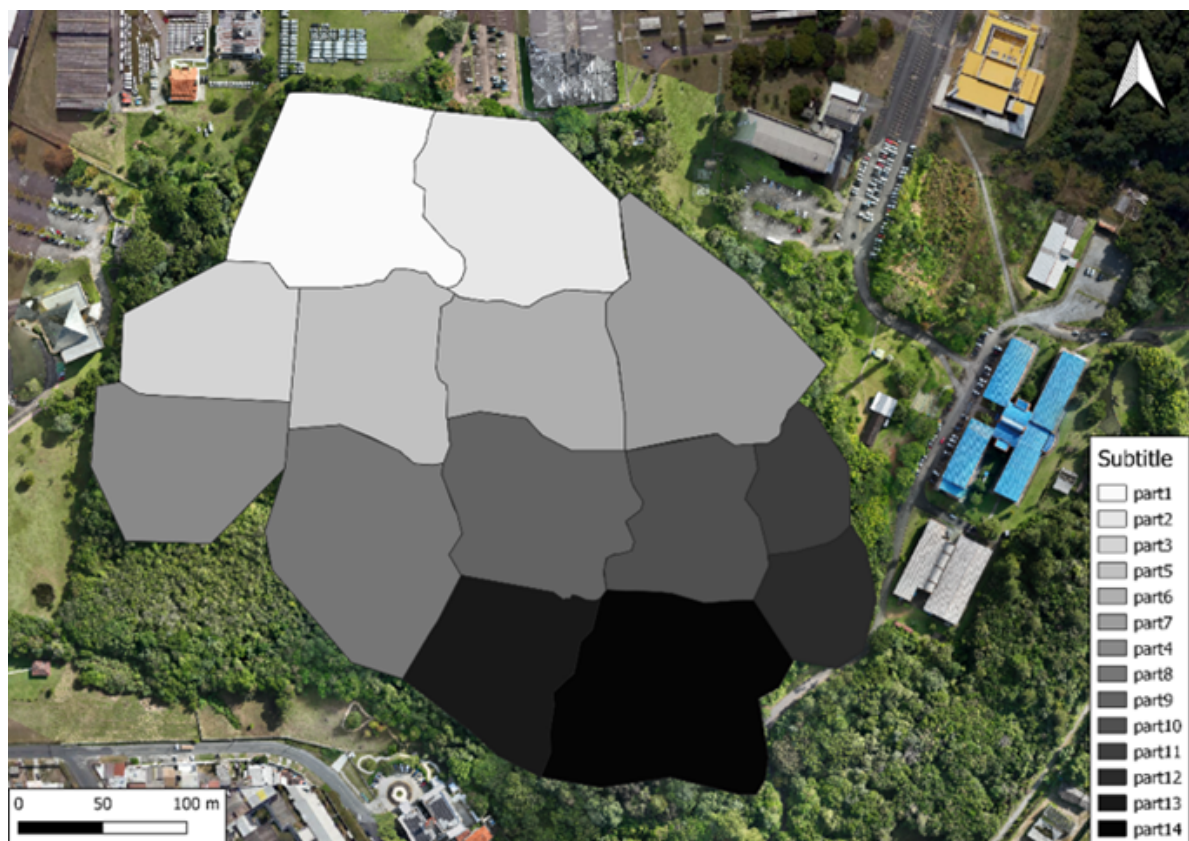


Figure 2

Splitting the orthomosaic into smaller sections in QGIS for processing in Roboflow

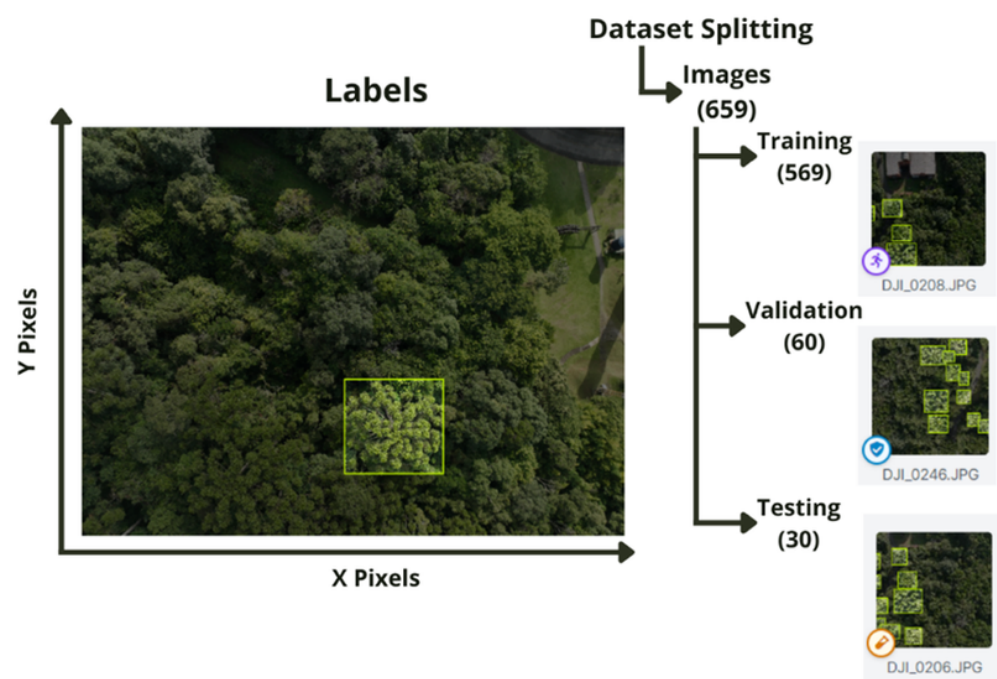


Figure 3

Page 14/18

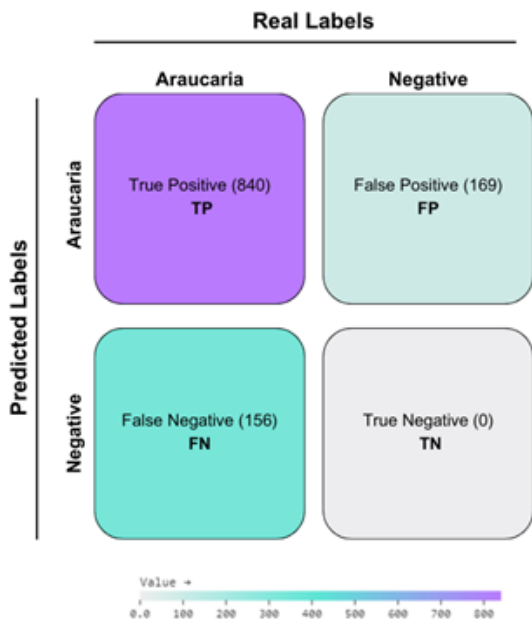


Figure 4

Confusion matrix of the YOLOv7 model

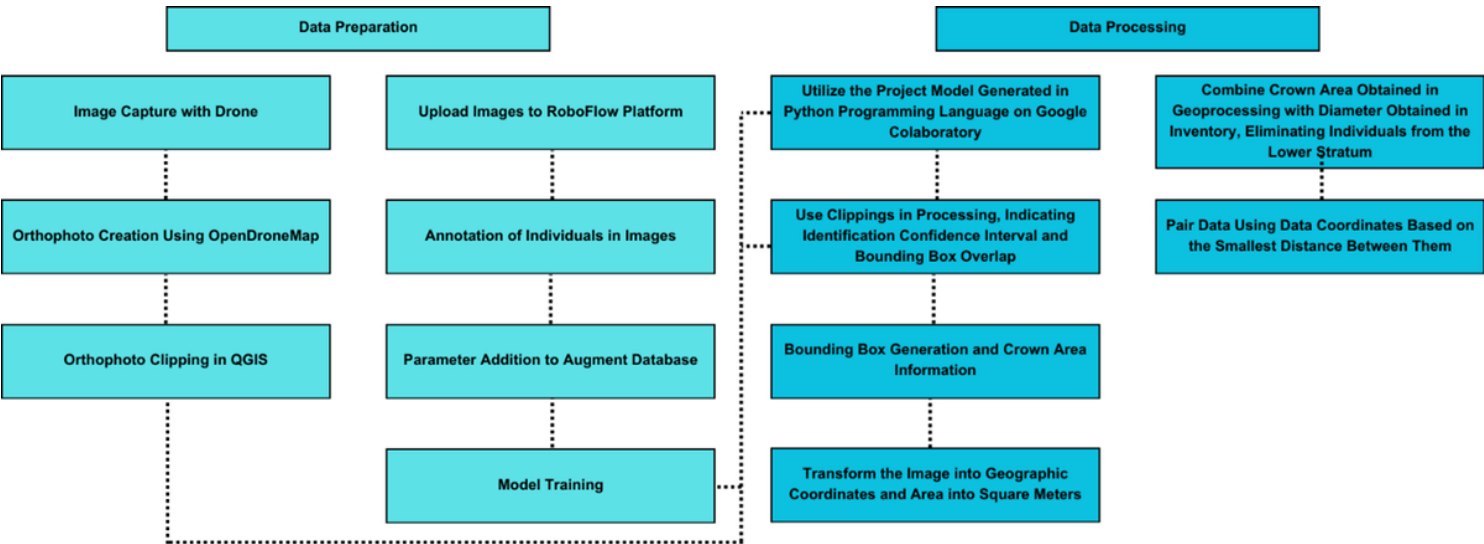


Figure 5

Flowchart of the work methodology

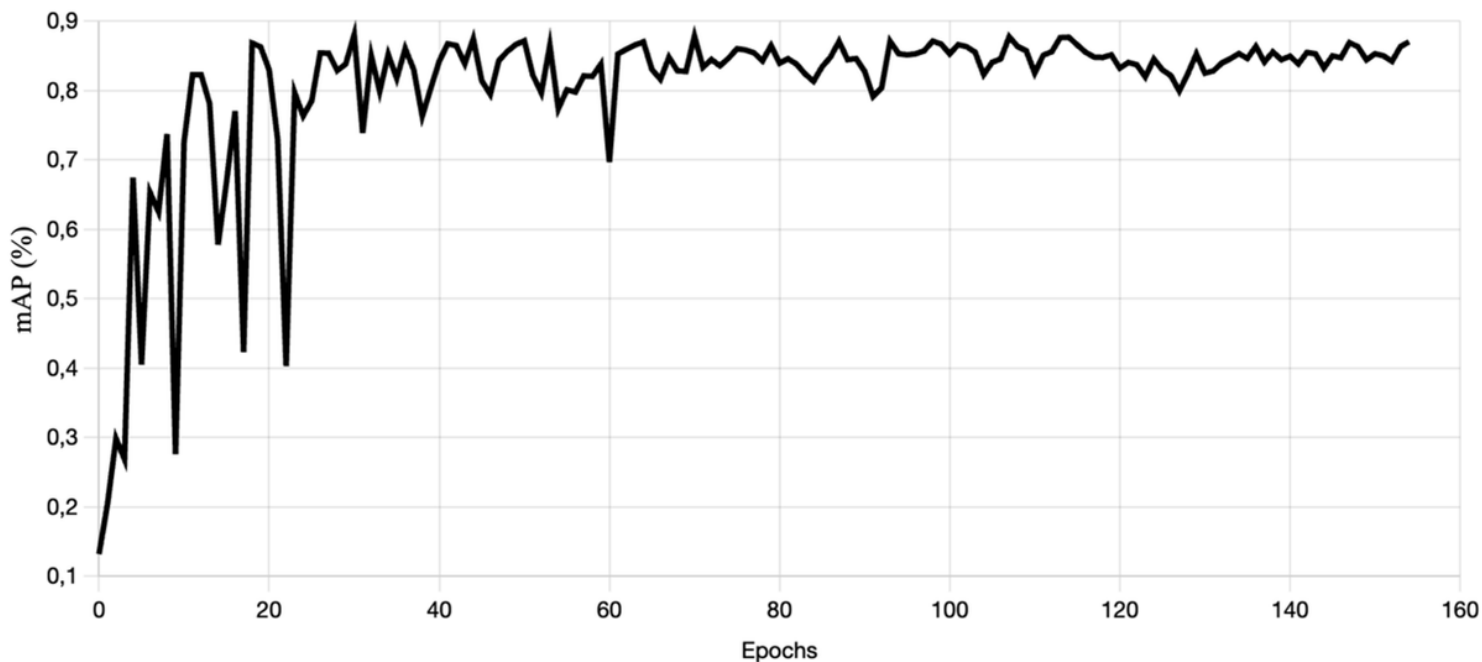


Figure 6

Performance of the YOLOv7 model in relation to the mAP metric during the training periods

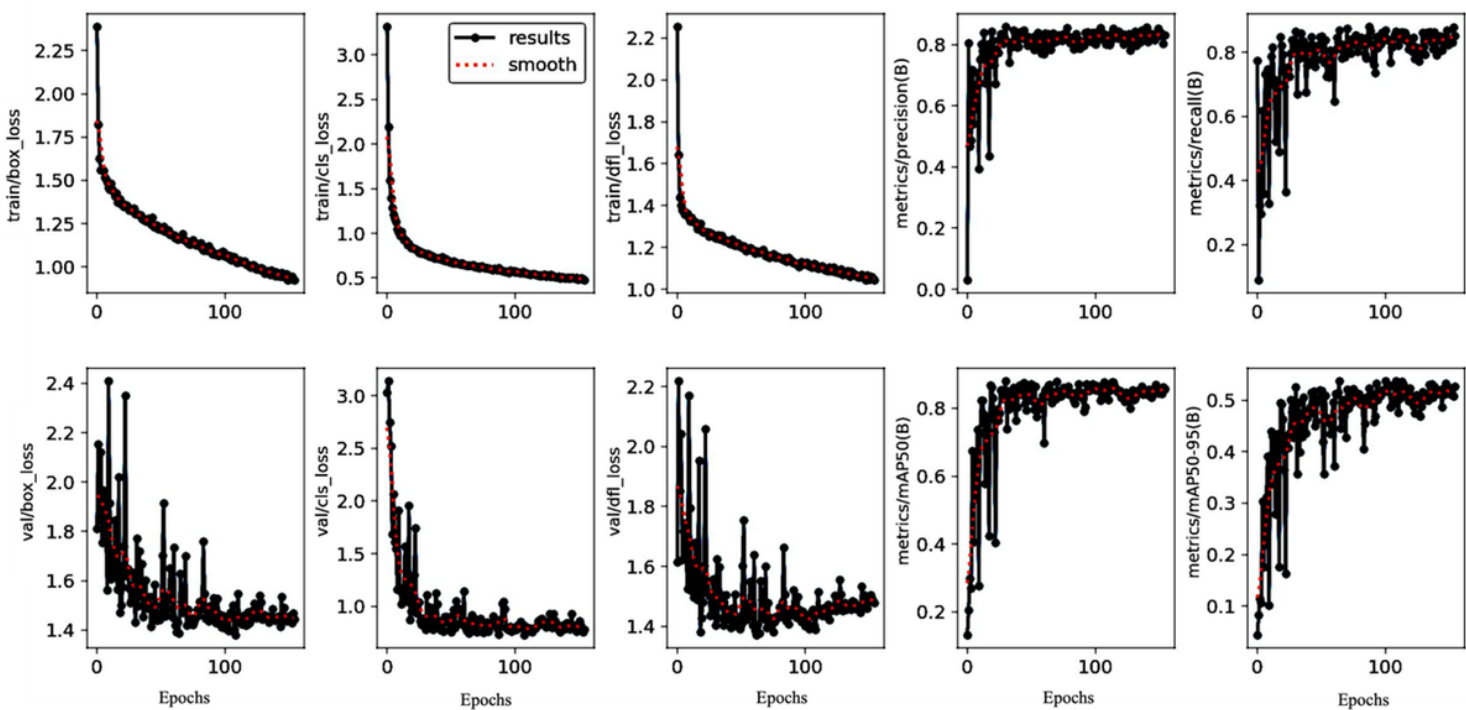


Figure 7

YOLOv7 model performance curves during the training and validation stages

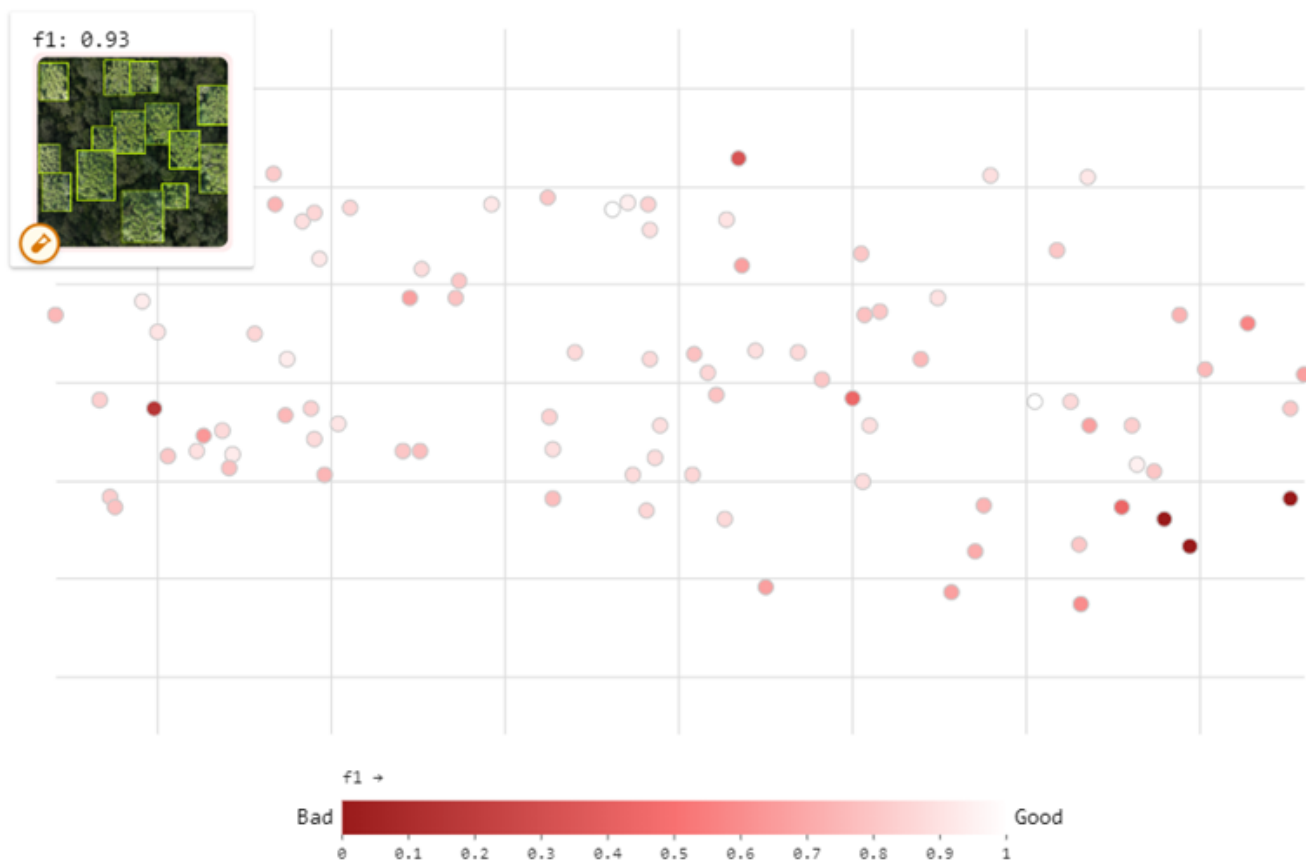


Figure 8

F1 score of YOLOv7 model for detecting *A. angustifolia*

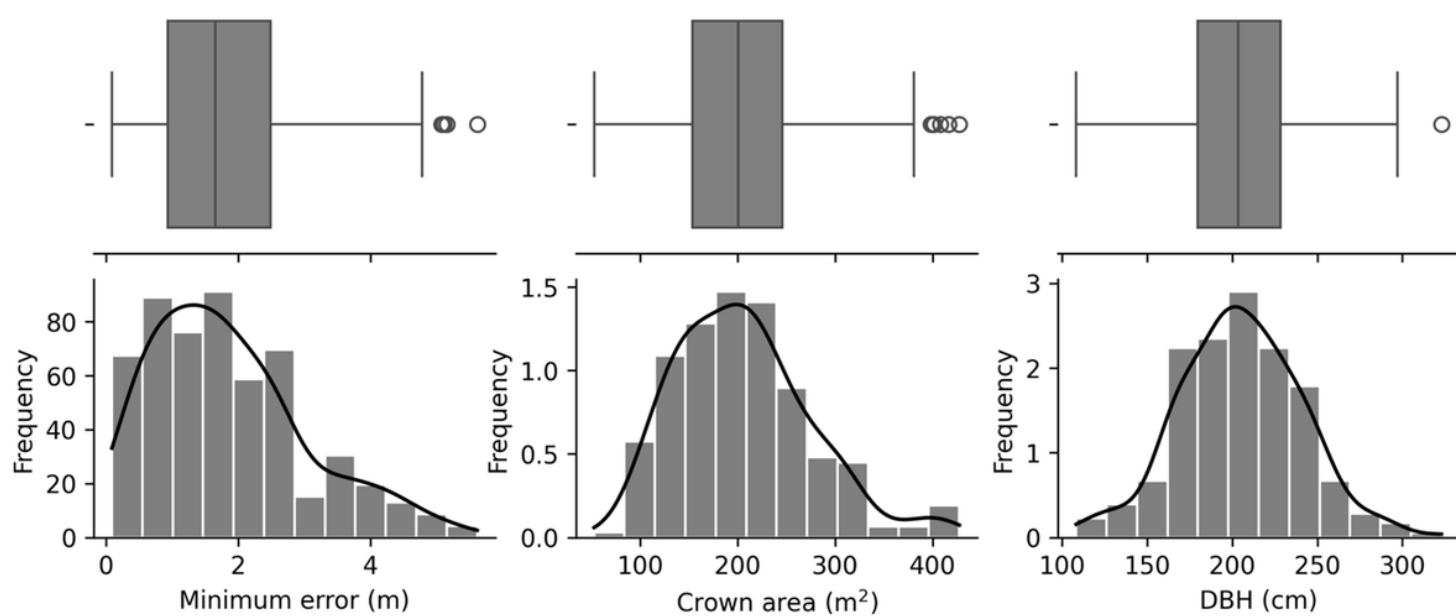


Figure 9

Descriptive statistics for minimum error, crown area and DBH

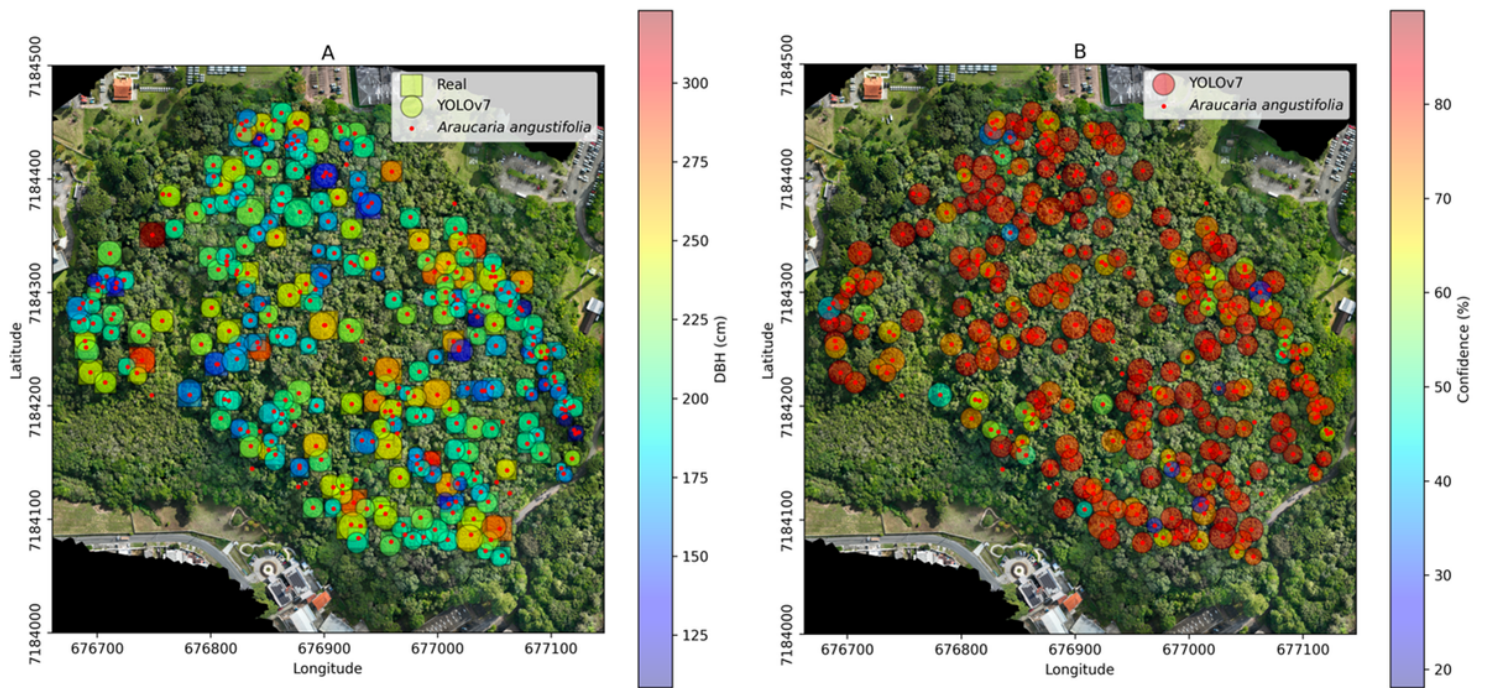


Figure 10

YOLOv7 model classification for *A. angustifolia* trees in the urban forest located in Curitiba, Paraná, Brazil