First Insights into Brazilian Pine Detection in Open Fields Using YOLOv11 and UAV Data

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Abstract

Araucaria angustifolia (Bertol.) Kuntze, an iconic and endemic species of the Mixed Ombrophilous Forest, plays a key ecological and economic role within the Atlantic Rainforest. However, it is currently threatened by historical overexploitation and its sensitivity to climate change. This study examines the application of deep learning for the automated detection of A. angustifolia individuals in high-resolution imagery collected by Unmanned Aerial Vehicle (UAV) at selected sites in Santa Catarina, Brazil. The YOLOv11x model, a state-of-the-art convolutional neural network (CNN) architecture, was trained using two distinct datasets: a heterogeneous set and a more homogeneous one, the latter evaluated with K-Fold cross-validation. Results showed that model performance improved with increased data uniformity, with average precision (AP) rising from 21% to 27% and the F1-score from 54% to 61%. While detection accuracy remains below optimal levels, the findings highlight the model's potential for species identification. Enhancements in annotation quality, dataset diversity, and hyperparameter optimization are recommended to improve performance further and support more robust monitoring and conservation efforts for A. angustifolia.

1. Introduction

The Mixed Ombrophilous Forest, also known as Araucaria or Brazilian Pine, is part of the Atlantic Forest biome, which is considered a global conservation hotspot (Myers et al., 2000). This forest is characterized by the endemic species Araucaria angustifolia (Bertol.) Kuntze, which has suffered various anthropogenic disturbances over the years, including extensive logging in the 1950s (Saad et al., 2021).

The *A. angustifolia* is a perennial coniferous tree, with an average height ranging from 10 to 35 meters and a diameter at breast height (DBH) between 50 and 120 centimeters. At full maturity, it can reach heights of up to 50 meters and diameters of 250 cm at breast height (DBH) (Carvalho, 2003). Before the colonization of Brazil, it covered large, continuous areas in the Southern Region, extending into the states of São Paulo, Minas Gerais, Rio de Janeiro, and Espírito Santo. Today, however, it is restricted to small, isolated patches, mainly in the colder and higher regions of these states (Wendling and Zanette, 2017).

A candelabra-shaped crown characterizes the species and is highly valued due to the strength and durability of its wood. Its edible seed, the pine nut (pinhão), represents an important economic resource for local communities (Saad et al., 2021). It is estimated that in the state of Santa Catarina alone, around ten thousand rural families rely on the pinhão as part of their income (EPAGRI, 2025). However, due to decades of exploitation, the *A. angustifolia* is now considered threatened with extinction (BRASIL, 2022).

Understanding the spatial distribution of trees and stands is crucial for the effective conservation of biodiversity and the development of strategies for climate change adaptation (Mu et al., 2025; Sertel and Topgul, 2025). The detection and classification of individual trees in forested areas represent an important field of study for achieving more detailed mapping of forest environments, which can significantly contribute to sustainable development and forest conservation (Abreu-Dias et al., 2025).

The study by Cysneiros et al. (2024) brought new insights into the Brazilian subtropical Atlantic Forest, highlighting the central role of the araucaria in the dynamics of these forests. The authors demonstrated that this species has a more significant impact on stand structure than species diversity itself, contributing positively to increases in carbon stock. As a key factor in this process, the araucaria proves essential in addressing global climate change. Thus, conservation plans must go beyond biodiversity protection and incorporate strategies that promote carbon sequestration, recognizing the araucaria as one of the main drivers of these stocks.

However, other studies suggest that the species is sensitive to climate change. Simulations of its distribution under increasing average temperature scenarios indicate a reduction of up to 30% in its potential distribution area compared to the current range (Bernardinis et al., 2023; Schlickmann et al., 2020).

Therefore, detailed mapping of the *A. angustifolia's* occurrence areas is necessary to develop management plans aimed at its conservation and regeneration.

In recent decades, remote sensing techniques have emerged as an effective and reliable means of forest monitoring, utilizing high-resolution imagery obtained from Unmanned Aerial Vehicle (UAV).

Alongside the use of high-resolution imagery for tree detection, artificial intelligence techniques such as machine learning (ML) and deep learning (DL) have gained popularity. Deep learning methods, particularly those utilizing convolutional neural networks (CNNs), have been widely applied in recent years across various fields to solve complex problems, such as image classification, semantic segmentation, and object detection (Li et al., 2024).

For object detection, CNN-based methods such as You Only Look Once (YOLO) have become increasingly popular. YOLO is an end-to-end object detection framework that formulates detection as a unified regression task (He et al., 2025). YOLOv11 is one of the latest models developed by the Ultralytics team. Designed as a highly efficient, accurate, and robust detection system, YOLOv11 demonstrates exceptional performance in handling complex environments, dynamic scenes, and small object detection tasks (He et al., 2025).

This study aimed to use YOLOv11 for the detection of *A. angustifolia* in UAV imagery collected from field sites within the Mixed Ombrophilous Forest formation in the state of Santa Catarina.

2. Materials and Methods

2.1 Data acquisition

The images used for training, validation, and testing of the model were obtained through aerial surveys conducted on different days and in different municpalities, namely: Lages, Santa Cecília, Orleans, Grão-Pará, Bom Retiro, Frei Rogério, Monte Carlo, and Fraiburgo—all located in the state of Santa Catarina, Brazil (Figure 1). All sites were rural environments, predominantly consisting of open fields and forest fragments. The UAV used was the DJI Phantom 4 Pro V2 model, and the flight altitude was 120 meters.
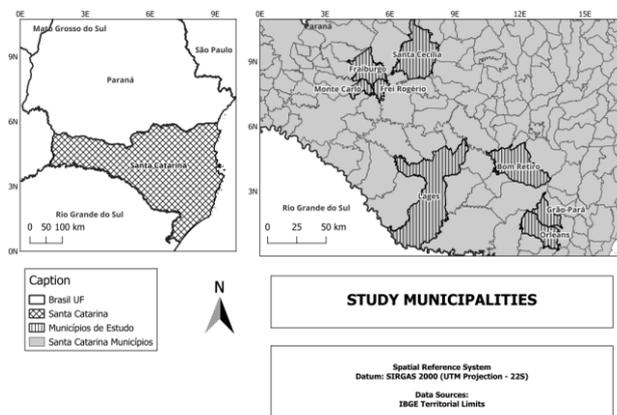

Figure 1. Study area location within Southern Brazil context.

2.2 Data Labeling

Objects to be detected by YOLO must be labeled, with each label represented by a bounding box and the object class. For this purpose, the MakeSense platform (MakeSense AI, 2025) was used, where each *A. angustifolia* tree was individually outlined with a bounding box (Figure 2). In each image, all visible trees, whether isolated or grouped with others of the same species in open field landscapes, were labeled. At the same time, those located within dense forest fragments were disregarded.

Figure 2. Labeling of Araucaria Angustifolia with bounding box

In this study, individuals of *A. angustifolia* located in forest remnants were excluded from the training dataset to reduce the complexity of the model's learning process at this initial stage. Forest remnants are characterized by higher tree density, greater species diversity, and the presence of multiple vertical strata, including overlapping canopies, intense shading, and dense vegetation, all of which hinder the precise delineation of individual crowns. These conditions also demand substantially more manual effort during the annotation process, increasing the risk of errors and inconsistencies.

2.3 Model training

The object detection model YOLOv11x (Khanam and Hussain, 2024) was used, which is pre-trained on the benchmark COCO dataset (Lin et al., 2014). This pre-training helps the model converge more quickly and perform better on smaller datasets. For standardization, the images were resized to 640 × 640 pixels. The configuration settings used for training the model are shown in Table 1.

Settings	Value
learning rate	0.002
Flipud	0.5
Fliplr	0.5
hsv_h	0.015
hsv_s	0.7
hsv_v	0.4
Scale	0.75
Degrees	15
Shear	0.2
Perspective	0.0001
Translate	0.1
Mosaic	1.0
Mixup	0.2

Table 1. Parameters of the selected model.

Data augmentation techniques were applied to improve the variability of the training data. The values used were based on parameters recommended for models of the YOLO family, with

slight adjustments to color settings (hsv_h, hsv_s, hsv_v) to simulate natural variations in lighting. Horizontal (fliplr = 0.5) and vertical (flipud = 0.5) flipping were applied to increase the positional variability of tree crowns, simulating different flight orientations and camera perspectives. Geometric transformations (degrees, shear, perspective, scale, and translation) contributed to a greater diversity of crown shapes and angles, making the model less sensitive to natural variations or visual noise. The mosaic technique was applied at maximum intensity (mosaic = 1.0), promoting the combination of four distinct images into a single composition, which simulates varied groupings and increases contextual diversity. The parameter mixup = 0.2 was used to partially combine images and labels, reducing the risk of overfitting.

Training was conducted on a Linux machine equipped with two NVIDIA GeForce RTX 4090 GPUs, each with 24 GB of GDDR6X memory (NVIDIA Corporation, Santa Clara, CA, USA). The operating system used was Ubuntu 22.04.5 LTS (Jammy Jellyfish) (Canonical Ltd., London, UK) (64-bit). Processing was performed using a 13th Gen Intel® Core™ i9-13900KF processor (Intel Corporation, Santa Clara, CA, USA).

2.4 Experiment 1

To better evaluate the performance of YOLOv11 for *A. angustifolia* detection, two experiments were conducted. The first consisted of applying the model to a dataset containing 891 images and 10,473 labeled *A. angustifolia* individuals. The dataset was split into 70% for training, 20% for validation, and 10% for testing. The model was trained for 104 epochs with a batch size of 32.

2.5 Experiment 2

In the second experiment, a smaller dataset from a single aerial survey conducted in the city of Lages, SC, was used. This set consisted of 210 images with 3,154 labeled *A. angustifolia* trees. The objective was to reduce image variability, as a single flight provides images with consistent lighting and landscape patterns. The K-fold validation technique was applied, in which the dataset is divided into training and validation subsets, ensuring that all images are used in both stages. The data were split into five folds (k=5), with 80% for training and 20% for validation. A batch size of 8 was used, and each fold had a different number of epochs, ranging from 79 to 186.

2.6 Metrics

To evaluate the model's performance in each experiment, we used Precision, Recall, F1-score, and Average Precision (AP), calculated considering only detections with a confidence threshold of ≥ 0.5. Precision (1) is the proportion of detected objects that are correct. Recall (2) represents the proportion of objects present in th e image that were detected. The F1-Score (3) reflects the model's generalization capability. Average Precision (AP) represents the area under the Precision-Recall curve, expressing the balance between these metrics across different confidence thresholds.

$$Precision = \frac{TP}{TP + FP} \qquad (1)$$

$$Recall = \frac{TP}{TP + FN} \qquad (2)$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (3)$$

where:

TP (True Positive): the number of objects correctly classified as positive by the model.

FP (False Positive): the number of objects incorrectly classified as positive by the model.

FN (False Negative): the number of positive objects that were not detected by the model.

3. Results

The results of the two experiments using YOLOv11x are presented in Figure 3. It can be observed that the results are not yet ideal, but the model showed potential for detecting *A. angustifolia*, as the second experiment demonstrated a performance improvement.
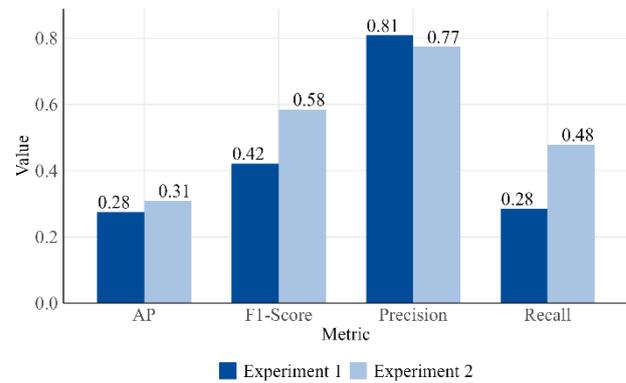

Figure 3. Accuracy metrics of the experiments.

Experiment 2, conducted with images of homogeneous characteristics from a single aerial survey in Lages, SC, showed superior results in all evaluated metrics compared to Experiment 1, which used a larger and more heterogeneous dataset. The F1-Score increased from 42% to 58%, and the AP rose from 28% to 31%.

In Figure 4, an example of the model's behavior in Experiment 1 is shown. In (A), the bounding box is generated in blue, with a confidence score of 37%, incorrectly labeling another tree as an *A. angustifolia*, constituting a false positive. In (B), two situations are demonstrated: an Araucaria correctly identified by the model with 62% confidence, indicated by the blue bounding box (true positive), and highlighted in red, an *A. angustifolia* that the model failed to detect (false negative).
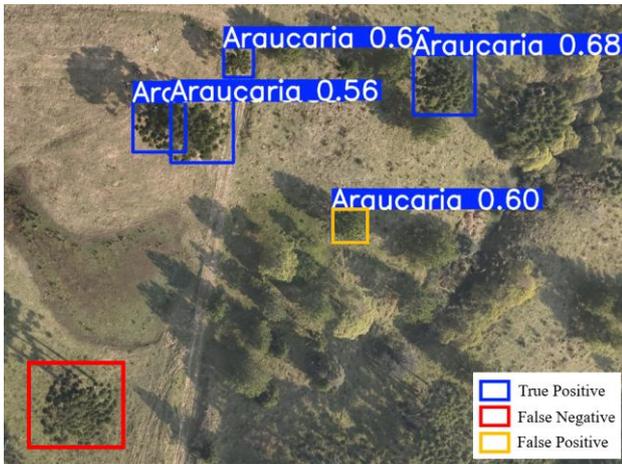
Figure 4. Results of the detection, where TP in blue, one FN in red and FN in orange.

In both experiments, Precision was higher than Recall. In Experiment 1, the model correctly identified 55% of the detected objects but failed to identify about 47% of the *A. angustifolia* trees present in the images (Recall = 53%). In Experiment 2, Precision was 64%, while Recall reached 59%.

4. Discussion

The increase in metrics observed in Experiment 2 compared to Experiment 1 indicates that homogeneity in the dataset can contribute to more efficient model learning (Huang et al., 2024), as the visual pattern of the images seems to have facilitated the identification of *A. angustifolia*. This is also evidenced by the AP results, since this metric integrates model performance over multiple confidence thresholds (He et al., 2025), showing a positive response with more homogeneous data. However, it is essential to emphasize the importance of incorporating heterogeneous data into training for enhanced model applicability across diverse natural scenarios (Thapa et al., 2025).

Another factor that may have contributed to the model's improvement was the use of the K-Fold validation technique in Experiment 2. By involving all images in both training and validation, the model was exposed to a more representative variety of visual patterns. The variation in the number of epochs among the folds also demonstrates the influence of data composition on results. The study by Karasinski et al. (2025), which applied YOLOv7x for *A. angustifolia* detection in urban environments combined with K-Fold validation, reports that this methodology was fundamental to ensuring robustness and reliability of model results, showing good performance and generalization capacity in detecting *A. angustifolia* across different urban contexts.

The F1-Score is a critical metric for evaluating model performance in classification tasks. It represents the harmonic mean of precision and recall, providing a balanced measure of both. When precision and recall values are similar, the F1 score is high, whereas significant discrepancies between the two lead to lower scores. The score ranges from 0 to 1, with values closer to 1 reflecting superior precision and consistency in classification (He et al., 2025). In our study, F1-Score values ranged from 0.42 to 0.58. Similar results were found by Xu et al. (2023) when using YOLOv7 for individual tree detection. The authors associate the model's limitation in detecting certain tree species with complex environments resulting from high canopy density or unclear morphological features due to the image background.

The Precision and Recall results demonstrate that the model is more cautious when issuing a detection, resulting in more omission errors (false negatives) than commission errors (false positives). Therefore, the model tends to identify *A. angustifolia* trees when recognized correctly but fails to detect their totality, which may be related to areas of higher complexity (Chen et al., 2023; Sun et al., 2025), such as shadows, the presence of shrubs, or overlapping *A. angustifolia* trees. These locations pose visual challenges for detection, due to reduced contrast between the *A. angustifolia* crown and the background, or the presence of morphologically similar elements. Low-contrast environments make objects of interest more susceptible to variations in illumination and environmental noise, often leading to a noticeable decline in detection accuracy (Chen et al., 2025). Additionally, in areas with clustered *A. angustifolia* individuals, clearly delineating individual crowns becomes difficult, contributing to omission errors.

Another factor that contributed to omission errors was the size of *A. angustifolia* crowns, as smaller crowns were more likely to be omitted (Figure 5). Smaller crowns may be associated with younger plants or trees suppressed by canopy competition, indicating that the model tends to underestimate the natural regeneration of the species.
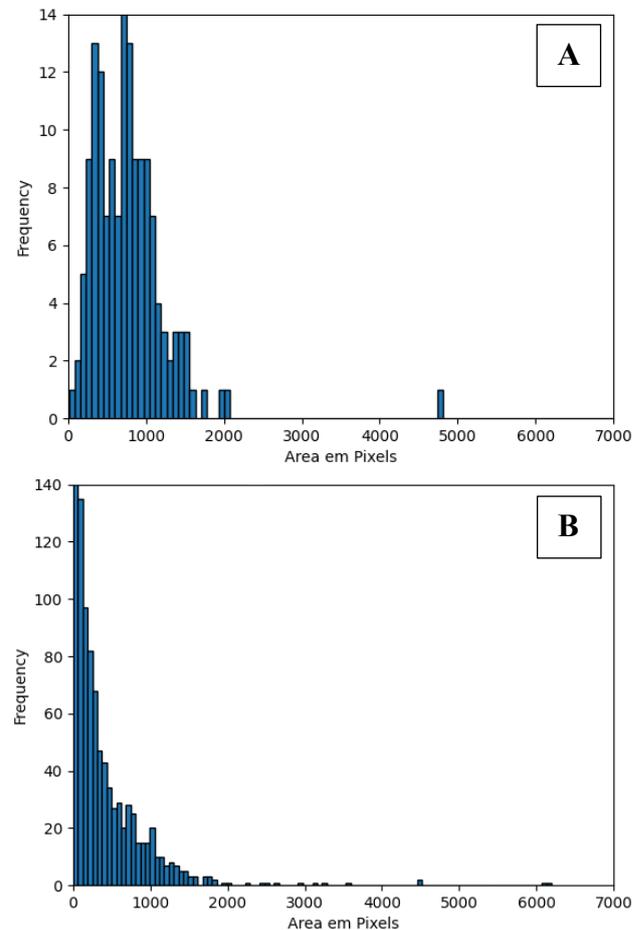

Figure 5. Histogram of the number of omissions by *A. angustifolia* crown size in pixels for Experiment 1 (A) and Experiment 2 (B).

In Experiment 1, omission errors decreased as crown size increased. Experiment 2 also revealed a relationship between crown size and omission errors, which were higher for smaller

crowns but concentrated mainly in crowns up to approximately 1000 pixels.

Previous studies suggest that the attention mechanism present in some versions of YOLO, including v11, performs better in scenarios with a low incidence of small objects, whereas images containing a large number of such objects may overload the attention mechanism (Chen et al., 2025; Tariq and Javed, 2025).

In Figure 6, it is possible to observe that many of the omitted individuals had smaller canopies, were spatially close to others, or were partially confused with the image background.
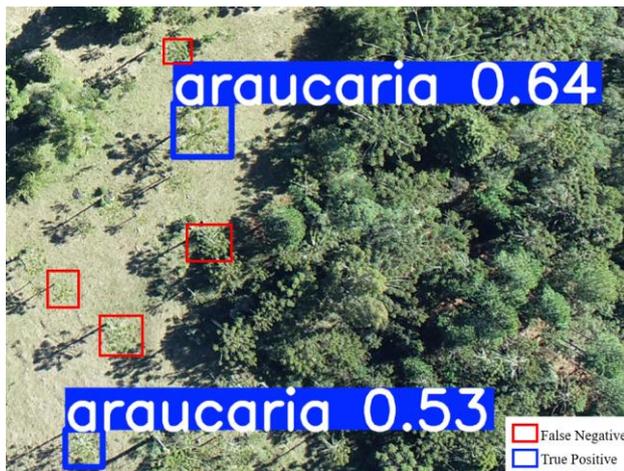

Figure 6. Detection results highlighting the False Negatives

Despite the improvement in metrics in Experiment 2, the AP of 0.31 remains quite low, indicating that, on average, the model performs poorly in correctly detecting and classifying *A. angustifolia*. This means that, when varying the confidence threshold, the model can only balance precision and recall to a limited extent; in other words, it correctly identifies few *A. angustifolia* trees while making many errors (false positives or false negatives) (He et al., 2025; Thapa et al., 2025). Further experiments aim to collect multispectral and Light Detection and Ranging (LiDAR) data from UAVs to enhance the accuracy of tree detection.

5. Conclusions

In this study, the results obtained using YOLOv11x for *A. angustifolia* detection did not reach satisfactory levels; however, the model shows promise, especially when incorporating the K-Fold validation technique.

The next steps of this research will focus on improving the annotations of *A. angustifolia* specimens and revising the dataset by including a greater diversity of samples under different environmental conditions. New tests will be conducted using various data augmentation values and hyperparameter tuning.

It is noteworthy that, with model improvements, this approach could become a useful tool for automated mapping of the species, providing technical support that will aid in conservation strategies, management, and public policies aimed at protecting Araucaria and its associated ecosystems.

Acknowledgements

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