Bridging UAV and Satellite Remote Sensing: Advancing Palm Detection for Amazonian Conservation

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1. Introduction

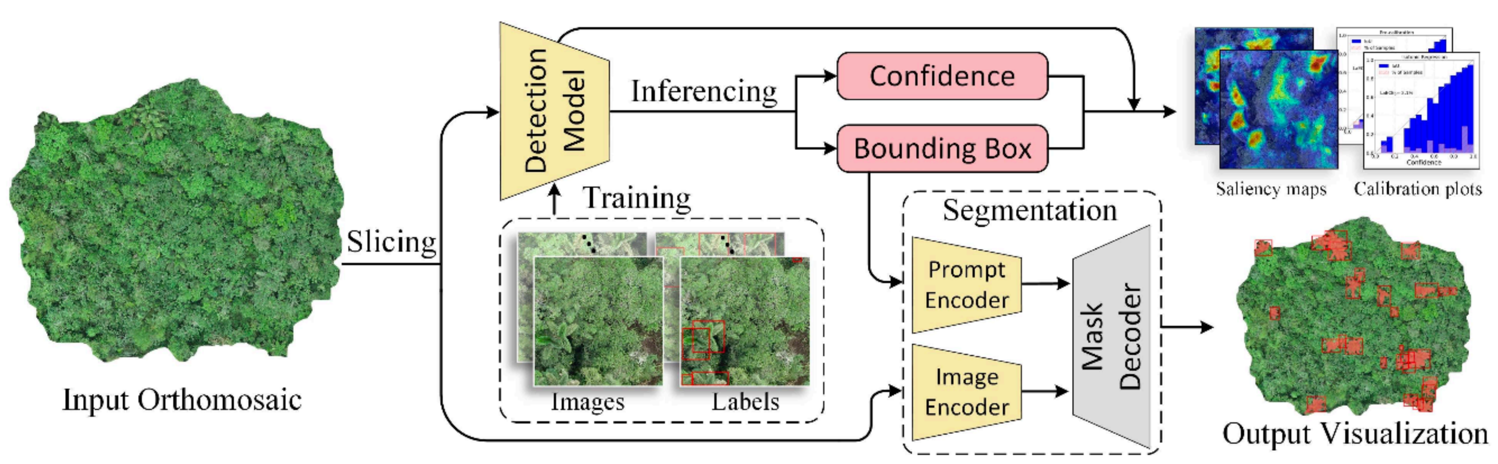
- **Palms & Why They Matter:** Palm trees are critical indicators of tropical forest health, biodiversity, and human activity. They provide vital resources for both wildlife and human communities.
- **The Problem:** The ability of automated palm detection tools and their ability to generalize to new regions with different ecological conditions is unknown.
- **Our Approach:** We apply the preexisting PRISM Pipeline [1] , a model previously trained on Ecuadorian data, to a new region in Iquitos, Peru.
- **Main Goal:** We evaluate how well the original model performs and demonstrate that regional adaptation is key to making the pipeline a reliable tool for global monitoring.

Figure 1: Drone in Jungle [2]

2. Methods

- **Original Ecuador Dataset:** Our baseline was a dataset of 1,500 images (800x800 pixels) from two reserves in western Ecuador, manually annotated by three experts.
- **New Peru Dataset:** For our new dataset, we used large UAV images (6000x4000 pixels) from Iquitos, Peru. Using Roboflow, these were partitioned into 150 non-overlapping patches, resulting in 294 annotated samples (400x400 pixels), each with a manually labeled bounding box and center point.
- **Models & Pipeline:** We used the PRISM pipeline and systematically compared five versions of the YOLO model (YOLOv8 to YOLOv12) [3-7] to evaluate its geographic transferability.
- **Training Regimes:** Our experiment focused on two key regimes: an Ecuadorian Baseline trained exclusively on the Ecuador dataset to measure out-of-distribution performance, and a model fine-tuned on a mixed dataset from both Ecuador and Peru(Mixed Data).

Figure 2: PRISM Pipeline Overview: The detection model trained on the Ecuadorian dataset.



Ecuadorian Palm Tree

Iquitos Palm Tree

3. Results

- **Ecuadorian Baseline Results:** The Ecuador-trained models showed low overall performance when applied to the new Peruvian environment.
- **Peruvian/Mixed Data:** The adapted models saw a huge jump in scores, with the most significant gains in Precision, measures the proportion of correct detections, and Recall, measures the model's ability to find all palms.
- **Overall:** Regional adaptation is crucial for this type of research. The best-performing model, **YOLOv11**, achieved a peak mAP@0.5-0.95 of 0.386, a 62% improvement over the best baseline model.

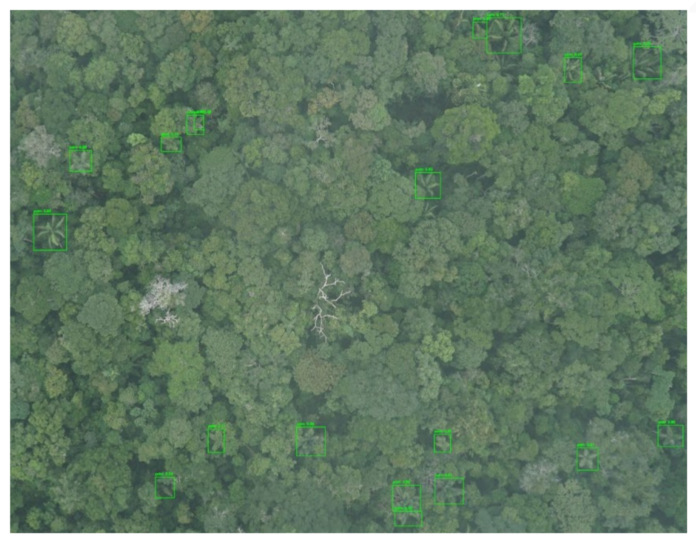
Table 1: Detection performance of models trained only on Ecuador data.

Model	Precision	Recall	F1-score	mAP@0.5	mAP@0.5-0.95
YOLOv8	0.366	0.110	0.170	0.229	0.137
YOLOv9	0.421	0.136	0.206	0.218	0.124
YOLOv10	0.494	0.127	0.202	0.317	0.179
YOLOv11	0.443	0.101	0.164	0.269	0.155
YOLOv12	0.464	0.367	0.410	0.401	0.239

Table 2: Detection performance of models trained on mixed data from Iquitos.

Model	Precision	Recall	F1-score	mAP@0.5	mAP@0.5-0.95
YOLOv8	0.779	0.458	0.577	0.592	0.344
YOLOv9	0.792	0.432	0.559	0.632	0.382
YOLOv10	0.677	0.474	0.558	0.612	0.359
YOLOv11	**0.798**	0.468	**0.590**	**0.649**	**0.386**
YOLOv12	0.630	**0.481**	0.545	0.564	0.340

YOLOv11(Mixed Data) trained on mixed data from Iquitos →



4. Conclusions and Future Directions

- **Key Findings:** The Ecuador-trained baseline model failed to generalize to the new Peruvian data. However, fine-tuning it with a small amount of regional data significantly improved its accuracy.
- **Limitations & Drawbacks:** This work is a crucial first step, but it has limitations. The Peruvian/mixed dataset is relatively small, and we only tested one new region. Therefore, our conclusions are not yet globally generalizable.
- **Future Work:** Our next steps are to expand this research to include more diverse locations, investigate alternative model designs, and incorporate additional data sources to create a truly scalable tool for global ecological monitoring.

References

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