The Peruvian Amazon Forestry Dataset: A Leaf Image Classification Corpus

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Outline

1. Motivation
2. Dataset description
3. Experiments and baseline results
4. Conclusion

Motivation

Motivation

The Amazon rainforest

- has over 15,000 tree species
- 21% of the global forest cover
- narrow global warming impact
- provides natural resources
- main economic livelihood of the region
- sustainable management

Motivation

OSINFOR publishes the protocol "Technical Criteria for the Evaluation of Timber Resources"

- based on species classification
- unify product quality
- protect timber species

The first phase of the protocol is the elaboration of a “Forest management plan”.

- Specimens ubication
- Specimens classification

Motivation

Cited violations in logging concessions supervised by OSINFOR

Forest and Wildlife Law No. 27308		
Article 18	*Grounds for revoking harvesting rights*	
a	Failure to comply with the General Forest Management Plan	**79.4%**
b	Failure to pay for harvesting rights	25.5%
c	Timber extraction outside of the concession limits	**57.8%**
d	Promote timber extraction through a third party	11.8%
Regulations of Forest and Wildlife Law No. 27308		
Article 91A	*Grounds for cancellation of a concession*	
a	Failure to present management plans within the established timeframe	15.7%
b	Failure to implement management plans	**63.7%**
d	Failure to pay harvesting rights within the established timeframe	19.6%
e	Timber extraction outside of the concession limits	**55.9%**
f	Promote illegal timber extraction through a third party	16.7%
h	Waiver of concession rights by the concessionaire	10.8%
Article 363	*Forestry Infractions*	
i	Unauthorized timber extraction or extraction outside authorized zone	**79.4%**
k	Cutting seed or regeneration trees	14.7%
l	Failure to comply with established harvesting methods	**61.8%**
n	Timber extraction exceeding authorized volumes	2.9%
q	Acquisition, transformation, or marketing of illegally extracted timber	3.9%
t	Submission of false or incomplete information	**63.7%**
w	Use concession to facilitate extraction, transport, or marketing of illegally extracted timber	**71.6%**

Source: Finer, M., Jenkins, C. N., Sky, M. A. B., & Pine, J. (2014). Logging concessions enable illegal logging crisis in the peruvian amazon. Scientific reports, 4, 4719.

Motivation

- It is difficult to assign classification specialists to every concession.
- The protocol suggest the classification performed by a non-specialist (Matero).
- Matero classifies trees by looking barks.
- Matero classifies trees using common names.

Motivation

- It is difficult to assign classification specialists to every concession.
- The protocol suggest the classification performed by a non-specialist (Matero).
- Matero classifies trees by looking barks
- Matero classifies trees using common names

Cumala → Virola pavonis

Cumala → Virola sebifera

Cumala → Dipteryx micrantha

Motivation

The problem gets worse when it also affects to CITES (Convention on International Trade in Endangered Species of Wild Fauna and Flora) listed species.

Big leaf Mahogany

Swietenia macrophylla

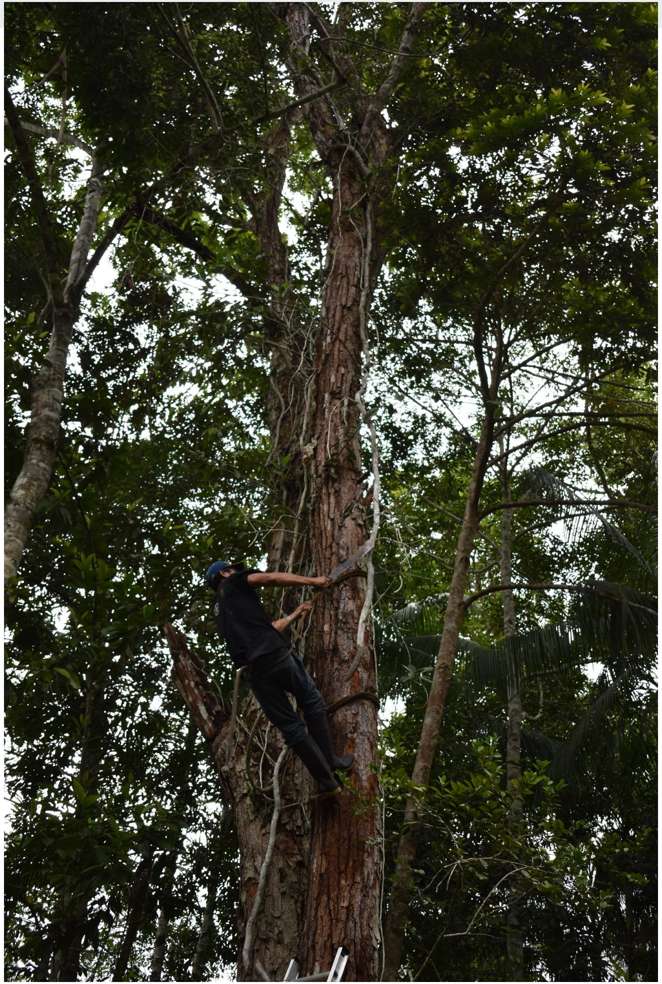
Spanish Cedar

Cedrela odorata

Dataset Description

Dataset

- The Peruvian Amazon Forestry Dataset collects 59,441 leaf images from ten timber tree species from the Allpahuayo-Mishana National Reserve, Peru.
- The dataset is gathered in differents excursions and conditions.

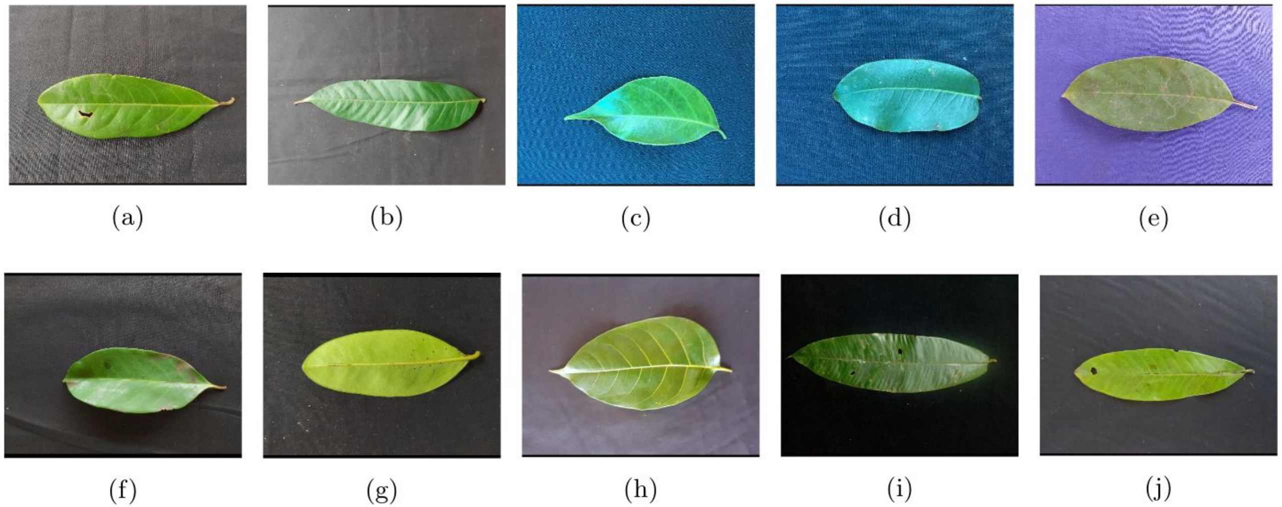


Dataset

1. Specialists in tree recognition identify and select specimens from the reserve.
2. They extract some leaves from each specimen.
3. Massive digitalization of leaves with a dark background using 6 cameras.

Dataset

- The images have a single leaf on a dark (black and purple) background.



(a) Aniba rosaeodora. (b) Cedrela odorata. (c) Cedrelinga cateniformis. (d) Dipteryx micrantha. (e)Otoba glycycarpa. (f) Otoba parvifolia. (g) Simaruba amara. (h) Swietenia macrophylla. (i) Virola flexuosa. (j) Virola pavonis.

Dataset

The dataset has high inter-class similarity and intra-class variability

Dataset distribution

Species	Samples						
	DC	**CP1**	**CP2**	**CP3**	**CP4**	**CP5**	**Total**
Aniba rosaeodora	1529	1547	1547	1537	402	—	6562
Cedrela odorata	1302	1302	1304	1303	188	127	5526
Cedrelinga cateniformis	1232	1232	1232	1230	177	176	5279
Dipteryx micrantha	1248	1248	1248	1248	480	340	5812
Otoba glycycarpa	1271	1281	1260	1268	136	322	5538
Otoba parvifolia	1745	1713	1712	1716	385	—	7271
Simarouba amara	980	1216	1216	1210	172	388	5182
Swietenia macrophylla	1564	1586	1568	1572	146	—	6436
Virola flexuosa	1030	1042	1040	1042	190	—	4344
Virola pavonis	1841	1842	1832	1840	136	—	7491
Total	13742	14009	13959	13966	2412	1353	**59441**

Experiments and baseline results

Data distribution

According to the cameras:

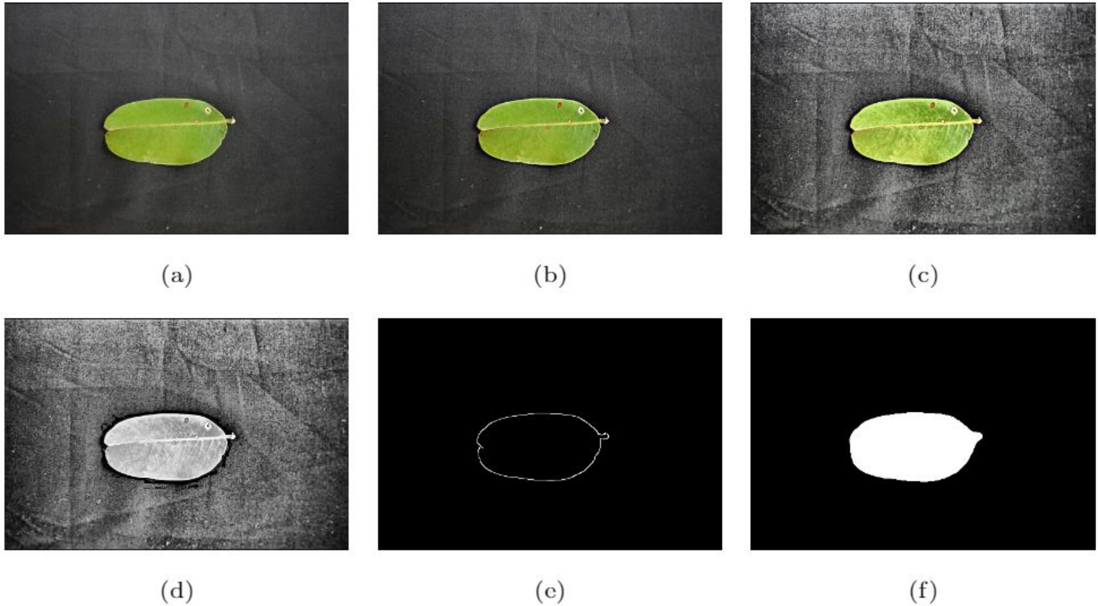
- 70.12% for training (DC, CP1, CP2)
- 1.69% validation (DC, CP1, CP2)
- 28.19% for testing (CP3, CP4, CP5)

Experiments

We fine-tune four well-known models: **AlexNet**, **VGG-19**, **ResNet-101**, **DenseNet-201**

Each model is trained twice with two types of samples: **raw** images, and pre-processed ones with **background removal**.

Background Removal



(a)Input image. (b)Sharpen image. (c)Adaptive equalization of the Luminance. (d)Green channel. (e)Edge detection. (f)Segmented leaf

Results

- Pre-processed images do not enhance any model's result
- AlexNet and VGG-19 models provide better outcomes that ResNet-101 and DenseNet-201

Model	Accuracy					
	Raw			Pre-processed		
	Train	Validation	Test	Train	Validation	Test
AlexNet	**98.75 %**	97.16%	**96.16 %**	**98.21 %**	**97.92 %**	95.98 %
VGG-19	96.77 %	**98.30 %**	95.15 %	96.94 %	**97.92 %**	**96.52 %**
ResNet-101	82.25 %	89.04 %	83.30 %	77.25 %	79.02 %	75.44 %
DenseNet-201	93.71 %	91.30 %	86.48 %	91.61 %	87.33 %	86.29 %

Accuracy of the models w/wo pre-processing

Results

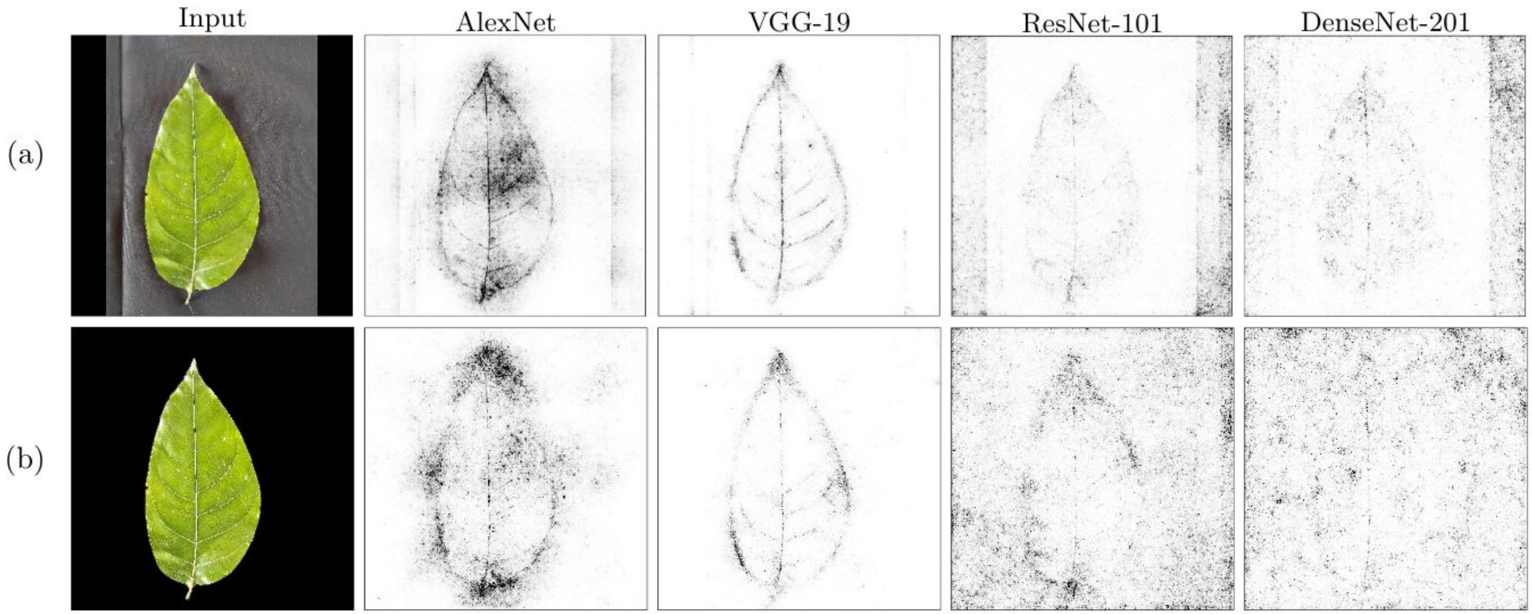
On model robustness show that the models suffer an accuracy drop.

- 13% for raw images
- > 17% for pre-trained ones.
- ResNet-101 and DenseNet-201 decrease up to 52%.

Model	Accuracy	
	Raw $\rightarrow$ Pre-processed	Pre-processed $\rightarrow$ Raw
AlexNet	82.35 %	54.76 %
VGG-19	**82.70 %**	**78.87 %**
ResNet-101	69.22 %	29.56 %
DenseNet-201	65.26 %	33.97 %

Results

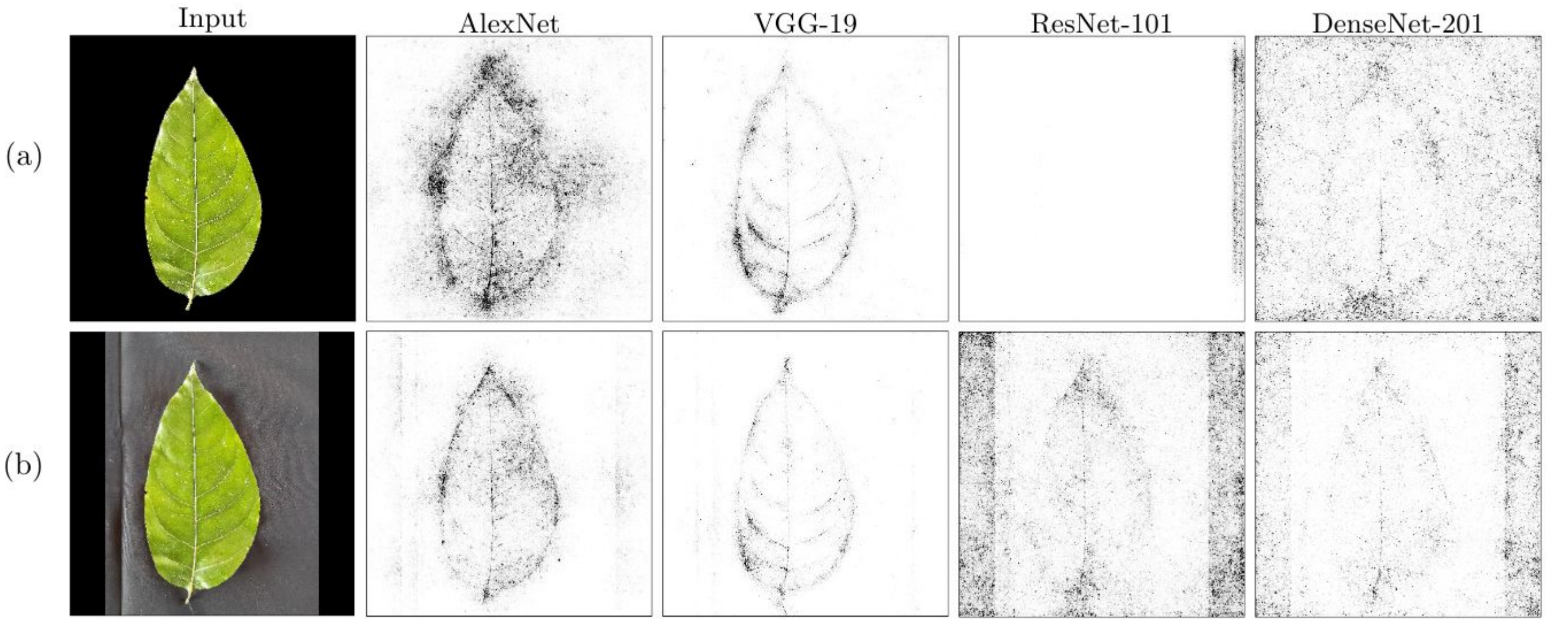
We apply the Integrated Gradients methods over each model



Feature visualization of the models (trained with raw images) given a (a) raw input, or a (b) pre-processed input.

Results

We apply the Integrated Gradients methods over each model



Feature visualization of the models (trained with pre-processed images) given a (a) pre-processed input, or a (b) raw input.

Results

We apply the Integrated Gradients and SmoothGrad methods over each model

- AlexNet & VGG-19
  - learn high-level leaf features
  - venations and shapes
- ResNet-101
  - learned to classify based on lateral sections,
  - ignoring the leaf
  - exploited an error in the background removal

Conclusion

Conclusion and Future Work

- We suggest using AlexNet and VGG-19 for future real-world solutions
- Shape and Venations are the most trustworthy morphological features
- We demonstrates the benefits of training models with raw inputs to achieve robustness and accuracy

- We will extend the dataset by adding more species
- Scale to IoT solutions

Thank you for your attention!