Multi-channel regression for plant trait prediction

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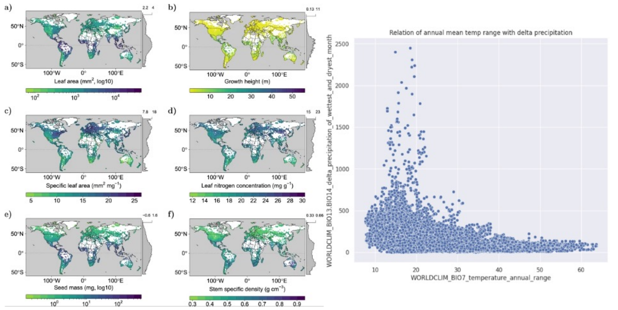
Plant photos can be used to predict plant traits

Plant traits are crucial for understanding ecosystems and their responses to factors like climate change, impacting diversity and productivity. [1] Citizen science photos hold valuable data on plant species, appearance, and location, with over 20 million images available spanning various ecosystems globally. [2]
However, current datasets lack integration of plant traits with images, hindering the understanding of how traits manifest visually. However, research linking the two data types showed that basic CNN models could be used to predict plant traits from photos. [3]

Objective: Predict 6 plant traits from image and tabular data

To improve the geographic resolution of plant trait distribution globally, we use plant images with species labels from iNaturalist and 4 separate geodatasets mapped to the photograph locations to predict 6 important plant traits which can manifest visually.

Plant traits are correlated with geographic data



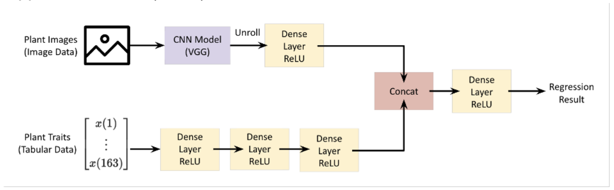
6 Datasets: 69362 images and tabulated data in 80/20 train/test split

Data	Type, Size/Entry	Source
WORLDCLIM: Temp. and Rainfall	Tabular Geodata, 6x1	WorldClim global climate [4]
SOIL: Global soil properties.	Tabular Geodata, 61x1	ISRIC SoilGrids2 dataset [5]
MODIS: Satellite geodata	Tabular Geodata, 60x1	MODIS/Terra [6]
VOD: Radar geodata	Tabular Geodata, 36x1	VODCAv2 [7]
Plant Traits: SD and Mean of 6 Traits	Tabular Plant species data, 12x1	TRY plant trait database [8]
Plant Photographs	Image, 512x512x3	iNaturalist database [9]

Multi-class, multi-modal ensemble learning

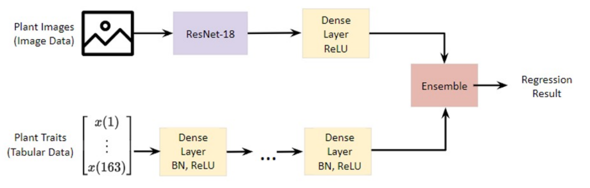
We construct the model to predict 6 plant traits simultaneously to enable the model to capture relations between different plant traits. In our dataset, besides climate data, additional predictors are also used, such as soil information, and optical and radar satellite data. We use both the plant image (trained using a CNN) as well as a vector combining the tabular data (trained using MLPs) to predict plant traits. The image and tabular pipelines are trained in parallel before merging into a dense layer for the result.

Approach 1: CNN (unroll) + tabular data --> MLP



Since there are two data types, we use CNN to extract the representation in image, then combine the prediction with the tabular data to produce regression result. Transforms were applied to the image data to increase robustness and number of samples, While the tabular data was scaled and normalized to improve training.
The image pipelines were trained using basic CNNs, and pretrained attention models to find the best result.

Approach 2: CNN ResNet-18(image) and MLP (tabular) --> ensemble by weighted average

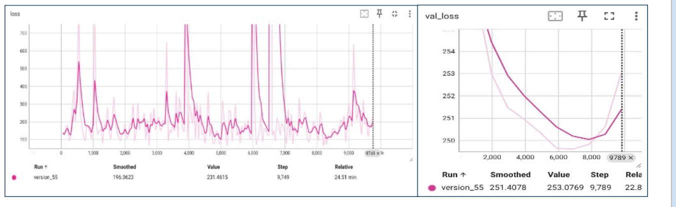


We used weighted average ensemble learning to tune overall prediction by leveraging the predictions from both the CNN (ResNet-18) and MLP model. The predictions were then weighted to produce the regression result.

Results

Approach 1

Training loss | Validation loss



Training/validation loss function
L2-norm loss function is selected given this is a regression problem.
We use R2 (Coefficient of Determination) to measure the performance of the model.

Key Takeaways
Approach 1 is observed to be better in predicting the plant traits given the higher R2 score.
This is likely because the final MLP layers concurrently learn from both image (CNN output) and tabular data, enabling the model to better capture patterns from both datasets simultaneously.

Future Work
Use more complex image prediction models such as ViT architectures with tabular data. Also, hyperparameter tuning on learning rates, and separate early stopping for image and tabular pipelines may help to improve the result.

References:

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