Deep learning can be used to classify and segment plant cell types in xylem tissue

Sean Wu[1], Reem Al Dabagh[1], Anna L. Jacobsen[2], Helen I. Holmlund[1], Fabien Scalzo[1]
1. Seaver College, Pepperdine University, Malibu, CA 90265. 2. California State University Bakersfield, Bakersfield, CA 93311.

Background

- The goal for this research project is to classify three functionally distinct plant cell types found in the xylem tissue (Fig. 1):

1. Vessels: Elongate tubes with a large diameter for the passive transport of water, which is pulled through the plant by evaporation from the leaves. They have a thick secondary cell wall and are dead upon maturity, facilitating their function of long-distance transport.
2. Fibers: Elongate cells that function primarily as mechanical support for the stem or root by means of their thick cell walls with a narrow lumen.
3. Parenchyma: Short cells that have thin primary cell walls and are typically alive at maturity. They function in short-distance transport and storage of water and long-term sugar reserves (starch)

- Our objective is to construct a machine learning model that learns the features of these plant cell types alongside its surrounding characteristics to classify them with high accuracy.

- We propose a faster means of measuring key characteristics of xylem anatomy which would greatly broaden the scope of questions that can be asked about plant structure and function.

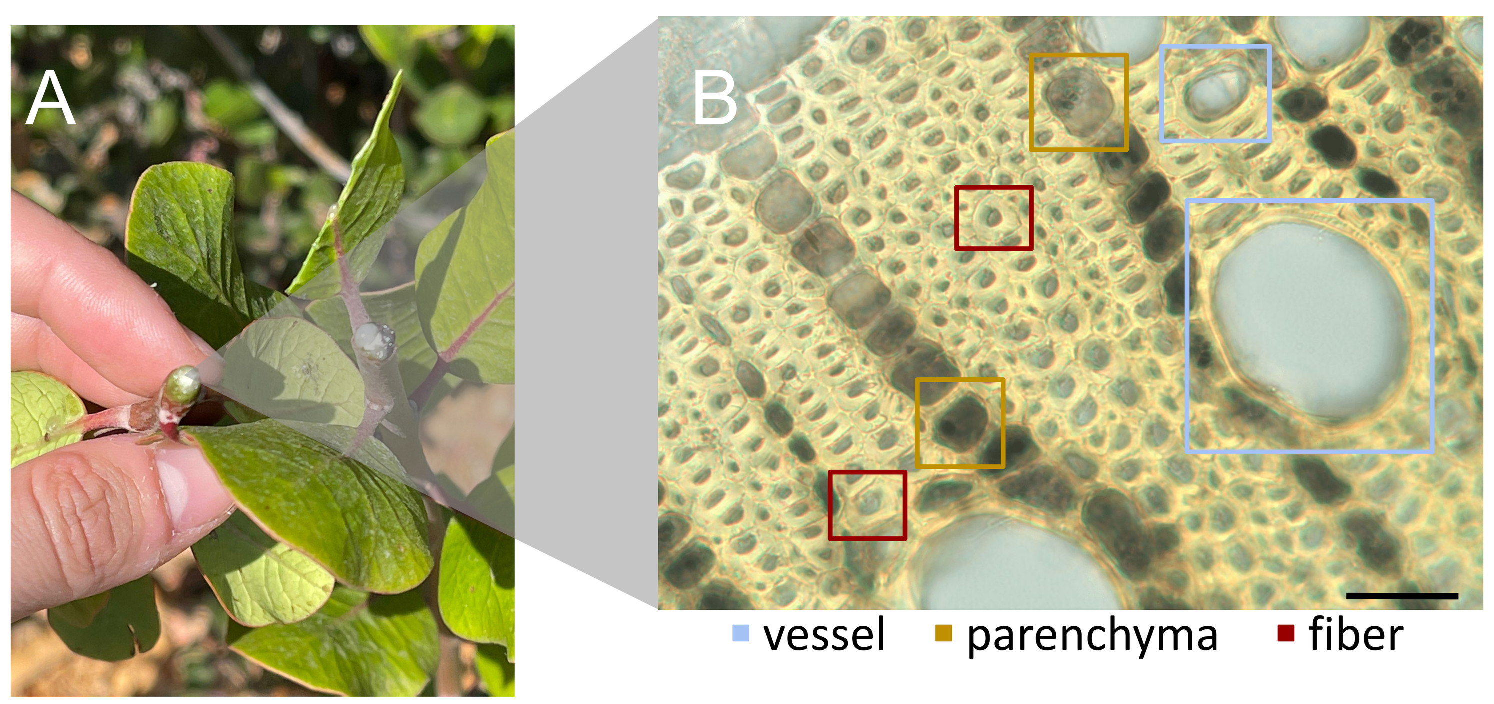

Fig. 1: (A) Chaparral shrub stem cut transversely as to prepare cross sections. (B) Micrograph of transverse cross section with labeled cell types. Boxes are placed as for cropping. Scale bar = 50 µm.

Methods

- We utilized a manual image cropping software called makesense.ai to gather our cropped image data from three different species: *Ceanothus oliganthus, Ceanothus crassifolius* and *Rhamnus californica.* We used a total of 85 cross sections to get 250 vessels, 264 fibers and 276 parenchyma cropped images.

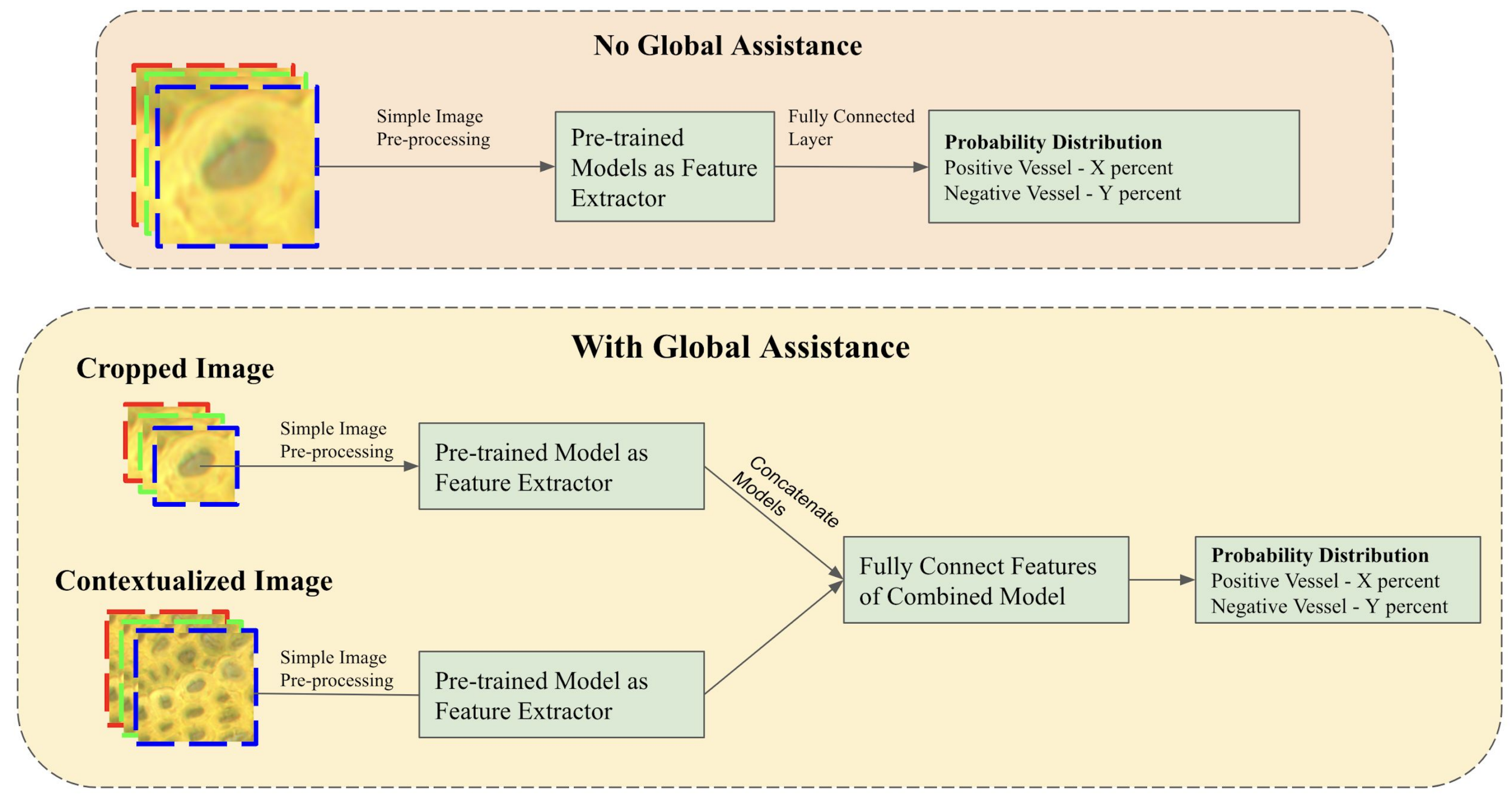

Fig. 2: Two models are trained for each subproblem. One for a simple cropped image classification, and one for a cropped image with contextualized image classification.

- We perform a comparative analysis between Deep Learning models built from pre-trained deep neural networks ResNet-18 and VGG-16, alongside other techniques such as Data Efficient Vision Transformer (DeiT).

- To give our model more generalization, each image aside from the testing data is replicated ten times on a rotation transformation ranging from 0-180 degrees.

- While local patches can capture detailed information about the texture of a cell, it lacks the contextual information necessary to classify some cells. We decided to extract the features of the local and the globalized image patch separately in a chosen feature extraction model.

- A cascade-like framework was implemented such that one model was trained to classify a plant cell's vessel vs other cell types, and another model to classify a plant cell's fiber vs parenchyma.

- We permute three shrub species as train and testing sets.

- The accuracy of each of our models are evaluated based on the number of predictions the model gets correct on the external test set divided by the length of the test set.

Results

- ResNet-18 - the best performing models supports that a deep learning neural network that includes a contextual image in addition to the cropped cell image bolsters model learning and accuracy.

- Upon data augmentation, and image pre-processing of standardizing data to have a mean value of zero and standard deviation value of one, the contextualized image helped our vessel vs other cell type model get 99.06% and fiber vs parenchyma model get 97.22% accuracy.

Accuracy for Final Models	Vessels vs Non-Vessels	Fiber vs Parenchyma	Overall Accuracy
ResNet-18: large patches + data augmentation	99.1 ± 1.2%	97.2 ± 4.3%	98.1 ± 2.6%
ResNet-18: data augmentation	93.4%	94.4%	93.9%

Conclusion

- Our experiments demonstrate that a supervised deep learning model can be trained to classify the vessel, fiber, and parenchyma cell types by dispatching a cropped cell image alongside its global counterpart to achieve extremely accurate results. The next step is to utilize this classification model to be able to detect and count the number of cell types of their respective classes in a microscopic cross section.

References

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