Automated Root Nodule Detection

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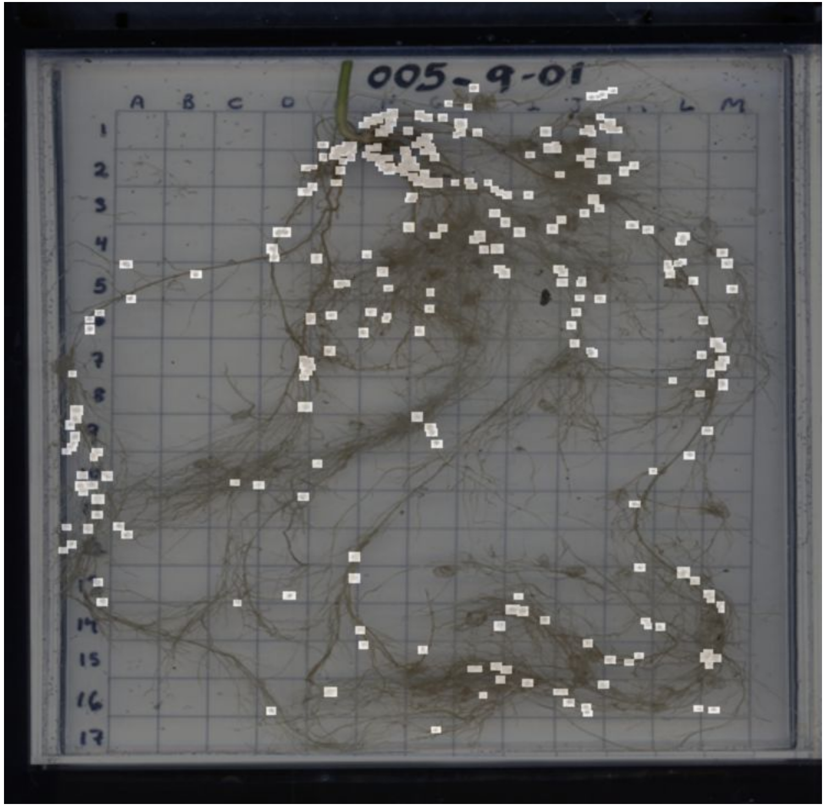
Introduction

- The quality and number of plant root nodules are a core indicator of plant development and health in ammonia-poor soils.
- In order to avoid excess fertilizer use and pollution of the environment, farmers have to keep track of natural ways bacteria can extract nitrogen from the air and convert to ammonia for the plants to use
- Root nodules are essentially sacks of such bacteria and we will be exploring methods to detect where in roots these nodules may exist.

Dataset

- The dataset includes ten unique 12 megapixel images of plant roots and hand-labeled bounding boxes indicating the location of each root nodule.
- By default all images were resize to 500x500 image and bounding boxes were realigned.



Reformulate as a Classification Problem

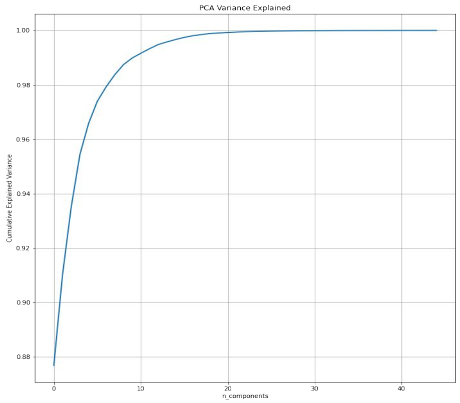
The purpose of this project is to predict where the nodules are on the roots. We decided to first attempt this as a classification problem

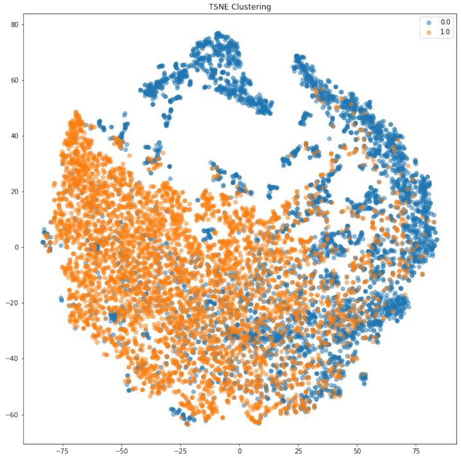
- We calculated that the average size of a bounding box was roughly 5 by 7 pixels, so with a two pixel buffer, we split our image into patches of size 3 by 5, with 3 channels
- Each patch was then labeled with a binary classifier for if the patch included a nodule.
- There were significantly more patches without nodules so we randomly sampled to balance our dataset
- For training, these patches (flattened to a vector of length 45) were passed to a model to predict their class
- For inference, an image is split into patches, each patch is predicted as 0 or 1, and then the patches are reconstructed back to the original image shape for our final predictions

Dimensionality Reduction

Due to the large input feature length of 45, we first tested some dimensionality reduction techniques

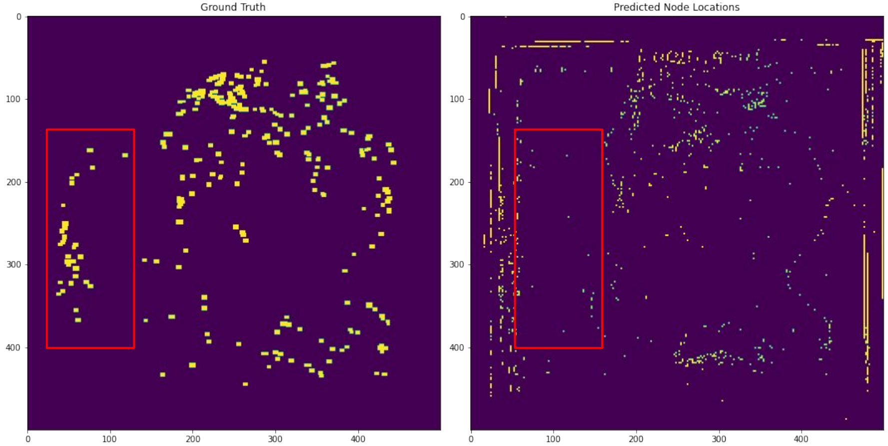
- PCA showed that we only needed **20 components** to explain the majority of the variance
- TSNE visualizes that there are some differences between patches with and without nodes, but there is a large overlap (most likely due similar color features between nodules and the roots themselves)





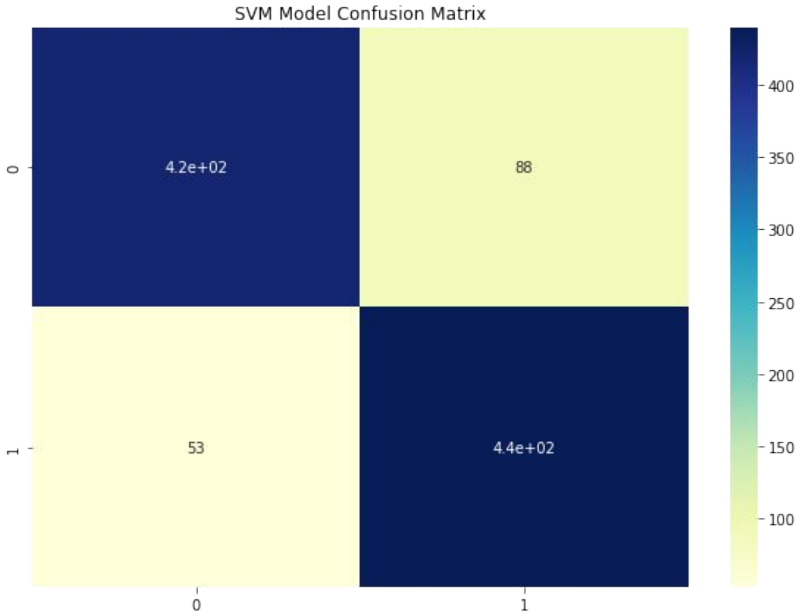
Random Forest

- Because we knew the problem was reduced to resolving fine color differences between nodules and roots, we thought an ensemble model like Random Forest would give good results
- We were able to get an 84.5% accuracy without PCA compression and 87.3% accuracy with first 20 components of PCA for classifying a patch as a node
- Although we had strong predictive performance on patches, we see that the model also predicts the borders and roots as patches. Entire sections of roots were also missed due to overlaps (boxed in red)



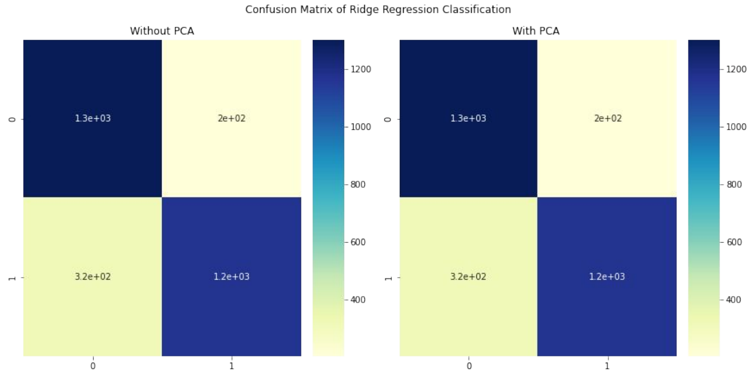
Support Vector Machine + HOG

- SVM classifier applied directly on PCA compressed data with patch size 2x4 gives us an accuracy score of 85.9%
- Given the limited availability of training images, we reduce the chance of model overfitting by using a high regularization value 100
- HOG + SVM: Using HOG to extract features per every 2x2 pixel and then feeding input to SVM classifier increases accuracy to 96%
- Since HOG works by identifying gradients of the root nodes, we see a higher predictive performance



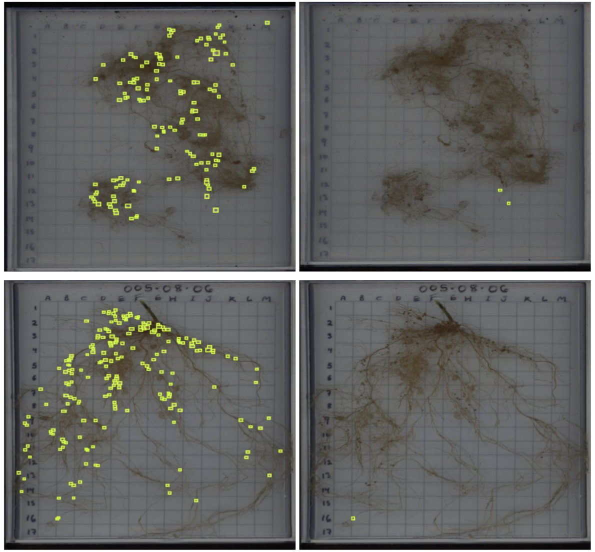
Ridge Regression

- Given the limited availability of training images, we would like to make the learning on the training set as generalizable as possible.
- With its ability to penalize large coefficient values, ridge regression classifier gives us the ability to reduce the chance of model overfitting.
- The classification accuracy is 80.35% without PCA and 82.5% with PCA dimensionality reduction.



Object Detection: YOLO

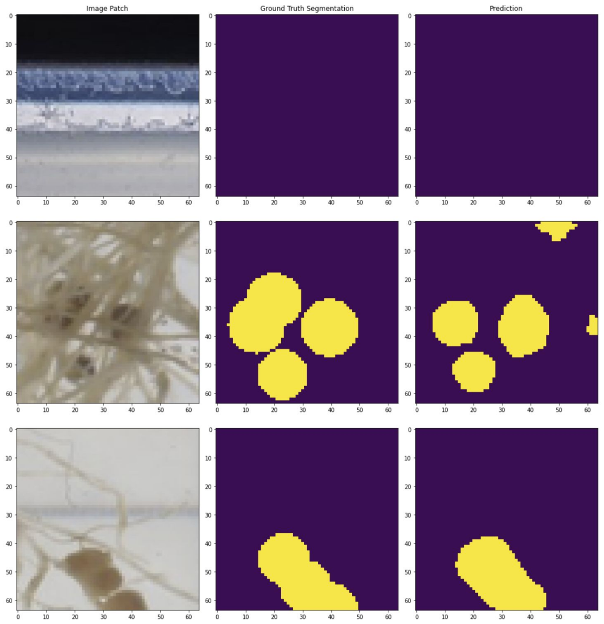
- Having the knowledge of global context in the training could be valuable when positive labels are relatively scarce.
- Our YOLO model fails to generalize its learning and identify the majority of the root nodes in the validation/testing images.



Semantic Segmentation: UNet

Semantic Segmentation is another powerful tool to find nodules

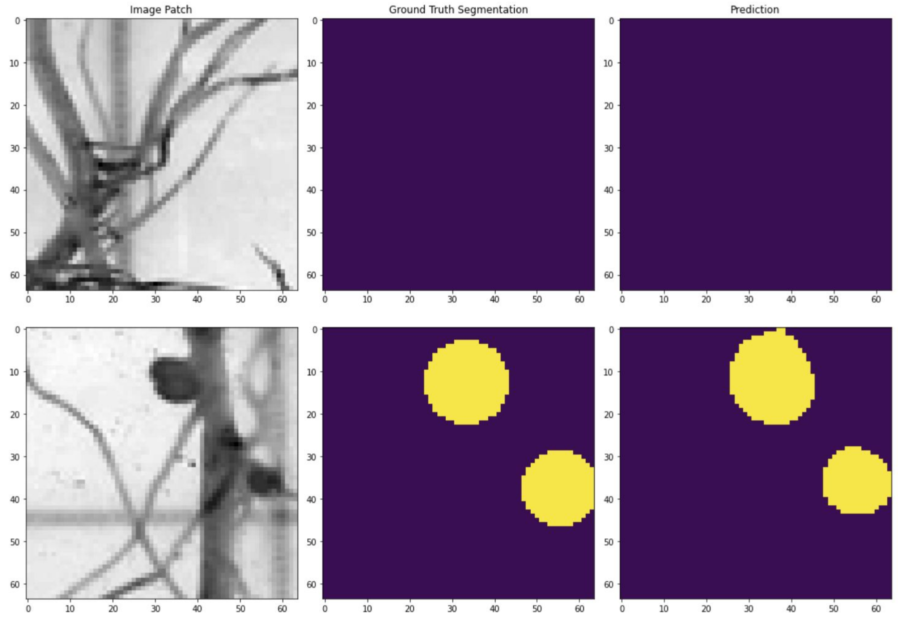
- In many of the previous methods were flattening our patches into feature vectors, depending completely on RGB color values, where the easiest way to detect these nodules is by their circular shape
- UNet allows us to detect nodules that were even occluded by other roots (something we have to do in any real world detection problem)



Importance of Spatial Features

To test our hypothesis that spatial features are of higher interest than just color, we trained our UNet to take the same patches in but now in Grayscale.

- By converting to grayscale we were able to actually improve our mIoU performance by one percent to about 69.7%



Conclusion and Next Steps

- Overall we were able to get strong performance from our testing, where UNet was able to detect even hidden nodules.
- Next Steps:
  - Use SVM to directly detect the bounding boxes rather than if a patch included a nodule
  - Explore an unsupervised pre-training approach on many unlabeled images of roots to see what other downstream tasks can be accomplished
  - Repurpose the UNet model to perform Instance or Panoptic segmentation to not only detect where nodules are in an image but also how many exist.