Exploring the use of 3D point cloud data for improved plant stress rating

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Abstract

Currently, automated canopy stress classification for field crops rely on single-perspective, two-dimensional (2D) photographs, typically top view imaging via UAV. However, plant stress symptoms may appear throughout the canopy, and a single viewpoint photograph may not capture the entire region affected by the stress. Recent developments in efficient, large scale, 3D point cloud capture of agricultural fields open up the possibility of more comprehensive stress identification and rating. We hypothesized that utilizing the 3D point cloud will allow multi-perspective construction of plant canopy, and subsequent training of more accurate plant stress identification and its rating in field. We utilize a RGB 3D point cloud of a field where a diversity panel of soybean under Iron Deficiency chlorosis (IDC) stress was grown. We explore both multiview projection as well as area-preserving map projection methods to obtain parameterized 2D images depicting the complete 3D canopy surface. This approach allowed us to create models agnostic to canopy size/shape, while allowing us to leverage pretrained deep learning models – trained on 2D image data. Our preliminary results are promising, and we continue to finetune these machine learning pipelines for classifying plant stress expression.

Introduction

Plant stress classification is crucial in ensuring a good yield. Soybean, a major crop contributing significantly to the overall production in the United States often suffers from Iron Deficiency Chlorosis (IDC) when grown on soil with high pH. This deficiency causes a significant decline in the yield and quality of the crop. Traditionally, IDC ratings were performed manually, by evaluating stress symptoms across the canopy. However, this method is subjective, labor-intensive, and prone to inter- and intra-rater inaccuracy (Singh et al. 2021). Recently, automated high-throughput stress classification algorithms have been created using single viewpoint, predominantly top view RGB (Naik et al. 2017), multispectral, and hyperspectral images of the canopy. This method is reliable, but under performs when the stress expression is on the lower part of the plant canopy, or other regions that cannot be easily imaged using aerial imaging platforms.

Three-dimensional scanners are used in current plant phenotyping systems (Jin et al. 2021; Paulus 2019). These scanners are capable of capturing a three-dimensional point cloud of the canopy, as well as RGB and hyperspectral data. Depending on the time of imaging, one can construct reasonably dense point clouds of the complete canopy and thus provide more views of the canopy compared to conventional UAS based orthomosiaced images. We argue that such 3D point cloud data – from 3D scanners, or from 3D point cloud reconstructions from multi-view 2D images — are better inputs for stress classification algorithms.

Our objective is to utilize these 3D point cloud data into well-developed 2D image/stress classification models. Additionally, we ensure that the stress rating is based only on color and texture rather than shape and size of the canopy by utilizing ideas from projective geometry and cartography. Specifically, we project the 3D point cloud onto a unit sphere to ensure that the dataset is made agnostic to shape and size. Subsequently, we utilize area-preserving projections used in cartography to map the 3D surface to 2D images. These 2D images are then used to train pre-trained deep neural networks.

Methods

We employ multiple views projection and map projection methods to represent the 3D point clouds in 2D.

Multi-View Projection

Multi-view projection of the point cloud data of a canopy are obtained at eight different angles. There are two approaches to utilize these multiple views. The first approach uses feature vectors obtained from each of the views and concatenates them and feeds it to a classifier to predict the IDC labels as implemented in Su et al 2015 (Su et al. 2015). The second approach involves, (a) stacking multiple views to form a single image, (b) obtaining a 2D cylindrical projection of the 3D point cloud and feeding it to a pre-trained image classifier.

Multi-view Convolutional Neural Networks (MVCNN) MVCNN in Su et. al. 2015's paper uses multiple views of a 3D point cloud for classification. An existing architecture like ResNet is used as the base block to extract features from each of the 8 views and a classifier block is built on top of it. Multiple base blocks are created for each view. The base block is loaded with weights trained on a large dataset like ImageNet. Transfer learning has proved to be

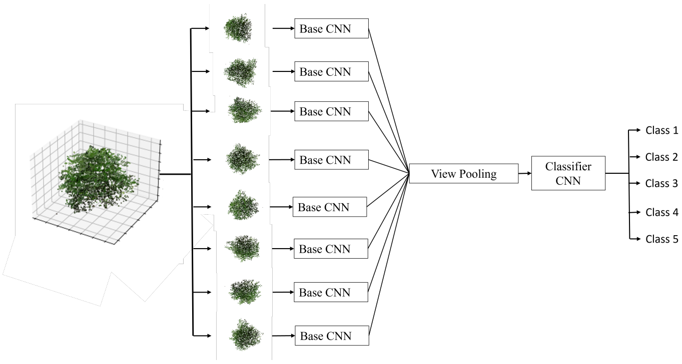

Figure 1: Architecture of MVCNN classifier

helpful in problems with datasets that are similar to ours that contain only a few images for training. These feature maps are concatenated to form the input to the classifier block. To make the model invariant to the order in which the views are fed into the network, an average view pooling layer is used. The training phase involves training only the classifier block while keeping the weights of the base block fixed and unfreezing all the weights later to train both the blocks. The class imbalance issue is addressed by using class weights. The weight for each class is the reciprocal of the number of instances of each class. The architecture of MVCNN is depicted in Figure 1.

Map projection and Composite single view

Equidistant and Equal Area Projections: Map projections involve transforming a 3D globe to a 2D world map. Depending on the type of projection, either the area of the points or the distance between points is distorted while preserving the other. For the same purpose, the given point cloud (Figure 2) is projected onto the surface of the unit sphere as mentioned in Karara et. al. 2021's implementation (Karara, Hajji, and Poux 2021). The points are normalized to fit into a unit sphere before projecting. The line that passes through the point in the normalized point cloud and the center of the unit sphere intersects with a point on its surface. Finding the points of intersection of every point in the canopy gives the spherical projection of the point cloud as shown in Figure 3. The cartesian coordinates are converted to spherical coordinates. The transformed point cloud is projected into a 2D plane using a variety of cylindrical map projections.

(a) Equirectangular projection The converted spherical coordinates on one axis correspond to the longitude while the other corresponds to the latitude of the equirectangular projection of the point cloud as depicted in Figure 4. This projection preserves the distance between any two points on the sphere's surface but distorts the area of the points.

(b) Cassini projection (wik 2021a) The unit sphere is rotated to be oriented along its meridian rather than its equator. Equirectangular projection is applied on the rotated sphere to obtain this equidistant projection. The latitude and longitude of spherical coordinates, φ and λ respectively are mapped to cartesian coordinates x and y of 2D projection using the equation below.

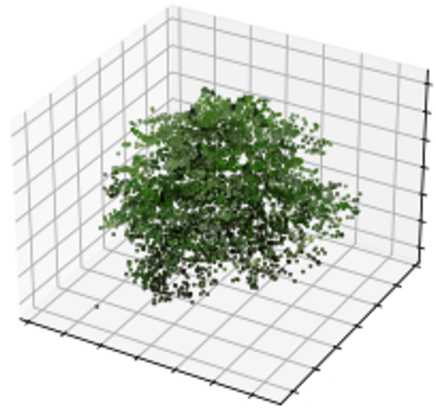

Figure 2: Point cloud of canopy

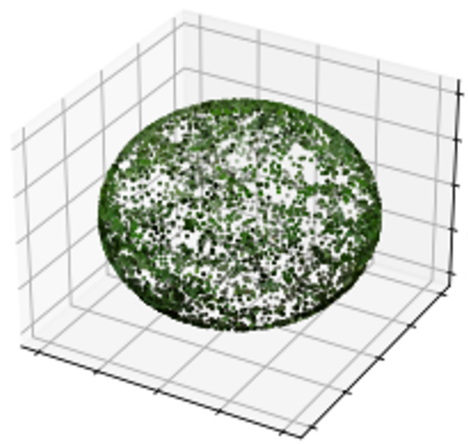

Figure 3: Point cloud projection on unit sphere

$$\text{x}= \sin^{-1}(cos(\varphi) * \sin(\lambda))$$
$$\text{y}= \tan^{-1}(tan(\varphi)/\cos(\lambda))$$

The resultant projection is shown in Figure 5.

(c) Lambert projection (wik 2021b) Lambert projection is an area preserving cylindrical projection where the distortion of area increases from the equator towards the poles. Gall Peters is a derivative of Lambert projection which produces lesser distortion than the original. The projection equations below produce the projection shown in Figure 6. φ and λ are the latitude and longitude coordinates whereas λ_c represents the central meridian

$$\text{x}=\lambda - \lambda_c$$
$$\text{y}=\sin(\varphi)$$

Concatenated Views: The eight views taken from different angles are stacked vertically into two rows to form a single image as shown in Figure 7.

The obtained projections are used with existing architectures liked ResNet, VGG etc. which are pretrained to obtain IDC classification scores. Class weights are used for the class imbalance.

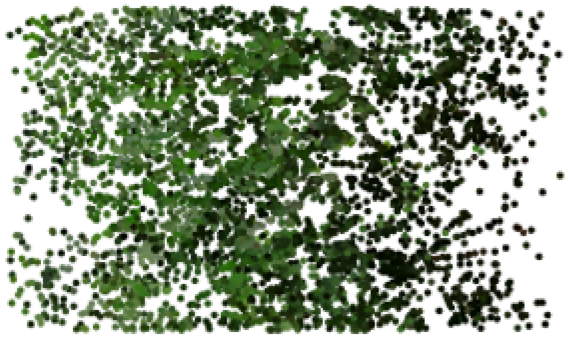

Figure 4: Equidistant equirectangular projection

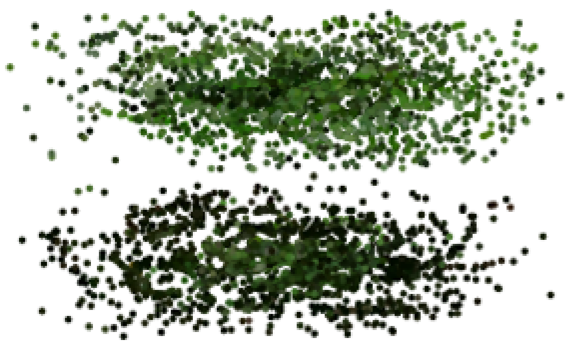

Figure 5: Cassini equidistant projection

Dataset

The entire field with soybean canopies was scanned on seven different days to get seven registered point cloud data scans. The scans are processed, and the ground pixels are separated from the canopy pixels and the individual canopies are segmented from the field. The segmented canopies are indexed by row and column numbers. The indexed canopies are mapped to the plot map to assign the canopies to the respective IDC classes. The original 20-point scale IDC ratings are binned into 5 classes. There is a class imbalance, and it is overcome by using class weights during training of the classifier. A total of 1150 soybean canopies mapped with their stress ratings are obtained from the scans.

IDC occurs when the soil has a higher pH which decreases the solubility of iron and consequently reduces the intake of active iron by the leaves and causes chlorosis. Stress class 1 indicates no chlorosis and leaves of the canopy are green; 2 indicates plants with slight yellowing of upper leaves; 3 indicates plants with interveinal chlorosis in the upper leaves; 4 indicates plants having leaves with interveinal chlorosis and stunting growth; and 5 indicates plants with extreme chlorosis, stunted growth, and necrosis in the new leaves.

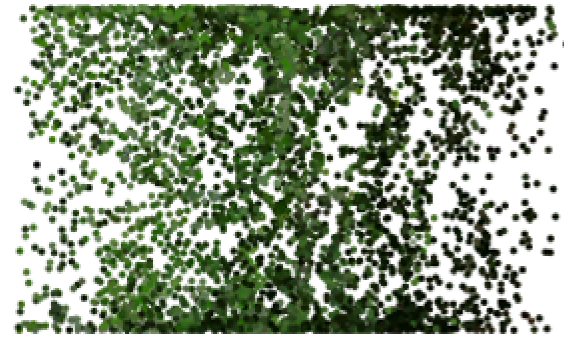

Figure 6: Lambert equal-area projection

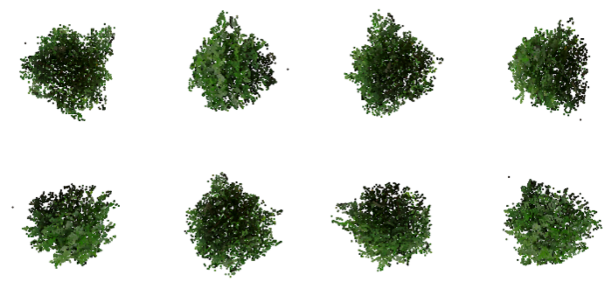

Figure 7: Concatenated views of point cloud projections

Results

Using the multiple views of the point cloud, we were able to successfully run the MVCNN framework. We are currently working on hyper-parameter tuning to achieve the desired accuracy. Different cylindrical projections obtained would be used for training an image classifier and their predictions from the classifiers would be compared against each other to identify the projection that works best for identifying the IDC severity.

Conclusions

We proposed classification using 3D image data that encloses complete information about the canopy with well-known 2D image classifiers to leverage its benefits as it is more widely studied. Different methods like MVCNN, projection-based methods that have reported reasonable accuracies in applications deployed in the past were outlined with its methodology. Using these models to automate the prediction of IDC scores would save human effort, time, and the error due to human bias introduced during FVR to a great extent. Making use of 3D data that contains more information that its 2D counterpart is expected to improve the performance of the classification model and hence better accuracy in prediction.

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