Unsupervised Image Segmentation using Convolutional Neural Networks for Automated Crop Monitoring

Prakruti Bhatt, Sanat Sarangi and Srinivasu Pappula
TCS Research and Innovation, Mumbai, India

Keywords: Unsupervised Segmentation, Severity Measurement, Crop Monitoring.

Abstract: Among endeavors towards automation in agriculture, localization and segmentation of various events during the growth cycle of a crop is critical and can be challenging in a dense foliage. Convolutional Neural Network based methods have been used to achieve state-of-the-art results in supervised image segmentation. In this paper, we investigate the unsupervised method of segmentation for monitoring crop growth and health conditions. Individual segments are then evaluated for their size, color, and texture in order to measure the possible change in the crop like emergence of a flower, fruit, deficiency, disease or pest. Supervised methods require ground truth labels of the segments in a large number of the images for training a neural network which can be used for similar kind of images on which the network is trained. Instead, we use information of spatial continuity in pixels and boundaries in a given image to update the feature representation and label assignment to every pixel using a fully convolutional network. Given that manual labeling of crop images is time consuming but quantifying an event occurrence in the farm is of utmost importance, our proposed approach achieves promising results on images of crops captured in different conditions. We obtained 94% accuracy in segmenting Cabbage with Black Moth pest, 81% in getting segments affected by Helopeltis pest on Tea leaves and 92% in spotting fruits on a Citrus tree where accuracy is defined in terms of intersection over union of the resulting segments with the ground truth. The resulting segments have been used for temporal crop monitoring and severity measurement in case of disease or pest manifestations.

1 INTRODUCTION

Robotic farm surveillance, automatic process control, and automated advisory for any event in the farms are becoming extremely important to increase quality of food production all over the world given the increasing population and limited availability of resources such as agricultural experts and farm labor. To achieve this, automated plant phenotyping is important, and precise segmentation is a key task for this. Presence of occlusions, variability in shapes, shades, angle and imaging conditions like background and lighting make it challenging. In most of the crops, generally the diseases and deficiencies manifest themselves as yellowing or browning of leaves in form of patches or spots and scorching. Also, different parts of the plant usually have different shapes, textures or colors. Presence of insects and pests can also be visibly identified. Image processing techniques have been used to detect color and texture of the disease affected area (Singh and Misra, 2017), (Wang et al., 2008) on a single leaf placed at the center of a plain background.

Considering that the deep convolutional networks based approaches have surpassed other approaches in terms of accuracy, various CNN based methods have been applied in leaf segmentation (Aich and Stavness, 2017), (He et al., 2016), (Pound et al., 2017) with impressive results in segmenting out the leaves. These methods are fully supervised where the CNN based models are trained on annotated data of images captured with similar resolution, same lighting and background conditions in the lab. In a real scenario however, the images would be with different backgrounds, occlusions, overlap and lighting conditions. Parts of plants have reasonable amount of variation especially in different growth stages. Applying supervised methods for segmentation of multiple crops in different regions would need a huge amount of annotated data. Variations in the crop at different stages and multiple manifestations of a disease or pests in different sizes make the annotations and data collection a time consuming task. Hence, we propose to use unsupervised methods to segment the images in order to make it applicable to multiple crops and use-cases. We propose a novel system comprising (i) an unsupervised

Bhatt, P., Sarangi, S. and Pappula, S.
Unsupervised Image Segmentation using Convolutional Neural Networks for Automated Crop Monitoring.
DOI: 10.5220/0007687508870893
In *Proceedings of the 8th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2019)*, pages 887-893
ISBN: 978-989-758-351-3

method for segmentation based on a fully convolutional network as a feature extractor with back propagation of the pixel labels modified according to the output of a graph based method – Normalized cut (Shi and Malik, 2000), and (ii) a method to identify different segments based on color, texture, and size to closely monitor different plants in indoor and outdoor farms. We have presented the results for segmentation of parts of plants, and disease and pest affected regions in them for 6 different crops viz. yellowing in Variagated Balfour Aralia and Dracaena, Helopeltis pest in Tea leaves, Black Moth in Cabbage, Anthracnose in Pomegranate, and fruit in a Citrus tree.

2 RELATED WORK

Supervised image segmentation methods (Farabet et al., 2013), (Badrinarayanan et al., 2017), (Ronneberger et al., 2015), (Hariharan et al., 2014) based on CNN have been widely used for many applications like autonomous vehicles and medical image analysis. These methods have achieved state-of-the-art results in semantic as well as instance level segmentation, but these models require to be trained with a large number of images along with their ground truth annotations at the segment level. Weakly supervised methods have also been proposed where the training data for semantic segmentation is a mixture of a few object segments and a large number of bounding boxes (Chang et al., 2014), or the dataset only contains the class specific saliency maps (Shimoda and Yanai, 2016). Recently, unsupervised methods for obtaining segmentation maps have been proposed in (Kanezaki, 2018) and (Xia and Kulis, 2017). In (Kanezaki, 2018), the cluster labels of the pixels in a super-pixel obtained by SLIC are corrected and used for back propogation to train the convolutional blocks. Authors in (Xia and Kulis, 2017) have used two U-Nets (Ronneberger et al., 2015) as an autoencoder, where encoding layer produces a pixelwise prediction and post-processing involving Conditional Random fields (CRF) and hierarchical segmentation for the encoder end to segment the image.

Fully convolutional networks (FCNs) (Long et al., 2015) have been proven as effective for solving the semantic segmentation problem. One advantage of using them is that images of arbitrary size can be input to the network and the segmentation map of the same size can be obtained. Conditional Random fields have been applied to smoothen the segmented boundaries. Liu et. al in (Liu et al., 2015) have used CRF as a post-processing step after the inference from CNN to refine the segmentation map. Chen et al. in (Chen et al., 2015) have proposed to train a FCN followed by fully connected gaussian CRF to accurately model the spatial relationships of the pixels in the images.

We perform Unsupervised segmentation using a FCN, and jointly optimize the image features and cluster label assignment for any image given as input. The pixel groups obtained through adjacency information using normalized cut once over the image is used to update the image features by updating the network weights.

3 METHOD

The aim is to obtain possible segments from the image based on pixel features in unsupervised manner. These segments can be further used to make an understanding out of the image. These features are different for every image and generally dependent on the color, edges and texture of pixel groups in the image. Such groups of pixels with similar features constitute a segment whose label is unknown in our case. These features are calculated using the convolutional network in our application. Consider $\{x_n \in R^d\}_{n=1}^N$ as a d-dimensional feature of an input image I with $\{p_n \in R^3\}_{n=1}^N$ pixels and let $\{l_n \in Z\}_{n=1}^N$ be the segment label assignment for each pixel where N is the total number of pixels in the image. The task of getting this unknown number of labels for every pixel can be formulated as $l_n = f(x_n)$ where $f : R^d \to Z$ is the cluster assignment function. For a fixed x_n, f is expected to give the best possible labels l_n. When we train the neural network to learn x_n and f for a fixed and known set of labels l_n, it can be termed as supervised classification. However, in this paper, we aim to predict the unknown segmentation map l_n while iteratively updating the function f and the features x_n. Effectively, we jointly

1. predict the optimal l_n for an updated f and x_n
2. Train the parameters of neural network to get f and x_n for the fixed l_n.

Humans tend to create segments according to the common salient properties of the objects or patches in the image like colors, texture, shape. Hence, a segmentation method should also be accurately grouping spatially continuous pixels having such similar properties into same class or label. Also, it must assign different labels to the pixels having different features. So as in (Unnikrishnan et al., 2007) (Kanezaki, 2018) (Xia and Kulis, 2017), we also apply the following criteria in our method: (i) Pixels with similar features must be assigned same label. (ii) Spatially continuous pixels are desired to be having same cluster label. (iii) Large number of unique labels is desired so that even the smaller segments are not missed. These criteria obviously have a trade-off and need to be balanced for good segmentation results. Our way of jointly optimizing them gives reasonably good results i.e l_n for application in images captured for crop monitoring. Figure 1 illustrates the implemented method for unsupervised segmentation of crop images. The size of FCN in the diagram are the ones that were used in the implementation for the results shown in this paper. The length of the network and the size of filters can be changed for better performance. Following subsections and the Algorithm 1 explain the method in detail.

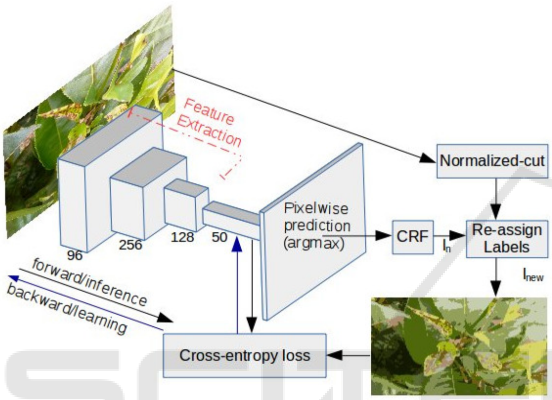


Figure 1: Block Diagram of the Proposed Approach.

3.1 Feature Calculation and Label Assignment

We calculate the d dimensional feature vector $\{x_n\}_1^N$ for the pixels of image I using Fully convolutional network architecture built using locally connected layers, such as convolution and pooling. The downsampling path in the neural network architecture captures the semantic information within the image and the upsampling path helps to recover the spatial information (Long et al., 2015). B blocks of convolutional layers followed by pooling are used to calculate the features. The output after these convolutional layers is termed as the features or feature-map $\{x_n\}_{n=1}^N$ of the image I and can be as $\{x_n = W_c p_n + b_c\}_{n=1}^N$. After these convolutional blocks, the last convolutional layer $1 \times 1 \times M$ fully convolutional layers are used for classification of pixels into different clusters, where M can be considered as the maximum possible unique labels in which the pixels can be clustered. The response-map of this layer is denoted as $\{W_{op} x_n + b_{op}\}_{n=1}^N$. After applying the batch normalization, we obtain the response map $\{y_n \in R^M\}_{n=1}^N$ that has M dimensional vector of values with zero mean and unit variance for every pixel in the image. Using this helps to achieve a higher number of clusters, thus satisfying the third criterion as mentioned in Section 3. The index of the value that is maximum in y_i can be considered as the label for the i^{th} pixel. It can be obtained by connecting argmax layer at the output. The total number of unique segments or the labels assigned in an image are between 1 to M and is determined by the image content and training of the neural network at every iteration. Since the convolutional networks are known to learn generalized features in the images well, they help satisfy the first criterion of assigning same cluster label to same pixels. Post-processing step of using CRFs on the map of cluster labels help in increasing the segmentation accuracy by refining boundaries.

3.2 Label Re-assignment and Feature Update

For every image, the network self-trains in order to segment it into certain number of clusters. After making the inference at every iteration, the labels of pixels in every superpixel is re-assigned on the premise that all pixels in a superpixel belong to same segment. We apply the normalized cut method on the same image to find the superpixel output. While, we have used Region Adjacency Graph (RAG) along with Normalized Cut (Shi and Malik, 2000) on the image, any super-pixel algorithm (Achanta et al., 2012), (Felzenszwalb and Huttenlocher, 2004) can be used to obtain the over-segmented map of an image. The super-pixel level output of the normalized cut method applied on the same image is used to update the cluster assignment denoted by $\{l_{new_n}\}_{n=1}^N$ of pixels in every super-pixel. After prediction from neural netwok, the pixels belonging a particular superpixel might have different cluster labels denoted by $\{l_n\}_{n=1}^N$. All these pixels are re-assigned the single label possesed by maximum number of pixels in that superpixel. These updated cluster labels are then used for backpropogation to train the feature extraction network. The cross entropy loss is calculated between the response-map $\{y_n \in R^M\}_{n=1}^N$ and the super-pixel refined cluster labels $\{l_n ew\}_{n=1}^N$ and then backpropagated to update the weights of the FCN for say T iterations. Using superpixels helps to compute features on more meaningful regions. They help to get disjoint partitions of the image and preserve image boundaries. Also, every superpixel is expected to represent connected sets of pixels. This helps to satisfy the second criterion of having spatially continuous pixels in same segment. Here, training of the neural network involves the learning of parameters $\{W_c, b_c\}$ of the convolutional layers of the FCN that contributes in getting image features and also $\{W_{op}, b_{op}\}$, the parameters of output $1 \times 1 \times M$ layer used to get cluster map for each pixel. This is termed as feature updation as shown in the step 10 of the Algorithm 1

Algorithm 1: Unsupervised Segmentation.

Input: $I = \{p_n\}_{n=1}^{N}$in R^3
Output: Labels $\{l_n\}_{n=1}^{N}$

1: $\{S_k\}_{k=1}^{K} \leftarrow NormCut(\{p_n\}_{n=1}^{N})$
2: **for** i from 1 to T: **do**
3: $\quad \{x_n\}_{n=1}^{N} \leftarrow GetFeatures(I, \{W_c, b_c\})$
4: $\quad \{y_n\}_{n=1}^{N} \leftarrow BatchNorm(W_{op} * x_n + b_{op})$
5: $\quad \{l_n\}_{n=1}^{N} \leftarrow argmax(\{y_n\}_{n=1}^{N})$
6: $\quad \{l_n\}_{n=1}^{N} \leftarrow CRF(\{l_n\}_{n=1}^{N}, \{p_n\}_{n=1}^{N})$
7: $\quad$ **for** i from 1 to K: **do**
8: $\quad\quad l_{new_n} \leftarrow argmax|l_n| \forall n \in S_k$
9: $\quad\quad loss \leftarrow CrossEntropy(\{y_n, l_{new_n}\}_{n=1}^{N})$
10: $\quad \{W_c, b_c, W_{op}, b_{op}\} \leftarrow UpdateFeatures(loss)$

4 RESULTS

In accordance to the block diagram in Figure 1, the considered neural network for experiments has 4 convolutional layers. More layers of different filter dimensions, pooling and upsampling can be used to evaluate if they give better feature learning. The last convolutional layer is $1 \times 1 \times 50$ where 50 can be assumed as maximum possible number of labels. CRF is used as the post processing step for refining the segments. The over-segmented map for the final step of refined cluster assignment is obtained by using Normalized Cut over the region adjacency graph (RAG) of the image. Cross-entropy loss between the predicted output of the last convolutional layer and the refined labels is calculated for backpropagation. Stochastic Gradient Dscent with a learning rate of 0.01 and momentum of 0.9 is used to train the neural network for $T = 500$ iterations. We have evaluated the segmentation performance using the measure in Equation 1. Here, A denotes the accuracy of predicted cluster labels l_n for all pixels with respect to the ground truth labels $\{gt_n\}_{n=1}^{N}$, and is defined by ratio of correctly predicted pixels to the total number of pixels N in the image.

$$A(l_n, gt_n) = \frac{\text{Number of correct } l_n}{N} \forall n \in [1, N] \quad (1)$$

For images of different crops, we applied the proposed segmentation method and have obtained acceptable results in terms of segments and their count. Column (b) in Figure 2 gives the crop-wise segmentation results using our method where the optimal number of clusters and segments are obtained. The color of every segment in the plotted result is the average of the RGB values of pixels assigned that particular segment label.

Refering to the images in Figure. 2, we obtained 4 segments (unique labels or clusters) in Variegated Balfour Aralia with 92% accuracy, 3 segments in Dracaena, 7 segments in Tea with 81% accuracy, 6 segments in Cabbage with 94% accuracy, 9 segments in Pomegranate with 67% accuracy, 6 segments in Citrus with 93% accuracy. Considering the trade-off between the number of segments and the way pixels are assigned the cluster labels, more number of segments are helpful for detecting any change in an image for crop monitoring. We could successfully obtain the segments of interest in all of these images, i.e. yellow segments in Aralia and Dracaena, black region in cabbage due to Black Moth, brown regions in Tea and Pomegranate due to attack of Helopeltis and Anthracnose respectively, as well as appearance of a fruit in a Citrus tree.

The main disadvantages in using the conventional methods of clustering are (a) finding the correct features that help in getting correct clusters and (b) the need to specify the desired number of clusters as input along with the image. These methods are also sensitive to the imaging conditions like light exposure and clarity. Column (c) in Figure. 2 shows the segments obtained by using a conventional method of color based clustering (K-means) over the same images. The number of clusters is fixed to 5 and the images were converted to CIELAB format before clustering. We obtained best results collectively for all the considered images when converted to CIELAB format with the number of clusters fixed to 5 in K-means method. Even if the image got segmented according to the difference in pixel values, we did not achieve the segments of interest. The color of each segment shown in the results is representative of the average of RGB values of all pixels in that cluster. The cluster labels in column (c) of Figure 2 are mixed up and we could not make out which segment corresponds to the color change, while the segments of yellow color on the leaves of Aralia and Dracaena are easily visible in column (b) images. Hence the proposed method helps to achieve better results in plant images by accurately and efficiently assigning the segment labels as expected.

Once the image is satisfactorily segmented, different ensembles of computer vision methods can be applied to achieve maximal automation in plant monitoring as described in the next section.

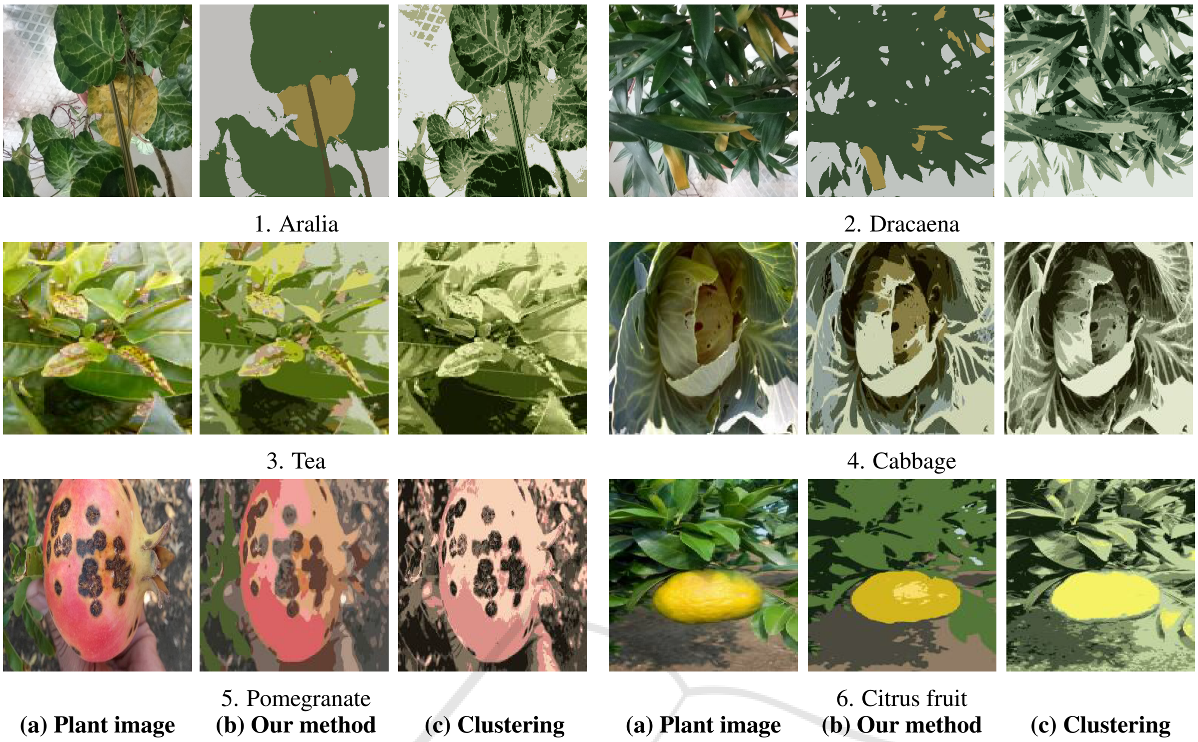


Figure 2: Segmentation results on different plant images with our method and K-means clustering in columns (a), (b) and (c).

5 APPLICATIONS

Our proposed unsupervised segmentation method while developed specifically for plant images is general enough to be applicable in other domains. As discussed in Sec. 1, the segmentation and measurement of any event in case of plants is challenging due to high inter-class variations. Moreover, annotating the small segments like Helopeltis in tea or Anthracnose in pomegranate as seen in Figure. 2 is a tedious task. As mentioned before, most manifestations of diseases and pests can be identified as change in color and texture on the crop parts. The real-time performance of this method enables easy deployments on edge devices like mobile phones, or camera installations in the fields.

5.1 Detecting Change in Plant Appearance

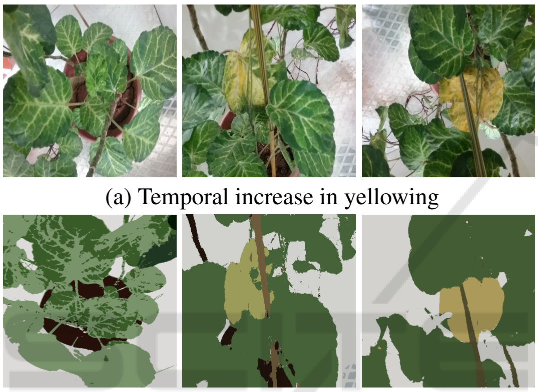
In applications like monitoring plants through a temporal sequence of images, it helps to use change detection methods to identify changes of interest. By detecting the growth stages of the plant, suggestions on fertilizers or pesticides can be made. This can also used to notify agri-experts about the events in the farm. As seen in Figure. 2, yellowing on leaves has resulted in an additional yellow segment on the images of Dracaena leaves and Aralia leaves, brown spots on tea leaves and pomegranate fruit, and brown holes on cabbage. The colors of these segments is identified by using the HSV values of the pixels in the newly emerged segments. If the color value of the additional segments is between yellow and brown, it is usually an indication that the plant suffers from low soil moisture or Nitrogen deficiency or is affected by some pest or disease.

5.2 Estimating Severity of Plant Health Condition

Pests and diseases contribute to some of the largest losses in crop yield around the globe. Moreover, due to lack of knowledge, chemicals are applied either at wrong growth stage or in wrong quantities. The diseases and pests can be easily detected using existing classification methods, but the idea of severity and stage is necessary to take actions at the correct point of time. Measuring the diseased region out of the image gives an idea of severity and hence the quantity of the pesticide. Once we obtain the color information of all the clusters, we measure the severity of the plant according to Equation 2. Here, c_{ij} denotes the i_{th} cluster that lies inside the boundary of the j_{th} segment of interest.

$$Severity = \frac{\sum \text{Number of pixels} \in \{c_{ij}\}_{i=1}^{nc}}{\text{Total pixels} \in c_j} \quad (2)$$

For example, in case of Helopeltis pest in tea leaves (Figure 2(c)), we consider all the group of pixels that (i) belong to all the *nc* labels that have pixels of brown value ($\{c_{ij}\}_{i=1}^{2}$) as well as (ii) are inside the leaf boundary i.e. surrounded by pixels with green value (c_j)) as the set of pixels representing pest on the leaves. Here $nc = 2$ as we have two different labels of brown shade that represent pests, and the severity measure for it is 11.41%



(a) Temporal increase in yellowing

(b) Segmentation using proposed method

Figure 3: Temporal increase of yellowing in leaves of Variagated Balfour Aralia (left to right).

The images can be analyzed for temporal events using this method for monitoring the rate of change in the segmented regions in consecutive images. For example, the three temporal images in Figure. 3 illustrate different health conditions of the same plant i.e. Aralia. The image in first column is that of a healthy plant, the middle column has some part of leaf yellowed and the last column has whole leaf in yellow which is a condition on a higher level of severity. The severity for these health stages in Aralia is 0% , 7.27% and 14.29% respectively. The lighter to darker shades of the segment also show the level of yellowing in the plant. The colors imply the mean of pixel values in the corresponding segments. All the experiments were done using Keras (Chollet, 2015) for building and training the neural network and OpenCV (Bradski, 2000) for image processing.

6 CONCLUSION

We have proposed an innovative method to carry out semantic segmentation through unsupervised feature learning with an FCN followed by CRF. This enables image segmentation into optimal number of clusters without any prior information or training. Different architectures of neural network for feature calculation as well as various ways of backpropogation can be explored to evaluate the performance on various images. Experimental results on different crop images prove utility of the method for automated crop monitoring which is a challenging application given interclass variations. Deployment of the model on the edge is also feasible for flagging crop related changes as it works real-time on images taken in uncontrolled conditions. In future, we would also evaluate for hyper-parameters and other network structures that could further enhance the quality of segmentation in the considered and other datasets. We aim to evaluate other methods like the pixel adjacency, texture difference, edges and gradient information to reassign the cluster labels in order to get more refined segments.

REFERENCES

Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., and Ssstrunk, S. (2012). Slic superpixels compared to state-of-the-art superpixel methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(11):2274–2282.

Aich, S. and Stavness, I. (2017). Leaf counting with deep convolutional and deconvolutional networks. *IEEE International Conference on Computer Vision Workshops (ICCVW)*, pages 2080–2089.

Badrinarayanan, V., Kendall, A., and Cipolla, R. (2017). Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(12):2481–2495.

Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools*.

Chang, F., Lin, Y., and Hsu, K. (2014). Multiple structured-instance learning for semantic segmentation with uncertain training data. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 360–367.

Chen, L., Papandreou, G., Kokkinos, I., Murphy, K., and Yuille, A. (2015). Semantic image segmentation with deep convolutional nets and fully connected crfs. In *Proceedings of the International Conference on Learning Representations*.

Chollet, F. (2015). Keras. https://github.com/fchollet/keras.

Farabet, C., Couprie, C., Najman, L., and LeCun, Y. (2013). Learning hierarchical features for scene labeling. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(8):1915–1929.

Felzenszwalb, P. F. and Huttenlocher, D. P. (2004). Efficient graph-based image segmentation. *International Journal of Computer Vision*, 59(2):167–181.

Hariharan, B., Arbeláez, P., Girshick, R., and Malik, J. (2014). Simultaneous detection and segmentation. In Fleet, D., Pajdla, T., Schiele, B., and Tuytelaars, T., editors, *Computer Vision – ECCV 2014*, pages 297–312. Springer International Publishing.

He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778.

Kanezaki, A. (2018). Unsupervised image segmentation by backpropagation. In *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*.

Liu, F., Lin, G., and Shen, C. (2015). Crf learning with cnn features for image segmentation. *Pattern Recognition*, 48(10):2983–2992. Discriminative Feature Learning from Big Data for Visual Recognition.

Long, J., Shelhamer, E., and Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3431–3440.

Pound, M. P., Atkinson, J. A., Wells, D. M., Pridmore, T. P., and French, A. P. (2017). Deep learning for multitask plant phenotyping.

Ronneberger, O., Fischer, P., and Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention*, pages 234–241. Springer International Publishing.

Shi, J. and Malik, J. (2000). Normalized cuts and image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(8):888–905.

Shimoda, W. and Yanai, K. (2016). Distinct class-specific saliency maps for weakly supervised semantic segmentation. In Leibe, B., Matas, J., Sebe, N., and Welling, M., editors, *Computer Vision – ECCV 2016*, pages 218–234. Springer International Publishing.

Singh, V. and Misra, A. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information Processing in Agriculture*, 4(1):41 – 49.

Unnikrishnan, R., Pantofaru, C., and Hebert, M. (2007). Toward objective evaluation of image segmentation algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(6):929–944.

Wang, L., Yang, T., and Tian, Y. (2008). Crop disease leaf image segmentation method based on color features. In Li, D., editor, *Computer And Computing Technologies In Agriculture, Volume I*, pages 713–717, Boston, MA. Springer US.

Xia, X. and Kulis, B. (2017). W-net: A deep model for fully unsupervised image segmentation. *CoRR*.