



Leaf Segmentation Challenge Using UNET

Harish Kumar Patidar

Galgotias University, Greater noida

harishpatidar8432@gmail.com

Dr.D.Maria Manuel Vianny

Galgotias University, Greater noida

maria.vianny@galgotiasuniversity.edu.in

Abstract— concentrating at the hassle of segmenting tobacco and arbidopsis leaves from an RGB photo, an vital assignment in plant phenotyping. to complete this project this venture, we use ultra-modern deep gaining knowledge of architectures: UNET, a convolutional neural community for initial segmentation. assessment is done on the leaf segmentation task dataset at CVPPP-2017. despite the fact that the small variety of education samples on this dataset, in comparison to standard deep mastering photo sets, we attain exceptional overall performance on segmenting leaves from the inside the from of binary segmentation as a whole and we need to paintings in addition to be counted the range of leaves. comparing evaluation supplied against strategies evaluated on the previous opposition datasets.

Index Terms—UNET, RGB image, Segmentation

RELATED WORK

before everything look the hassle of leaf segmentation seems just like leaf identity and isolated leaf segmentation, despite the fact that as we are able to see later it is not. studies on these areas has been prompted by way of several datasets showing leaves in isolation cut from flowers and imaged for my part or showing leaves at the plant but with a leaf encompassing a large subject of view (e.g., with the aid of imaging thru a smart smartphone software). This trouble has been addressed in an unsupervised, shape- based, and interactive fashion. but, the problem handy is significantly

I. INTRODUCTION

traditional plant phenotyping, which involves guide measurement of plant developments, is a gradual, tedious and costly mission. In maximum instances, guide size strategies use sparse random sampling accompanied by the projection of these random measurements over the whole populace which would possibly contain dimension bias. in addition, plant phenotyping has been recognized because the current bottleneck in current plant breeding and research packages. therefore, interest in picture-based phenotyping strategies have accelerated swiftly over the past 5 years.

This paper offers a collation look at and analysis of several methods from the LSC venture [1], and also from the literature. We in brief describe the annotated dataset, the primary of its type, that became used to check and evaluate the strategies for the segmentation of character leaves in picture-based plant phenotyping experiments. RGB pictures in the dataset show pinnacle view of tobacco and arbidopsis flora. two datasets show exclusive cultivars of Arabidopsis at the same time as any other one shows tobacco underneath different remedies. The RGB images and annotated pics are given inside the records set itself, so we have to use those datasets and construct a network that predicts the binary picture for a brand new test photograph. several techniques are briefly presented.

one of a kind. The goal isn't to become aware of the plant species (typically recognised on this context) however to section correctly every leaf in an picture displaying an entire plant.

This multi-example segmentation hassle is rather complex within the context of this software. that is because of the range in shape, pose, and appearance of leaves, however additionally due to lack of actually discernible barriers amongst overlapping leaves with traditional imaging conditions where a top-view constant digital camera is used. the dimensions of the dataset is likewise in a small size. several authors have dealt with the segmentation of a stay plant from heritage to degree growth using unsupervised and semi-supervised strategies, but no longer of individual leaves. using shade in aggregate with depth photographs or a couple of pix for supervised or unsupervised plant segmentation is likewise commonplace practice. strain caused by environmental elements evokes dynamic modifications in plant phenotypes [2]. several authors have considered leaf segmentation in a tracking context, where temporal information is to be had.

for example, Yin et al. segment and tune the leaves of Arabidopsis in fluorescence snap shots the usage of a Chamfer-derived power practical to healthy available segmented leaf templates to unseen records [3]. statistics acquisition and preprocessing, segmentation of all frames from a plant video collection, and steady leaf monitoring and modeling of the segmented leaves [4].

use an active contour components to segment and music Arabidopsis leaves in time-lapse fluorescence photographs. Many famous graph-primarily based segmentation procedures along with graph cuts end up an increasing number of high priced as extra nodes are introduced to the graph, restricting picture length in exercise which can be used to clear up our problem [5]. Even within the widespread laptop imaginative and prescient literature, this form of comparable-look, multi-instance hassle isn't always properly explored. although several interactive techniques exist, person interplay inherently limits throughput. then again part detection can be used to section the leaves and within the equal way we are able to in addition work in this to get the remember of the leaves [2]. shape-based segmentation of leaves is evolved by means of the Andy Tsai gives higher effects for the bio- clinical troubles [6]. Cerutti and his tem work on this problem in a specific approach through geometrical descriptor for leaf picture retrieval is the Centroid- Contour Distance (CCD) curve though it can be implemented to any



form of item [7]. Wu and Nevatia present an technique that detects and segments a couple of, partially occluded items in pix, counting on a discovered, boosted complete object segmentor and several part detectors. using gradient vector optimization and probability De Vylder and others worked on the leaf segmentation problem but it consists of more expertise on opportunity [eight]. Mario Valerio and their group worked at the leaf counting in rosette leaf [9]. Semantic segmentation inside the 2d photograph area is presently the most famous project for RGB- D scene knowledge this is accomplished by Shuran tune and his crew [10].my crew and i worked in this project via the usage of the annotated snap shots which is similar to the work of scharr H and his team on annotated pics [eleven]. another exciting work relies on Hough balloting to collectively stumble on and segment objects. a way for the automatic analysis of pix from phenotyping experiments that's developed using the picture-based plant phenotyping with incremental mastering and lively contours [12].curiously, past pedestrian datasets additionally they use a dataset of residence home windows in which look and scale so that architectonics can learn the multiplex structures variant are excessive (as is not unusual additionally in leaves), effectively [21]. The lowest layer mediates between the however they do not overlap. The problem of segmentation may be solved by way of the usage of the space for object Matching CNN layers followed by 2X2 up convolution layer. advanced by way of Hausdorff [13].The PASCAL visual object instructions (VOC) challenge can be used to to categorise the one-of-a-kind objects however this can now not be appropriate for segmenting the leaves [14].an automatic segmentation technique, the ImageJ plugin multi otsu threshold implementation of the otsu threshold set of rules to find as much as 5 most fulfilling threshold stage (multilevel) of an image, does also get no longer supply the specified thresholds which can be used if there a sizable diversions in the records [15].photograph based that are learned while contracting the image will be used to totally leaf segmentation is used to phase and count the leaves that is the maximum commonplace approach in those form of number of contraction block . After that, the outcome mapping problems [16].And in another paper we came across the graph reduce approach to section the leaves by green segmentation of leaves in semi-managed conditions [17].sooner or later, graphical strategies have also been applied to resolve and overlapping gadgets, and had been tested also on datasets showing more than one horses.as soon as the version is prepared we will deploy the version right into a robotic which may be used to resolve the problems in farming [18].The study of impact of surroundings on the vegetation may be studied with the aid of applying artificial surroundings to the vegetation [19]. Evidently, until now the evaluation and growth of leaf segmentation algorithms using a general reference dataset of separate images without temporal information is lacking, and therefore is the main focus of this paper is to work with a model which gives extra accurate segmentation.

III. METHODOLOGY

The u-internet is a convolutional community structure for instant and unique segmentation of snap shots. The architecture looks as if a 'U' which justifies its name. This architecture includes 3 sections: The contraction, The bottleneck, and the enlargement segment [20]. The contraction phase is made of many contraction blocks. each block takes an enter applies 3X3 convolution layers followed through a 2X2 max pooling.

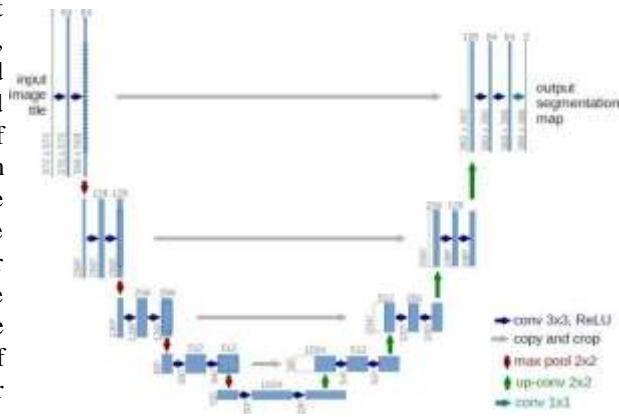


Fig. 1. UNET in Image Segmentation

The number of kernels or feature maps after each block doubles in the contraction layer and the expansion layer. It uses two 3X3 CNN layers followed by 2X2 up convolution layer.

But the heart of this architecture lies in the growth section. Similar to contraction layer, it also consists of several expansion blocks. Each block proceed the input to two 3X3 CNN layers followed by a 2X2 up sampling layer [22], [23]. Also, after each block number of feature maps used by convolutional layer get half to maintain regularity. However, every time the input is feature maps of the corresponding contraction layer. This action would ensure that the features learned while contracting the image will be used to remodel it. The number of enlargement blocks is as same as the number of contraction block . After that, the outcome mapping passes through another 3X3 CNN layer with the number of feature maps some to the number of segments desired.

A. Loss calculation in UNet

What form of loss one might use in such an internal photo segmentation? nicely, it is described definitely in the paper itself. The energy function is count via a pixel-wise smooth-max over the final function map mixed with the go-entropy loss function UNet uses a alternatively novel loss weighting scheme for each pixel such that there is a highest weight on the border of segmented items. This loss weighting scheme helped the U-internet model section cells in biomedical pix in a discontinuous style such that man or woman cells can be easily recognized within the dauble segmentation map. first of all, pixel-sensible softmax applied on the resultant image which is accompanied by go-entropy loss function. So, we're classifying each pixel into one of the instructions. The concept is that even in segmentation each pixel has to lie in a few category and we simply want to ensure that they do. So, we just converted a segmentation problem right into a multiclass type one and it accomplished thoroughly in comparison to the traditional loss features.

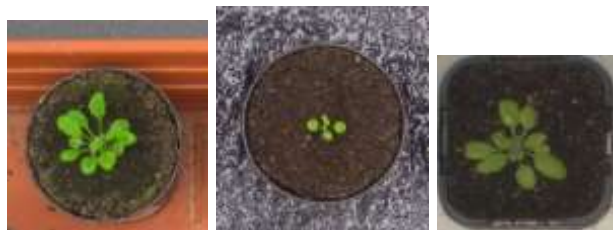


Fig. 2. Training and Validation loss curves

$$\frac{2 * |X \cap Y|}{|X| + |Y|} \quad (1)$$

With XX being our prediction matrix and YY our target matrix. $|X|$ stands for the cardinality of the set XX (the number of elements in this set) and \cap for the intersection between XX and YY.

B. UNet Implementation

We implemented the UNet version using Keras framework. snap shots for segmentation of rosette leaves with png format are used. There are varieties of dataset: (1). training information and (2). trying out records. education dataset consists of 4 folders and every folder consists of 3 styles of pictures and a .csv document. coloured photographs are the enter for our unet model, and the greyscale images are the pictures that is used by our model in learning technique [24]. This dataset is used for both LSC and LCC challenges and .csv record is used for LCC.

C. Dataset

The dataset includes four organizations i.e. A1, A2, A3 and A4 which contains the tobacco and arbidopsis leaves. The pictures includes the RGB snap shots of different dimensions and annotated photos are binary which incorporates two alternatives white and black. The shade snap shots are represented with the aid of rgb and annotated pix are represented by using fg extensions. The images are very finely annotated and converted them into .h5 layout. Then we added additional code to extract the .h5 layout and to regain the original .png documents. the subsequent are the sample image in the dataset. here A1, B1 and C1 are the shade pics and A2, B2 and C2 are the respected annotated images.

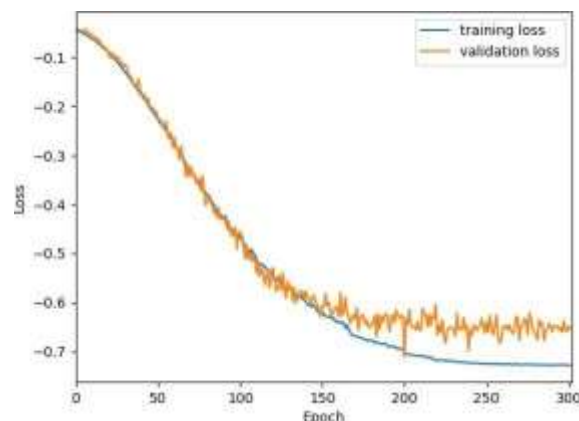


Fig. 3. Dataset Images a) A1 b) B1 c) C1

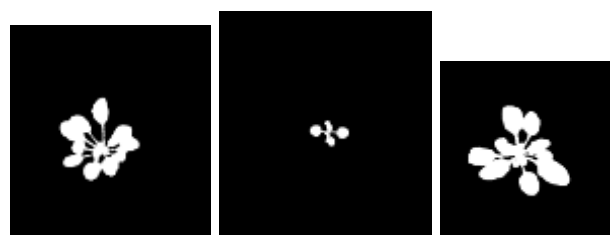


Fig. 4. Dataset Images a) A2 b) B2 c) C2

is less than the input by a stable border width. A pixel-wise soft-max count the energy function over the final feature map mixed with the cross-entropy loss function.

The input image and their reciprocal division to train the network maps is being used with problematic gradient descent. Because of unpadded complexity, the output image

The cross-entropy that correct at every position is explain as:

$$E = \sum_{\mathbf{x} \in \Omega} w(\mathbf{x}) \log(p_{\ell(\mathbf{x})}(\mathbf{x}))$$

The separation border is computed using morphological operations. The weight map is then computed as:

$$w(\mathbf{x}) = w_c(\mathbf{x}) + w_0 \cdot \exp\left(-\frac{(d_1(\mathbf{x}) + d_2(\mathbf{x}))^2}{2\sigma^2}\right)$$

Where w_c is the weight map to stability the class frequencies, d_1 designate the distance to the boundary of the near cell and d_2 denotes the distance to the boundary of the second near cell.

E. Prediction

After training, the model is set for the prediction phase. This prediction phase uses the test dataset which was in .h5 file format. The .h5 file should be converted to model readable format. To do that, we made use of a python code which reads the file and extracts the all the folders and files in it.

IV. EXPERIMENTAL RESULTS

Where A labelled images are the actual rgb images for prediction, B labelled images are the predicted images by model, C labelled images are the masked images of both A&B.

A. IoU Metric

The crossing over union (IoU) is a easy metric used to assess the performance of the segmentation algorithm. Given two masks x_{true} , x_{pred} we predict

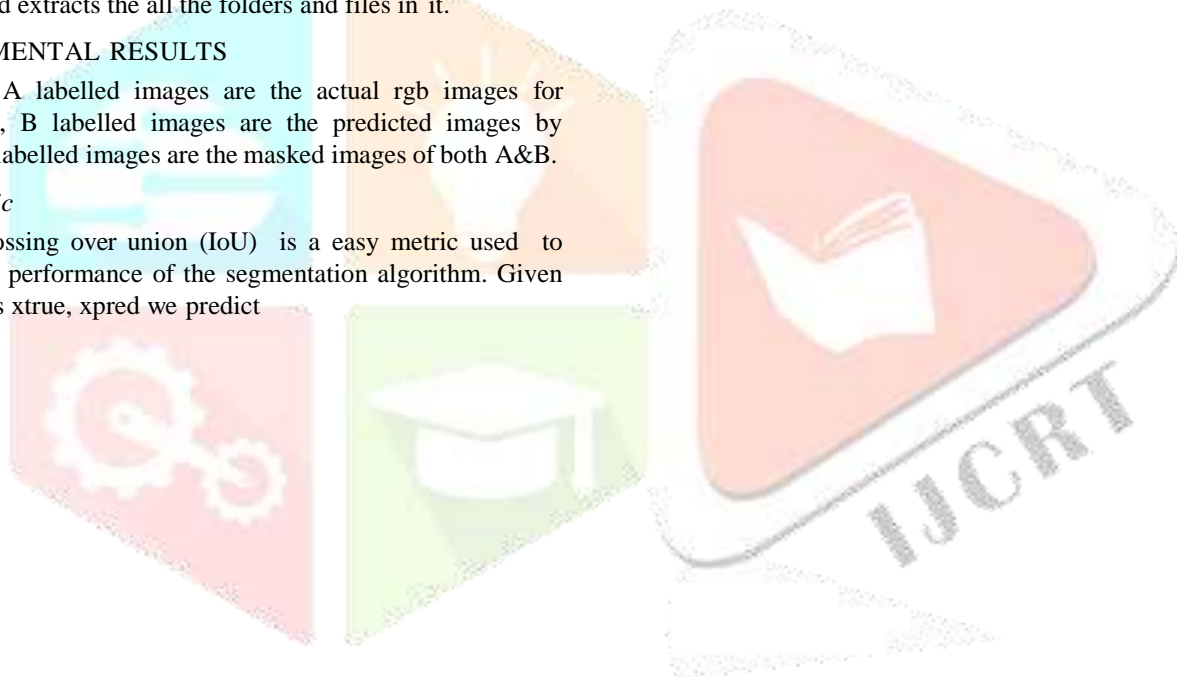




Fig. 5. Testing Images a) A1 b) B1 c) C1.



Fig. 6. Testing Images a) A2 b) B2 c) C2.

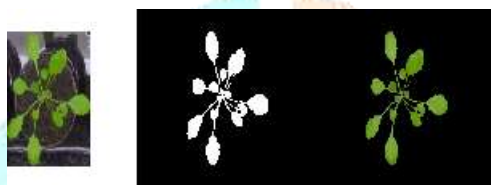


Fig. 7. Testing Images a) A3 b) B3 c) C3.

$$IoU = \frac{y_{true} \cap y_{pred}}{y_{true} \cup y_{pred}} \quad (2)$$

IoU Metric is an evaluation metric used to calculate the accuracy of an object detector on a particular dataset [25]. You have typically find crossing over Union used to assess the performance of Convolutional Neural Network detectors.

V. CONCLUSION

The u-net architecture achieves extremely good performance on very dissimilar biomedical division applications. Thanks to data accroissement with stretchy defor1mations, it only needs very few interpret images and has a very sensible training time of only 45 minutes for 100 epocs on a Google Colabo- ratory . We achieved an satisfactory Mean IOU of 92.7%.We provide the full Caffe-based implementation and the trained networks. It must be sure that the u-net architecture can be applied easily to many more tasks.

REFERENCES

- [1] "https://www.plant-phenotyping.org/ cvppp2017-challenge," *LeafSeg- mentation Challenge (LSC)*, 2017.
- [2] J. Canny, "A computational approach to edge detection," in *Readings in computer vision*. Elsevier, 1987, pp. 184–203.
- [3] H. Schar, M. Minervini, A. P. French, C. Klukas, D. M. Kramer, X. Liu, I. Luengo, J.-M. Pape, G. Polder, D. Vukadinovic *et al.*, "Leaf segmentation in plant phenotyping: a collation study," *Machine vision and applications*, vol. 27, no. 4, pp. 585–606, 2016.

- [4] E. E. Aksoy, A. Abramov, F. W. örgötter, H. Scharr, A. Fischbach, and B. Dellen, "Modeling leaf growth of rosette plants using infrared stereo image sequences," *Computers and electronics in agriculture*, vol. 110, pp. 78–90, 2015.
- [5] A. Tsai, A. Yezzi, W. Wells III, C. Tempany, D. Tucker, A. Fan, W. E. Grimson, and A. S. Willsky, "A shape-based approach to the segmentation of medical imagery using level sets," 2003.
- [6] G. Cerutti, L. Tougne, J. Mille, A. Vacavant, and D. Coquin, "Un- derstanding leaves in natural images—a model-based approach for tree species identification," *Computer Vision and Image Understanding*, vol. 117, no. 10, pp. 1482–1501, 2013.
- [7] M. V. Giuffrida, M. Minervini, and S. A. Tsafaris, "Learning to count leaves in rosette plants," 2016.
- [8] J. De Vylder, D. Ochoa, W. Philips, L. Chaerle, and D. Van Der Straeten, "Leaf segmentation and tracking using probabilistic parametric active contours," in *International Conference on Computer Vision/Computer Graphics Collaboration Techniques and Applications*. Springer, 2011, pp. 75–85.
- [9] M. V. Giuffrida, M. Minervini, and S. A. Tsafaris, "Learning to count leaves in rosette plants," 2016.
- [10] S. Song, S. P. Lichtenberg, and J. Xiao, "Sun rgb-d: A rgb-d scene understanding benchmark suite," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 567–576.