Analysis of nematodes in coffee crops at different altitudes using aerial images

Alexandre J. Oliveira, Gleice A. Assis,
Elaine R. Faria and Jefferson R. Souza
Federal University of Uberlândia (UFU)
{alexandre.oliveira, gleice, elaine, jrsouza}@ufu.br

Vitor Guizilini and Fabio Ramos
University of Sydney (USYD)
{vitor.guizilini, fabio.ramos}@sydney.edu.au

Kelen C. T. Vivaldini
Federal University of São Carlos (UFSCar)
vivaldini@dc.ufscar.br

Caio C. T. Mendes and Denis F. Wolf
University of São Paulo (USP)
{caiom, denis}@icmc.usp.br

***Abstract*—Precision agriculture presents several challenges, amongst them the detection of diseases and pests in agricultural environments. This paper describes a methodology capable of detecting the presence of the nematode pest in coffee crops and also analyzing the behavior of this pest in several altitudes using aerial images. An Unmanned Aerial Vehicle (UAV) is used to obtain high-resolution RGB images of a Brazilian coffee farm. The proposed methodology uses Convolutional Neural Networks (CNN) with U-Net and PSPNet architectures to classify areas into two classes: pests and non-pests. Results demonstrate the viability of the proposed methodology, with an average F-measure of 0.69 for the U-Net architecture with the image resolution 640×480.**

***Index Terms*—CNN, Nematodes, Coffee Crops, UAV, Altitudes.**

I. Introduction

With a planted area of 10.9 million hectares and world production of 153.6 million bags of 60 kg of coffee in 2016, coffee composes an essential agricultural activity throughout the world [1]. Brazil is one of the largest coffee producers, with 32.7% of the world's total [1]. According to the National Supply Company [2], the estimate for production of the Brazilian coffee crop (arabica and conilon) in 2019 is approximately 50.48 to 54.48 million bags.

Disturbances of diverse natures affect coffee crops, causing abnormalities that can result in a fall of production. Some of these disorders, with biotic causes, are known as pests and diseases. Among these, nematodes of the genus *Meloidogyne* represent economic losses that vary depending on the species located in fields [3]. The spreading *Meloidogyne* is a problem due to its high reproductive capacity [4]. Controlling the *Meloidogyne* is financially costly, since eradication is practically impossible. Thus, infestation control success depends on reducing the population level and preventing its multiplication.

The species *Meloidogyne paranaensis* has been the most dangerous to coffee crops [5], which has caused damage in the roots of the plants, demonstrating symptoms such as yellowing and defoliation in the plants. Also, with severe consequences such as the death of susceptible cultivars.

Producers and companies have great interest to any measure which would bolster the identification of the proliferation of such disease. One of these measure is the use of remote sensing applied in Precision Agriculture. Remote sensing uses images captures by satellites, piloted aircrafts and UAVs (Unmanned Aerial Vehicles) to evaluate and monitor crops yields. The monitoring of crops using UAVs performs temporal high-resolution, fast scanning of large areas and decreases data acquisition costs in comparison to manned aircraft, satellites or airborne platforms, while achieving similar goals [6].

In this way, we propose the use of UAVs to detect coffee plants with diseases symptoms, nematodes, as well as to promote changes in altitude during the flight to generate multiple resolution maps, with lower resolutions producing a larger field of view for faster initial surveys and higher resolutions producing more detailed representations for better classification accuracy of this pest in coffee crops (Fig.1). Our goal is to build a model on low flight altitudes and predicting the pest infestations areas at intermediate and higher altitude.

Lastly, this paper introduces a tool that would reduce production costs and contribute to sustainable coffee production.

Fig. 1: The Phantom 4 Pro used in our experiments.

The remainder of this paper is organized as follows: Section II shows a related work. Section III presents the proposed methodology. The results and analysis are shown in Section IV. Finally section V concludes and suggests future work.

II. Related Work

In precision agriculture, UAVs have been applied for several missions, such as plantation monitoring [7] [8], detection of planting failures [9] [10], estimation of productivity [11] and diagnosis of diseases [6], [12], [13].

978-9-0827-9703-9/19/$31.00 ©2019 IEEE

Garcia-Ruiz et al. (2013) [14] use multispectral images to detect greening allowed the classification of the diseases and healthy plants in citrus plantations. The highest classification accuracy was 85% with Support Vector Machines and UAVs in high-resolution images consisting of six spectral bands.

Otoboni et al. (2015) [15] used a hexacopter equipped with two GoPro cameras (one RGB and another modified to the near infrared) in soybean areas with *Meloidogyne incognita*. The UAV was used on a flight altitude of 80 meters for a spatial resolution of the image of 5 cm allowed the visualization of the damage caused by the nematodes pest to a specific area, with formation of different reefers concerning size and damage.

In [16] a Deep Convolutional Selective Autoencoder architecture was developed for rare object classification in Soybean Cyst Nematode (SCN) eggs images. This architecture was trained with labeled data to build a model for quantifying SCN eggs via microscopic image. In this way, the nematode eggs are correctly identified even in complex scenes, which are usually difficult for experts to determine quickly. The results show that using Deep Learning for pest management is useful.

A deep-learning-based method is applied in [17] to detect diseases and pests in tomato plants using images from an UAV. The authors considered Faster Region-based Convolutional Neural Networks (Faster R-CNN), Region-based Fully Convolutional Networks (R-FCN), and Single Shot Multibox Detectors (SSD). Additionally, each of these meta-architectures were combined with deep feature extractors such as VGG nets and Residual Networks. Results show that the proposed system recognizes 9 types of diseases and pests in tomato plantations.

III. Proposed Methodology

A. Data Collect

To obtain the aerial images, we used an aircraft Phantom 4 Pro. The aerial images were captured by an onboard camera of 4864×3648 pixel resolution (Fig. 2) and 72 dpi, flying at altitudes of 10, 15 and 20 meters on a coffee crops farm.

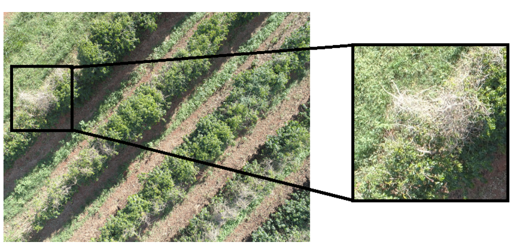


Fig. 2: Example of the nematoide pest from Phantom 4 Pro.

B. Training, Validation and Test Sets

A specialist in coffee pest manually labeled each one of the collected images, identifying pests with a bounding box. Then, to evaluate and compare the learning algorithms, we divided the data into training, validation and test sets. The measures used to assess the pixel-wise performance of the CNN architectures U-Net and PSPNet are precision, recall, and F-measure [18]. F-measure is a proper metrics for the analysis in problems with with imbalance among classes. Next, the complete proposed methodology is developed in Python.

C. Supervised Learning

We used two supervised learning algorithms, which are the convolutional neural networks (CNN) U-Net and PSPNet. Deep Learning (DL) methods are currently state-of-the-art in many problems, in particular, classification problems. One of the most popular DL methods in computer vision is CNN. This type of network is composed basically of convolutional layers, which processes the inputs considering local receptive fields. The main application of the CNN is for the processing of visual information since the convolution allows to filter the images considering its two-dimensional spatial structure [19].

1) U-Net: There is consent that successful training of CNN requires many thousand training samples. However, getting thousands of training images labeled considering coffee crops with the presence of nematodes is not a simple task. We need architectures that require few training images and provide good results. In this case, the U-Net [20] is highlighted because it uses a VGG16 [21] pre-trained network (transfer learning). During the U-Net training uses strategies like data augmentation to apply the labeled images efficiently [20].

CNN is characterized by having two stages. First, uses a number of convolutions and max-pooling layers which incrementally decreases the spatial resolution of the input while increasing the number of feature channels. This initial section is similar to the architecture proposed in [21]. Second, applies convolutions and transposed convolutions, reverting effects of first part, reducing feature channels and increasing resolution.

One characteristic of the U-Net is the use of "skip" connections, concatenates channel-wise the results of convolutions performed before each max-pooling to the effects of each transposed convolution. These skip connections are combined so that the result before the first max-pool layer is concatenated to the result of the last transposed convolution. The advantage of the connections is that they allow for the network to learn an initial result in few training steps without the need of modifying most network parameters. In a sense, they enable the training process to be incremental, where the parameters shown in the middle of the architecture can be the last to be learned and, as result, they help to avoid local minima.

2) PSPNet: One of the strategies used to improve the performance of semantic segmentation is the use of context cues [22]. However, the primary issue for current Fully Convolutional Networks (FCN) based models is the lack of a suitable strategy to use global scene category clues [23]. It is essential of the coffee crops the context because of the nematode pest is located between in coffee, causing defoliation and yellowing. In this way, we motivated to use an architecture based on spatial pyramidal pooling such as the PSPNet network [23].

PSPNet works with information from a context, aggregating this context with different regions using the Pyramid Pool (PP). This PP is useful for global contextual, which flatten and concatenates features on four pyramid levels. First level is responsible for producing a bin output. Second separates the feature map into sub-regions and makes pooled representation for multiple locations. The output of these levels contains the feature map with different sizes. To keep the global feature weight, authors apply a 1×1 convolution layer after each pyramid level to decrease the dimension of the context to $\frac{1}{N}$ of the original if the level size of the pyramid is N. Third is applied an upsample, which the low feature maps to obtain the same size feature using bilinear interpolation. Fourth concatenates features to produce the PP global feature.

The number of pyramid levels and size of each level can be modified, which are associated with the feature map size. The sub-regions formation with variable pooling kernels in fewer strides. Given an input image, PSPNet uses a pre-trained ResNet [24] with the dilated network strategy [25] to extract the feature map. The final feature map size is $\frac{1}{8}$ of the input image. Applying the 4-level pyramid, the pooling kernels cover the image. They are combined as the global, concatenate the previous with the original feature map, accompanied by a convolution layer to produce the final prediction map.

IV. Experimental Results

The samples for nematological analysis were collected in an area of 0.8 ha planted with cultivar Mundo Novo 379-19. A zigzag walk was carried out in the field, and soil and root samples of 15 plants were collected from the analyzed area. The soil was sampled in the projection of the coffee canopy in the depth of 20cm. The samples were homogenized, resulting in a composite sample containing 500g of soil and 100g of the root, and later analyzed in the Laboratory of Agricultural Nematology of UFU. A 150cm 3 aliquot of the homogenized soil was processed by sucrose centrifugation method for the nematodes extraction [26]. The obtained suspension was used to determine the number of juveniles of the second stage in the soil, with the help of Peters counting slide [1]. The presence of 2,400 youths and/or adults of Pratylenchus coffeae/150cm 3 of soil and 406 eggs and/or juveniles of the 2nd stage of Meloidogyne exigua/g of roots were found in the results of the nematological analysis. Both species detected in the field are parasitic nematodes of the coffee tree, being the genus Meloidogyne promoter of radicular galls and the genus Pratylenchus associated with the formation of root lesions.

The Phantom 4 Pro (Fig. 1) has a navigation system and critical situation (robot alerts base station when battery is low to make a route). The flight autonomy system has 5-directions of obstacle sensing and 4-directions of obstacle avoidance.

For image acquisition, the DroneDeploy free software [27] can be used to upload a map with a predefined route that must be covered by the UAV. The UAV flies over the route and takes photos, which are uploaded to a computer after the flight and merged into an image containing the whole area observed.

The evaluation for the precision, recall, and f-measure on test images is performed pixel by pixel, comparing the result of the labeled image with the prediction by the CNNs:

- If the predicted value is a pest and the labeled value is a pest, then it counts the amount of true positive (TP);
- If the predicted value is a pest and the labeled value is non-pest, then it counts the amount of false positive (FP);
- If the predicted value is non-pest and the labeled value is a pest, then it counts the amount of false negative (FN);

[1]used to identify and count nematodes under an optical microscope.

This paper presents two experiments aimed at the detection of the nematode pest from aerial images with the UAV. These experiments are explicitly divided into sections A and B.

A. Detection of the nematode pest using U-Net and PSPNet

Our first dataset was collected images from the UAV in a dry season period in Monte Carmelo - MG (Brazil), specifically a period that registered a mean of 27 millimeters of rain (represent 22,43% of the annual rainfall in 2018). Then, the images are more visible for the nematode pest. The first dataset is formed by 18 images, being 12 images for training (70%), 3 images for validation (15%) and 3 images for test (15%).

The first experiment focused on finding a proper model to represent the diseased and healthy areas of the coffee crops, specifically performing the detection of the nematode pest. Two CNN architectures were applied (U-Net and PSPNet) in our first dataset from 20 meters of height. P represents precision, R represents recall and F is the F-measure.

TABLE I: Comparison of architectures in different resolutions.

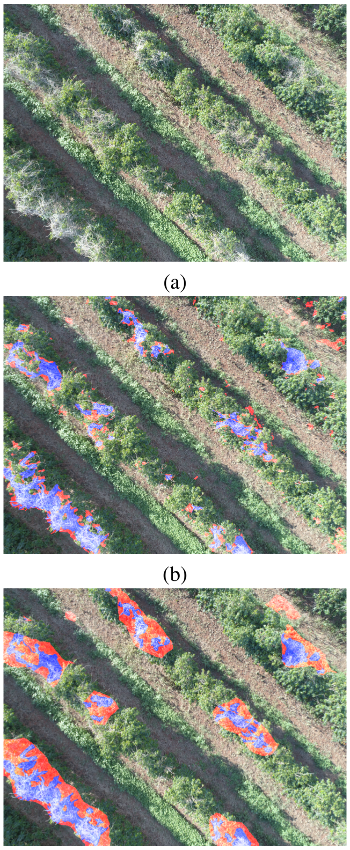
		640x480		960x640		1280x960	
Img		U-Net	PSPNet	U-Net	PSPNet	U-Net	PSPNet
1	P	0.67	0.70	0.68	0.57	0.72	0.58
	R	0.79	0.58	0.80	0.69	0.75	0.78
	F	**0.73**	0.63	**0.73**	0.63	**0.73**	0.66
2	P	0.61	0.41	0.54	0.38	0.58	0.45
	R	0.91	0.93	0.92	0.93	0.88	0.90
	F	**0.73**	0.57	**0.68**	0.54	**0.70**	0.60
3	P	0.70	0.15	0.73	0.34	0.67	0.95
	R	0.54	0.85	0.54	0.67	0.59	0.16
	F	**0.61**	0.27	**0.62**	0.45	**0.63**	0.28

U-net showed best performance considering the F-measure for three tests set in the three resolutions (TABLE I). As the three resolutions presented values of the equivalent F-measure, we adopted the resolution 640×480 for second experiment.

We noticed the value of the F-measure for image 2 with 0.73 for U-net compared to 0.57 of PSPNet (TABLE I). Highlighting the precision of both networks (0.61 and 0.41 respectively), we observed a difference of 20% between them. This difference can be seen in Figure 3, where Fig. 3 (b) shows the segmentation result in test image with U-Net compared to Fig. 3 (c) of PSPNet. We note that U-Net details better the regions containing the nematode pest compared to PSPNet, the areas in blue are labeled as pests and the network predicts correctly (true positive); and in the red areas are labeled as non-pests that the network predicts as a pest (false positive).

B. Altitude change analysis using U-net to detect nematode

Our second dataset is composed by images from the UAV in a rainy season period in Monte Carmelo - MG (Brazil), especially a period that registered a mean of 277 millimeters of rain (represent 230,20% of the annual rainfall in 2018). It is noted that rained ten times the period from the first dataset. Then, the excess rain inhibits the visible features of the nematode, and the plants are less noticeable for the



(a)

(b)

(c)

Fig. 3: (a) Original image. (b) Applied U-Net. (c) Applied PSPNet. Areas in blue are labeled as pests and the network predicts correctly (true positive); and the red areas are labeled as non-pests that the network predicts as a pest (false positive).

visual identification of the nematode. The second dataset is sub-divided in three distinctive datasets, which are formed by ten images for training and two images for validation in each altitude (10m, 15m, and 20m); totalizing 36 images. Lastly, we have 3 images for test set, being one image for each altitude.

The second experiment verified the implications of the U-net model using our second dataset from 10 meters of height, then performing the prediction of this model on images datasets in 10 meters, 15 meters and 20 meters of altitude for detection of the nematode pest. Also, from a U-Net trained model with 15 meters and then carry out the prediction in the three heights. Finally, a U-Net trained model with 20 meters and predict in the remaining three altitudes. P represents precision, R represents recall and F is the F-measure. Train-Val represents the training and validation data on a specific height.

TABLE II: Models prediction by U-Net for different altitudes.

Prediction		Train-Val-10m	Train-Val-15m	Train-Val-20m
10 meters	P	0.43	0.48	0.31
	R	0.77	0.45	0.63
	F	**0.55**	0.47	0.42
15 meters	P	0.31	0.38	0.25
	R	0.58	0.47	0.72
	F	0.41	**0.42**	0.37
20 meters	P	0.40	0.51	0.33
	R	0.40	0.34	0.58
	F	0.40	0.41	**0.42**

Table II shows a comparison of different models of U-Net on distinctive altitudes for the prediction of the nematode pest. We noted that the best model is the one trained with 10 meters and carried out the prediction in 10 meters. However, this model with 10 meters, when distanced to 15 meters and 20 meters it tends to decrease its effectiveness (decreases the values of the measure F). For the model with 20 meters, it obtained the lowest variation between the three heights (constancy) of the measure F. The tendency is that the model with 20 meters exhibits greater robustness because it does not degrade so much (it does not vary much to the measure F).

Fig. 4 shows the visual results of the prediction for the nematode pest using U-Net from the effects of the Table II.

V. Conclusions

An architecture for segmenting diseased plants has been proposed, using RGB images from a UAV. These features are processed by two distinct CNN architectures (U-Net and PSPNet), and the segmentation output was compared for the selection of the best model within the proposed methodology based on the F-measure evaluation metric. The aim is the detection of nematode (coffee crop disease in Brazil). Besides the analysis of different altitudes from UAV with the U-Net.

The result obtained by the proposed methodology shows that the F-measure metric average is 0.69 for the U-Net with resolution 640×480. The results encourage to search for improvements in the method from segmentation images. Also, we intend to investigate other Deep Learning architectures.

We noted that a U-Net trained model with 20 meters has less variation of the prediction in the nematode pest detection. The tendency is that model with 20 meters demonstrates greater robustness because it does not varies much to the F-measure. However, when a trained model with 10 meters was evaluated at greater heights, there was a marked fall in the nematode identification. For future work, we need to assess a higher number of heights to corroborate the results. The best result was generated when using images of greater heights for training, at three altitudes for prediction on test images considering the lower variation of the F-measure.

We believe these results are useful for the advancement of agriculture in Brazil. For future works, we will focus on applying techniques to work with the imbalanced data to improve the accuracy of the U-Net prediction model.

Acknowledgements

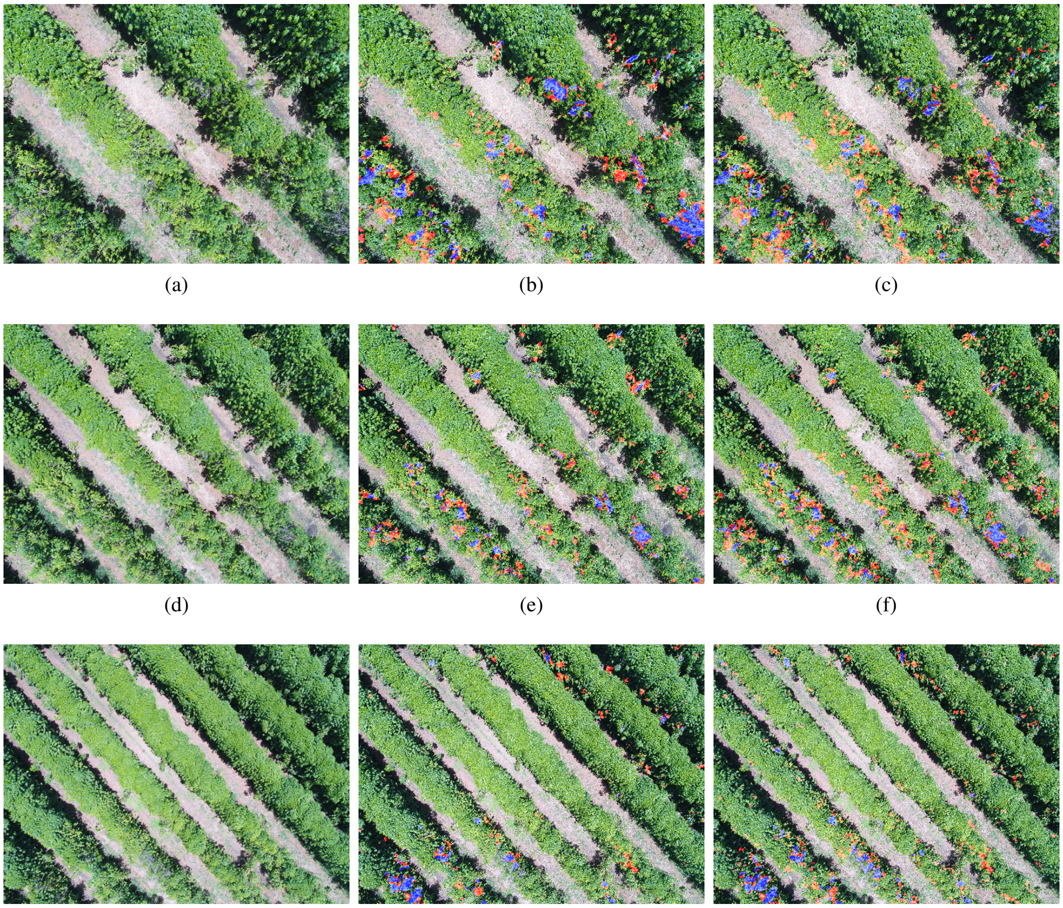
The Titan Xp used for this research was donated by the NVIDIA Corporation. This work was supported by the Federal University of Uberlandia, CNPq scholarship (process number 163641/2018-8) and CNPq under Grant 400699/2016-8.

References

[1] "Food and agriculture organization of the united nations," 2018. [Online]. Available: http://faostat.fao.org

[2] C. N. de Abastecimento, "Acompamento da safra brasileira : caf," *Companhia Nacional de Abastecimento*, vol. 6, no. 1, p. 62, 2019.

[3] M. Boisseau, J. Aribi, F. R. Sousa, R. M. D. G. Carneiro, and F. Anthony, "Resistance to meloidogyne paranaensis in wild coffea arabica," *Tropical Plant Pathology*, vol. 34, pp. 38–41, 2009.



(a) (b) (c)
(d) (e) (f)
(g) (h) (i)

Fig. 4: (a) Original image (OI) in 10 meters (m) of height. (b) U-Net trained with 10m and predicted with 10m. (c) U-Net trained with 20m and predicted by 10m. (d) OI in 15m. (e) U-Net trained with 10m and predicted by 15m. (f) U-Net trained with 20m and predicted by 15m. (g) OI in 20m. (h) U-Net trained with 10m and predicted 20m. (i) U-Net trained with 20m and predicted 20m. Blue areas are pests and network predicts correctly. Red areas are non-pests and network predicts pest.

[4] V. P. Campos and L. Villain, *Plant parasitic nematodes in subtropical and tropical agriculture*. Wallingford: CAB International, 2005.

[5] S. M. L. Salgado, J. C. Rezende, and J. A. R. Nunes, "Selection of coffee progenies for resistance to nematode meloidogyne paranaensis in infested area," *Crop Breeding and Applied Biotechnology*, 2014.

[6] K. C. T. Vivaldini, M. T. H., J. R. Souza, M. D. Oliveira, F. T. Ramos, and D. W. Wolf, "Uav route planning for active disease classification," *Autonomous Robots*, pp. 1–17, 2018.

[7] J. A. Navarro, N. Algeet, A. F., J. Esteban, P. Rodrguez-Noriega, and M. L. Guilln-Climent, "Integration of uav, sentinel-1, and sentinel-2 data for mangrove plant above bio monitor senegal," *Remote Sensing*, 2019.

[8] A. R. Larrinaga and L. Brotons, "Greenness indices from a low-cost uav imagery as tools for monitor. post-fire forest recovery," *Drones*, 2019.

[9] H. C. Oliveira, V. C. Guizilini, I. P. Nunes, and J. R. Souza, "Failure detection in row crops from uav images using morphological operators," *IEEE Geoscience and Remote Sensing Letters*, 2018.

[10] R. Kestur, "Detection of rows in agricultural crop images acquired by remote sensing from a uav," *IJIGSP*, vol. 8, pp. 25–31, 11 2016.

[11] G. Caruso, L. Tozzini, G. Rallo, J. Primicerio, M. Moriondo, G. Palai, and R. Gucci, "Estimating biophysical and geo. parameters of grapevine canopies by an uav and vis-nir cameras," *Vitis -Geilweilerhof-*, 2017.

[12] M. Pérez-Ortiz, P. A. Gutiérrez, J. M. Peña, J. Torres-Sánchez, F. López-Granados, and C. Hervás-Martínez, "Machine learning paradigms for weed mapping via unmanned aerial vehicles," in *ISSCI*, 2016.

[13] M. Popović, G. Hitz, J. Nieto, I. Sa, R. Siegwart, and E. Galceran, "Online info. path plan. for active classif. using uavs," in *ICRA*, 2017.

[14] F. Garcia-Ruiz, S. Sankaran, J. M. Maja, W. S. Lee, J. Rasmussen, and R. Ehsani, "Comparison of two aerial imaging platforms for identification of huanglongbing-infected citrus trees," *CEA*, vol. 91, 2013.

[15] C. E. M. Otoboni, A. Gabia, and A. S. Martins, "Det. áreas para manejo de nematoides em soja com o uso de imagens de vant," in *CBM*, 2015.

[16] A. Akintayo, G. L. Tylka, A. K. Singh, B. Ganapathysubramanian, A. Singh, and S. Sarkar, "A deep learning framework to discern and count microscopic nematode eggs," *Scientific Reports*, vol. 8, 2018.

[17] A. Fuentes, Y. Sook, S. C. Kim, and D. S. Park, "A robust deep-learning-based detec. for real-time tomato plant diseases pests," *Sensors*, 2017.

[18] Y. Sasaki *et al.*, "The truth of the f-measure," *Teach Tutor mater*, 2007.

[19] M. A. Ponti, L. S. F. Ribeiro, T. S. Nazare, T. Bui, and J. Collomosse, "Everything you wanted to know about deep learning for computer vision but were afraid to ask," in *SIBGRAPI*, 2017, pp. 17–41.

[20] P. F. O. Ronneberger and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," *CVPR*, 2015.

[21] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *CoRR*, 2014.

[22] Q. Yuan and Y. Fang, "A novel automatic grouping algorithm for feature selection," in *CCF Chinese Conference on Computer Vision*, 2017.

[23] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, "Pyramid scene parsing network," *Computer Vision and Pattern Recognition*, 2016.

[24] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *Computer Vision and Pattern Recognition*, 2016.

[25] L. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "Semantic image seg. deep conv. nets and fully connected," *CVPR*, 2014.

[26] W. R. Jenkins, "A rapid centrifugal-flotation technique for separating nematodes from soil," *Plant Disease Report*, vol. 48, 1964.

[27] "Dronedeploy," 2019. [Online]. Available: http://dronedeploy.com/