Scouting of Whiteflies in Tomato Greenhouse Environment Using Deep Learning*

Tomáš Tureček[1 [0000−0001−8872−3278]], Pavel Vařacha[1 [0000−0003−0042−9141]], Alžběta Turečková[1 [0000−0002−5566−7393]], Václav Psota[2 [0000−0002−7016−820X]], Peter Janků[1 [0000−0003−2899−3246]], Vít Štěpánek[2 [0000−0002−4902−456X]], Adam Viktorin[1 [0000−0003−0861−0340]], Roman Šenkeřík[1 [0000−0002−5839−4263]], Roman Jašek[1 [0000−0002−9831−9372]], Bronislav Chramcov[1 [0000−0002−3252−1578]], Ioannis Grivas[4 [0000−0003−4028−9649]], and Zuzana Komínková Oplatková[1 [0000−0001−8050−162X]]

[1] Tomas Bata University in Zlín, nám. T. G. Masaryka 5555, 760 01 Zlín, Czechia
{tturecek, varacha, tureckova, janku, viktorin, senkerik, jasek, chramcov, oplatkova}@utb.cz
http://www.utb.cz

[2] NWT a.s., třída Tomáše Bati 269, 760 01 Zlín, Czechia
{vaclav.psota,vit.stepanek}@nwt.cz
http://www.nwt.cz

[3] University of Thessaly General Department (Lamia), Greece
igrivas1@uth.gr

Abstract. This study shows the possibilities of how to replace tedious human labor - scouting of yellow sticky traps (YST) for whiteflies - using artificial cognitive vision, specifically deep convolutional network (CNN), as a part of the more complex system - BERABOT. The used CNN is the Faster R-CNN trained by deep transfer learning to substitute human scouting when the low whiteflies infection phase was specifically targeted. The training was conducted on pictures taken inside the heated and lighted tomato production greenhouse of "Bezdínek Farm" in Dolni Lutyne, Czechia. Used pictures were collected in a way suitable for future fully automated robotic applications in the BERABOT system. The achieved results were compared to the scouting results of a professional phytopathologist. The trained employee's scouting results against the professional phytopathologist accomplished root-mean-square error (RMSE) equal to 4.23 while the developed CNN model was evaluated to be 5.83. The results presented here open up new frontiers for further CNN model tuning leading to the potential in substituting an employee(S) in the future and make tomato production less expensive and less human labor dependent.

* Supported by the Technology Agency of the Czech Republic under the TREND Programme, project No. FW01010381, resources of A.I.Lab (ailab.fai.utb.cz) at the Faculty of Applied Informatics, Tomas Bata University in Zlin (TBU), and by Internal Grant Agency of TBU under the Project no. IGA/CebiaTech/2021/001.

Keywords: Whiteflies scouting · Tomato greenhouse · Deep transfer learning · Convolutional neural network · Faster R-CNN · Automated counting.

1 Introduction

The paper deals with developing a system for the scouting of pests in the tomato production greenhouse using artificial cognitive vision to substitute the tedious human labor. This is intended as a part of the system BERABOT[1] (Be-Bezdinek, Ra-tomatoes (rajčata in Czech), Bot-robot) developed by the company NWT (Zlín, Czechia), vegetable producer Bezdínek Farm (Dolní Lutyně, Czechia, www.farmabezdinek.cz) and Faculty of Applied Informatics (Tomas Bata University in Zlin, Czechia).

Globally, edible tomato (*Solanum lycopersicum* L.) is the most important vegetable in grown volume. In 2018, production reached more than 179 million tonnes. In 2019, it exceeded even 180 million tonnes [12]. Tomato's cultivation in modern hydroponic greenhouses eliminates many problems of outdoor field horticulture. Above all, it improves the efficiency of water management, precisely adjusts the dosage of fertilizers, and, to a large extent, adapts the indoor climate to set up ideal conditions for plant growth. Nevertheless, in such a semi-closed environment, one of the crucial risks of production losses is represented by pests and diseases.

The principles of integrated pest management (IPM) constitute the modern strategy of pests control, [9] preferring biological control methods and, if necessary, applying authorized synthetic chemical pesticides. Furthermore, across the European Union, there is constant pressure to reduce such chemical molecules' usage. Active substances with unsatisfactory ecotoxicological profiles are being banned to lower or zero pesticide residues levels in harvested crops [7, 1, 19]. Consequently, biological plant protection systems represent a key component in the cultivation of tomatoes. Monitoring of pests and diseases constitutes a crucial component of every IPM system. This activity supplies necessary data for the decision-making process considering biological or chemical intervention for crop protection. Thorough monitoring of diseases and pests using classical approaches and modern technologies allows for applying precision agriculture principles. Instead of the full-scale application of pesticides, locally infested hot spots are treated [20, 13, 11, 2].

1.1 Whiteflies

For tomatoes grown in a temperate zone of Europe inside the greenhouse, two of the most dangerous pests are the Greenhouse whitefly (*Trialeurodes vaporariorum* Westwood) and the Cotton whitefly (*Bemisia tabaci* Gennadius). Whiteflies belong to the group of sucking insect pests. They cause damage by herbivory of

[1] www.berabot.com

the plant's saps, and, as a result, the plant metabolism is disrupted. They also produce sticky honeydew on which molds are secondarily formed [22]. In addition, the species *B. tabaci* representing a vector of serious virus pathogens [6, 17]. Chemical control against whiteflies is often problematic, as many occasions of resistance to the active substances have been reported in the case of both above-mentioned species [10, 3, 14, 15].

Adult whiteflies (Fig. 1) are white and about 2 mm long. The wings and body are covered with powdery white wax. On its way from an egg to an adult, the whitefly undergoes four 4 larval intervals. Nevertheless, as a part of the monitoring, only the quantity of adults is considered in the vast majority of procedures.

Causing a telling decrease in yield, whiteflies are considered a serious pest with a significant economic impact. At higher whitefly densities, the fruits are also covered by sticky honeydew. As a rule, such fruits must be washed before being placed on the market or disposed of completely.

The economic losses caused by whiteflies in the tomato crop are estimated at tens to hundreds of millions of dollars worldwide. Furthermore, it should be noted that virus diseases transmitted by whiteflies cause additional significant losses indirectly [30].

(a) (b)

Fig. 1. Photos of the whiteflies captured in the greenhouse: (a) an adult whitefly in detail, (b) a tomato's leaf possess by whiteflies.

1.2 Traps inspection

Monitoring of the main pests of tomatoes grown in the greenhouse can be performed by several different methods. For the whiteflies, the yellow color's attractiveness has been utilized since the early 1920s [16]. Currently, standardized Yellow Sticky Trap (YST) is used worldwide as a common tool.

Considering the hydroponic greenhouse of Bezdinek Farm (Dolni Lutyne, Czechia) - the location where our study was performed, whiteflies (Insecta: Aleyrodidae) monitoring is conducted weekly. 40 to 50 YSTs are located at the level of the terminal top part of plants. The dimension of the used commercial YST is 25 x 10 cm (product Horiver by a producer Koppert). Black lines divide each YST into eight equirectangular squares to provide better orientation during the scouting.

Trapped whiteflies are counted by trained employees based on the visual inspection. An absolute number of whiteflies per card is recorded for the particular control date. In focus, there is mainly the change of whiteflies numbers in the time period (one week increase). Individual traps are changed continuously and regularly based on their contamination and a subjective evaluation of qualified personnel.

The quantities of whiteflies are not counted in the whole YST area if trapped whiteflies cover the card in equal density (higher than approximately 10 – 20 individuals per square). In such a case, whiteflies are counted only from one box, and the number is multiplied by eight (YST is divided into eight squares) to obtain the total of insects.

The critical source of the scouting error is caused by an extensive time period for which particular whitefly is being trapped as its body is continuously deteriorated by used glue. As an employee typically counts without more profound entomological expertise, a whitefly – especially a damaged one – can be misinterpreted as a different insect or vice versa. Commonly, whiteflies are confused with leafhoppers of the Cicadellidae family.

2 Motivation

Visual scouting of YSTs represents weary and tiresomely monotonous labor carried out within the grueling environment of a greenhouse. At the same time, scouting is prone to errors when conducted by inexpert personnel.

On the other hand, it will be costly to employ professional phytopathologists. For example, if performed on the entire tested area (11 ha), visual inspection of YSTs takes approximately two working days for one employee.

Such conditions constitute the primal motivation of this study following previously published studies, e. g. [21]. The proposed experiment (chapter 5) explores possibilities and efficiency of cognitive vision to perform scouting of YST to (i) reduce the cost of tomato production, (ii) decrease the error rate of YSTs' scouting, (iii) allow better redistribution of the human labor force within the growing process.

3 State of the Art

The first ascertainable attempt to construct an experimental system of automatic whiteflies scouting was published by Baush and Rath in 2005 [4]. Looking somewhat archaic these days, their interesting prototype contained an intricate sucking mechanism supplying trapped whiteflies to the optical part by a small conveyor belt.

Soon after this extraordinary experiment, more practical attempts to count whiteflies followed. In 2007, Cho et al. [8] proposed the first algorithm of automatic pest detection on YST. Using YUV color space and fixed thresholds, they examined 600 DPI pictures to count whiteflies, aphids, and thrips. In the same year, Martin and Thonnan [25] used the adaptive learning technique to adjust optimal parameters segmenting whiteflies out of leaves. Simultaneously, a more complex multidisciplinary cognitive vision approach based on the knowledge-base technique was designed by Boissard et al. [5] to count whiteflies on catted rose leaves in 2008. While in the same year, Qiao et al. [28] developed an effective counting system extracting whiteflies' distinctively white color out of the YST yellow surface. This approach was further improved by Moerkens et al. in 2019 [27] to distinguish different whiteflies species sufficiently.

In 2009, Solis Sánchez et al. scouted whiteflies on YST by segmenting their geometric features. Later he extended his method by scale-invariant feature transform (SIFT) [31] in 2011. Consequently, Xiao et al. [35] improved this method by applying the support vector machines (SVM) and bag-of-words (BOF) model in 2018. SVM was also used by Kumar et al. [23] to count whiteflies and greenflies from YST in the field conditions.

Additionally, Xia et al. (not to be confused with Xiao) developed methods of pest scouting, which are robust to field noise [34] (2012) and have a low computational cost [33] (2015).

In 2020, Tusubira et al. [32] applied cognitive vision methods to detect and count whiteflies (*Bemisia tabaci)* infecting in-field cassava. Two advanced techniques, Haar classifier and Faster R-CNN were trained and tested using an annotated dataset of 2 000 pictures with the approximated cost of the dataset labeling more than 330 working hours. While the Haar classifier proved to be insufficient for the task, Faster R-CNN provided precision of 98 % and a recall value of 81 %. In comparison with YST, Tusubira's study [32] was conducted in ideal conditions: a) whiteflies occurred on the cassava leaves almost exclusively, b) their white color contrasted on the green leaves' background, and c) whiteflies were captured *in vivo* unmolested by any trap.

Our proposed study and experiment seek to employ a similar CNN structure while labeling expenses are reduced by adopting Deep Transfer Learning.

4 Data preparation

For this study, a labeled dataset describing whiteflies on YST had not been available. Since its creation and labeling would be time-consuming and prone to mistakes, artificial images were generated instead. A similar approach of training set generation was used in other applied research papers, e. g. [24, 26].

Such method is commonly known as Deep Transfer Learning, and its practical applying is described in the chapter 4.1. To examine the trained models' performance on artificially generated data, real pictures captured in the greenhouse were utilized. These images were evaluated by a skilled laborer and a professional phytopathologist as described in the subsection 4.2.

4.1 Training and validation set

To prepare a training set, 10 different pictures of clear YST and 10 YST with sticked insects were taken. Masks of a whitefly (*Trialeurodes vaporariorum*) were manually segmented and transferred on a transparent background to generate the artificial data on a clear YST. Aside from it, several flies from the Diptera order (i.e., *Sciaridae* or *Agromyzidae*) and some mirid bugs (i.e., *Macrolophus pygmaeus* or *Nesidiocoris tenuis*) were similarly segmented to both enlarge the variability of training data and approximate the reality as much as possible. Examples of the insect's mask are depicted in Fig. 2.

(a) whiteflies *Trialeurodes vaporariorum* (b) small flies from the Diptera order (c) mirid bugs (*Miridae*)

Fig. 2. Examples of used insects' segmented masks to generate artificial YST images for the training set.

During the generation process, randomly chosen masks of these insects were selected and placed in the area of the segmented clear YST taken as a photograph in the initial phase. The background YST image was divided into several sections, and the insect's masks were incrementally placed in all of them to ensure the desired homogeneity of the covered space. This way, three hundred images were generated and used to train the deep learning models. Fig. 3 compares the picture of the YST captured in the greenhouse with the real occurrence of whiteflies (a) and the YST's photo with whiteflies generated and located artificially (b).

(a) (b)

Fig. 3. Comparison of the photo of the YST captured in the greenhouse (a) and the picture with artificial insertion of whiteflies (b).

4.2 Test set

The test set consists of 118 real captured photos of YST to verify the proposed deep learning model with the real number of whiteflies counted on YST.

Capturing pictures in the Greenhouse Pictures of YSTs were taken directly in the lighted tomato production crop in the greenhouse of Bezdínek Farm - a location of our study. The pictures were taken in the 11th week after planting. The plants were in the full production phase. YSTs were placed in the zones of the terminal apexes of the plants at that time. Therefore, a lift platform (Berg Hortimotive) was used when taking the pictures. YST was always removed from the hanging hook to take a shot in horizontal and vertical positions. An Olympus E-M1 camera was used for photography.

Counting whiteflies The whiteflies were counted both during the photography in the greenhouse by specialized personnel and after taking pictures on a computer monitor by a phytopathologist. In case of uncertainty, the relevant part was zoomed by a phytopathologist on a screen to confirm or refute the whitefly's presence. As part of this evaluation, visually similar specimens were observed and recorded too, especially from the Cicadellidae family, which might cause potential errors in the whiteflies identification and counting by the CNN.

The phytopathologist's outcomes are taken as the gold standard - the reference values defining the precision and recall of both the proposed method and the manual counting in the greenhouse.

Pictures' preparation for CNN The resolution of the original photos (more than 800×1024 pixels) exceeds the model's ability to process them at one pass. Therefore, the test images were processed patch-wise with the patch size 800×1024 pixels. The model predicts each patch separately, reconnecting the outputs into the final prediction. By this approach, the model was able to access submitted pictures in all details. This process is described in section 5.2.

5 Experiments

5.1 Deep CNN Model

A Faster R-CNN model [29] with a ResNet-50 backbone [18] was utilized in the experiments. The model was initialized with weights trained on the known COCO dataset and finetuned for the number of classes present in the relevant dataset. Even though the whitefly is the most important insect, it is better to have more classes in the dataset than only one. To increase the CNN effectivity, the following three classes are used for the prediction to highlight the whiteflies numbers and distinguish them from other insects: whitefly (*Trialeurodes vaporariorum*), small Diptera flies, and Mirid bugs.

5.2 Training and test set predictions

The automatically generated data were split in nine to one ratio into training and validation parts, respectively. The patches of the size 800×1024 pixels were cut from the generated picture to allow the model to process images with high resolutions and simultaneously enable quick pass through the model. The cut part's position in the image was generated randomly on the fly during the training process. Additionally, mirroring augmentation was applied. These techniques hugely increase the training data variability and help prevent overfitting.

The model had been trained for ten epochs, considering one epoch as a single pass through all training data. SGD (Stochastic gradient descent) with learning rate 5E-3, momentum 0.9, and weight decay of 5E-4 were utilized to optimize the model weights.

The same size patches (800×1024 pixels) were necessary to use also during the test set prediction. On the contrary to training, the test set images had to be inspected in the whole area. Therefore, the input test pictures were divided into several patches, and the model predicts each patch separately. After that, all outputs were reconnected to obtain the final predicted total for particular classes on one test YST. The non-maximum suppression technique was used on the final output bounding boxes to reduce multiple patch borders' detections.

6 Results

Comparing the achieved results by CNN with the human manual labor was necessary to set up the reference values to which all precision and recall measures will be related. As such gold-standard - reference ideal values, the counting of whiteflies performed by a professional phytopathologist during the inspection of photos on a computer monitor was taken. Firstly, the comparison of the visual counting by a trained employee in the greenhouse and reference values was evaluated. The cumulative amount of whiteflies on all 118 YSTs in the test set was 824 as counted by a phytopathologist on photos and 1161 whiteflies found on YST during the greenhouse inspection. Therefore there are less than seven to ten whiteflies per one YST on average. Such numbers are considered as the early phase of pest infestation. To correctly and timely detect this phase, the huge plant damages and losses can be avoided, which is considered a critical component of IPM (e. g. [5]), and at the same time, scientists (e. g. [27]) consider this phase most prone to errors.

Since the phytopathologist's values were used as the reference values, the precision and recall values were related to them. The employee labeled correctly almost the same number of whiteflies as the phytopathologist - the recall is 0.9946. However, many other insects were wrongly classified as whiteflies, which led to the evaluation of the precision as 0.6943. The recall and precision measures show obviously that the error was obtained. Root Mean Square Error (RMSE) was quantified to 4.23, representing the average per tested YSTs.

Consequently, the predictions of whiteflies by the Faster R-CNN model were compared with the above-described case of manual counting by a trained employee. The table 1 shows the RMSE, precision, and recall values assessed for the thresholds of selected bounding box detection scores ranging from 0.86 to 0.945. The recall is equal to 1 in the threshold of 0.86, but the precision is very low (many insects were labeled as whiteflies). On the contrary, the precision is computed as 1 in the threshold 0.945, but almost no whiteflies were detected (recall is 0.0216).

The best overall values were achieved with a threshold of 0.895, giving values of 0.5794 for precision and 0.7892 for recall. Simultaneously, the best RMSE of 5.83 was achieved by prediction with a threshold of 0.905. The evaluation of precision and recall are also displayed in a precision-recall graph in Fig. 4.

Table 1. The cumulative amount of whiteflies on YST detected by the Faster R-CNN model and it's RMSE, precision and recall assessed for thresholds of selected bounding box detection scores ranging from 0.86 to 0.945.

Threshold	Sum of whiteflies	RMSE	Precision	Recall
0.860	3495	25.54	0.2323	1.0000
0.865	3056	21.84	0.2638	0.9919
0.870	2617	18.03	0.3037	0.9784
0.875	2298	15.69	0.3372	0.9541
0.880	1912	12.29	0.3940	0.9297
0.885	1564	9.50	0.4712	0.9081
0.890	1313	8.03	0.5285	0.8514
0.895	1109	7.17	0.5794	0.7892
0.900	851	6.02	0.6443	0.6757
0.905	712	5.83	0.6821	0.5973
0.910	535	6.28	0.7172	0.4730
0.915	416	6.77	0.7684	0.3946
0.920	289	7.40	0.8473	0.3000
0.925	203	7.87	0.8804	0.2189
0.930	148	8.32	0.8939	0.1595
0.935	100	8.68	0.9545	0.1135
0.940	41	9.12	0.9474	0.0486
0.945	17	9.38	1.0000	0.0216

7 Conclusion and Discussion

This study shows possibilities of how to replace tedious human labor - scouting of YST for whiteflies - using modern computer vision methods. The case study was conducted using real pictures taken inside the heated and lighted tomato production greenhouse of Bezdínek Farm. The achieved results were analyzed and mutually compared between the reference values represented by the whitefly amounts counted by the professional phytopathologist and the trained employee or the CNN model in a recall, precision, and root-mean-square error (RMSE).

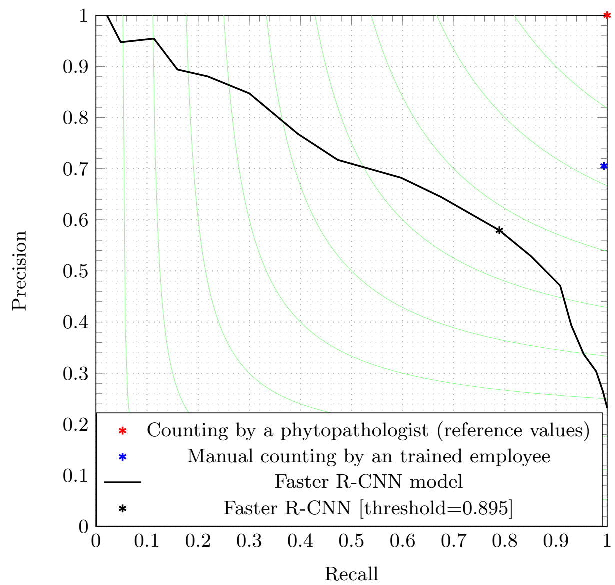

Fig. 4. Precision-Recall measure on iso-f curve for detection by Faster R-CNN model and manual counting by an trained employee.

RMSE for both cases were close to each other (4.23 for an employee and 5.83 for the developed CNN), which motivates the team to tune the CNN in the future to increase the model's potential for substituting an employee and make tomato production less expensive and less human labor dependent.

Future work will also cover the adjusting of the labeling data approach to overtake the human advantages in whitefly recognition and contribute to being the beneficial part of the system BERABOT.

References

1. EUR-Lex - 52019DC0640 - EN - EUR-Lex, https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1596443911913uri=CELEX:52019DC0640document2
2. IPM- Scouting and Monitoring for Pests in Commercial Greenhouses - Oklahoma State University
3. Ahmad, M., Arif, M.I., Ahmad, Z., Denholm, I.: Cotton whitefly (Bemisia tabaci) resistance to organophosphate and pyrethroid insecticides in Pakistan. Pest Management Science **58**(2), 203–208 (2002)
4. Bauch, C., Rath, T.: Prototype of a vision based system for measurements of white fly infestation. Acta Horticulturae **691**, 773–780 (2005)
5. Boissard, P., Martin, V., Moisan, S.: A cognitive vision approach to early pest detection in greenhouse crops. Computers and Electronics in Agriculture **62**(2), 81–93 (Jul 2008)
6. Brown, J.K.: Current status of Bemisia tabaci as a plant pest and virus vector in agroecosystems worldwide. FAO Plant Protection Bulletin **42**(1/2), 3–32 (1994)

7. Butler, D.: EU expected to vote on pesticide ban after major scientific review. Nature **555**(7695) (Mar 2018), publisher: Nature Publishing Group
8. Cho, J., Choi, J., Qiao, M., Ji, C., Kim, H., Uhm, K.B., Chon, T.: Automatic identification of whiteflies, aphids and thrips in greenhouse based on image analysis (2007)
9. Ehler, L.E.: Integrated pest management (IPM): definition, historical development and implementation, and the other IPM. Pest Management Science **62**(9), 787–789 (2006)
10. Elbert, A., Nauen, R.: Resistance of Bemisia tabaci (Homoptera: Aleyrodidae) to insecticides in southern Spain with special reference to neonicotinoids. Pest Management Science **56**(1), 60–64 (2000)
11. Ent, S.v.d., Knapp, M., Klapwijk, J., Moerman, E., Schelt, J.v., Weert, S.d., Jongen, M., Schumacher, M.: Knowing and recognizing: the biology of pests, diseases and their natural solutions. Koppert Biological Systems, Berkel en Rodenrijs, [third] revised and expanded edition of the second edition edn. (2017)
12. FAOSTAT: FAOSTAT (Jan 2021), http://www.fao.org/faostat/en/data/QC/visualize
13. Gacheri, C., Kigen, T., Sigsgaard, L.: Hot-spot application of biocontrol agents to replace pesticides in large scale commercial rose farms in Kenya. BioControl **60**(6), 795–803 (Dec 2015)
14. Gorman, K., Devine, G., Bennison, J., Coussons, P., Punchard, N., Denholm, I.: Report of resistance to the neonicotinoid insecticide imidacloprid in Trialeurodes vaporariorum (Hemiptera: Aleyrodidae). Pest Management Science **63**(6), 555–558 (2007)
15. Gorman, K., Hewitt, F., Denholm, I., Devine, G.J.: New developments in insecticide resistance in the glasshouse whitefly (Trialeurodes vaporariorum) and the two-spotted spider mite (Tetranychus urticae) in the UK. Pest Management Science **58**(2), 123–130 (2002)
16. Griepink, F.C., van Beek, T.A., Posthumus, M.A., de Groot, A., Hans Visser, J., Voerman, S.: Identification of the sex pheromone of Scrobipalpula absoluta; determination of double bond positions in triple unsaturated straight chain molecules by means of dimethyl disulphide derivatization. Tetrahedron Letters **37**(3), 411–414 (Jan 1996)
17. Hadjistylli, M., Roderick, G.K., Brown, J.K.: Global Population Structure of a Worldwide Pest and Virus Vector: Genetic Diversity and Population History of the Bemisia tabaci Sibling Species Group. PLOS ONE **11**(11), e0165105 (Nov 2016), publisher: Public Library of Science
18. He, K., Zhang, X., Ren, S., Sun, J.: Deep Residual Learning for Image Recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 770–778. IEEE, Las Vegas, NV, USA (Jun 2016)
19. Hillocks, R.: Impact of EU Pesticide Reduction Strategy and Implications for Crop Protection in the UK and the Rest of Europe. Outlooks on Pest Management **24**(5), 206–209 (Oct 2013)
20. Iost Filho, F.H., Heldens, W.B., Kong, Z., de Lange, E.S.: Drones: Innovative Technology for Use in Precision Pest Management. Journal of Economic Entomology **113**(1), 1–25 (Feb 2020), publisher: Oxford Academic
21. Jiang, J.A., Tseng, C.L., Lu, F.M., Yang, E.C., Wu, Z.S., Chen, C.P., Lin, S.H., Lin, K.C., Liao, C.S.: A GSM-based remote wireless automatic monitoring system for field information: A case study for ecological monitoring of the oriental fruit fly, Bactrocera dorsalis (Hendel). Computers and Electronics in Agriculture **62**(2), 243–259 (Jul 2008)

22. Johnson, M.W., Caprio, L.C., Coughlin, J.A., Tabashnik, B.E., Rosenheim, J.A., Welter, S.C.: Effect of Trialeurodes vaporariorum (Homoptera: Aleyrodidae) on Yield of Fresh Market Tomatoes. Journal of Economic Entomology **85**(6), 2370–2376 (Dec 1992)
23. Kumar, R., Martin, V., Moisan, S.: Robust Insect Classification Applied to Real Time Greenhouse Infestation Monitoring (2010)
24. Luna, R.G.d., Dadios, E.P., Bandala, A.A., Vicerra, R.R.P.: Tomato Fruit Image Dataset for Deep Transfer Learning-based Defect Detection. In: 2019 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM). pp. 356–361 (Nov 2019), iSSN: 2326-8239
25. Martin, V., Thonnat, M.: A Cognitive Vision Approach to Image Segmentation. In: Fritzsche, P. (ed.) Tools in Artificial Intelligence. InTech (Aug 2008)
26. Maryam Rahnemoonfar, Clay Sheppard: Deep Count: Fruit Counting Based on Deep Simulated Learning. Sensors **17**(4), 905 (Apr 2017)
27. Moerkens, R., Brenard, N., Bosmans, L., Reybroeck, E., Janssen, D., Hemming, J., Sluydts, V.: Protocol for semi-automatic identification of whiteflies Bemisia tabaci and Trialeurodes vaporariorum on yellow sticky traps. Journal of Applied Entomology **143**(6), 652–658 (2019)
28. Qiao, M., Lim, J., Ji, C.W., Chung, B.K., Kim, H.Y., Uhm, K.B., Myung, C.S., Cho, J., Chon, T.S.: Density estimation of Bemisia tabaci (Hemiptera: Aleyrodidae) in a greenhouse using sticky traps in conjunction with an image processing system. Journal of Asia-Pacific Entomology **11**(1), 25–29 (Mar 2008)
29. Ren, S., He, K., Girshick, R., Sun, J.: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence **39**(6), 1137–1149 (Jun 2017)
30. Sani, I., Ismail, S.I., Abdullah, S., Jalinas, J., Jamian, S., Saad, N.: A Review of the Biology and Control of Whitefly, Bemisia tabaci (Hemiptera: Aleyrodidae), with Special Reference to Biological Control Using Entomopathogenic Fungi. Insects **11**(9), 619 (Sep 2020), number: 9 Publisher: Multidisciplinary Digital Publishing Institute
31. Solis-Sánchez, L., Castañeda-Miranda, R., Garcia-Escalante, J., Pacheco, I., Guevara-Gonzalez, R., Castañeda-Miranda, C., Alaniz-Lumbreras, D.: Scale invariant feature approach for insect monitoring. Computers and Electronics in Agriculture **75**, 92–99 (Jan 2011)
32. Tusubira, J., Nsumba, S., Ninsiima, F., Akera, B., Acellam, G., Nakatumba, J., Mwebaze, E., Quinn, J., Oyana, T.: Improving in-field cassava whitefly pest surveillance with machine learning. vol. 2020-June, pp. 303–309 (2020)
33. Xia, C., Chon, T.S., Ren, Z., Lee, J.M.: Automatic identification and counting of small size pests in greenhouse conditions with low computational cost. Ecological Informatics **29**, 139–146 (Sep 2015)
34. Xia, C., Lee, J.M., Li, Y., Chung, B.K., Chon, T.S.: In situ detection of small-size insect pests sampled on traps using multifractal analysis. Optical Engineering **52**, 027001 (Mar 2012)
35. Xiao, D., Feng, J., Lin, T., Pang, C., Ye, Y., 1. College of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China, 2. Agricultural Aviation Research Institute of South China Agricultural University, Guangzhou 510642, China: Classification and recognition scheme for vegetable pests based on the BOF-SVM model. International Journal of Agricultural and Biological Engineering **11**(3), 190–196 (2018)