Agrochimica, Vol. 65 - Special Issue (2021)

Precision agriculture to improve the monitoring and management of tomato insect pests

Valeria Zeni[1,*], Giovanni Benelli[1], Luca Incrocci[1], Angelo Canale[1], Luca Ciampi[2], Giuseppe Amato[2], Stefano Chessa[3]

[1] Department of Agriculture, Food and Environment, University of Pisa, Pisa, Italy

[2] Institute of Information Science and Technologies National Research Council, Pisa, Italy

[3] Department of Computer Science, University of Pisa, Italy

Keywords: Agriculture 4.0, artificial intelligence, *Bemisia tabaci*, *Liriomyza* spp., *Trialeurodes vaporariorum*

Abstract: Human-based monitoring of arthropod pests of agricultural importance is usually a time-consuming and costly activity. The advent of technologies such as automatic traps opens new opportunities for remote monitoring. In this article, we present a novel Artificial Intelligence (AI)-based approach aimed to developing a smart trap for monitoring two major pests of greenhouse tomatoes, namely whiteflies, i.e., *Bemisia tabaci* and *Trialeurodes vaporariorum* (Hemiptera: Aleyrodidae), and leaf miner flies, *Liriomyza* spp. (Diptera: Agromyzidae).

Introduction

Environmental concerns about the overuse of pesticides, exploitation of natural resources, changing eating habits, and increased demand for food are leading to a new revolution in agriculture: Agriculture 4.0. As reported by Zhai et al. (2020), Agriculture 4.0 is characterized by four fundamentals: increasing productivity, distributing resources reasonably, adapting to climate change, and avoiding food wastes. Thanks to the application of technologies such as the Internet of Things (IoT), Artificial Intelligence, Big Data, and Cloud Computing, agricultural activities can be improved considerably. Of all the technology farmers can use, Artificial Intelligence is gaining wide acceptance. Encyclopedia Britannica defines artificial intelligence as "the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings". In other words, artificial intelligence is a powerful tool to gain insights from a large amount of data from the environment, relates to it, solves problems, and acts toward a specific goal. Artificial intelligence systems can adapt their

* Corresponding author: valeria.zeni@phd.unipi.it

DOI 10.12871/000218572022013

behaviour by analysing the effects of previous actions and working autonomously (Zhai et al., 2020; Liakos et al., 2018). For instance, agriculture involves a high number of processes and stages most of whom are manual; the role of artificial intelligence, through remote sensors placed in the field, may facilitate most of them being able to gain information and generate rich recommendations for farmers (Liakos et al., 2018) (Fig. 1).

Why smart traps for arthropod pest monitoring are needed?

From an entomological point of view, artificial intelligence can be used in Integrated Pest Management (IPM) programs. The goal of IPM programs is to manage crop pests by reducing pesticide use in favour of more precise and sustainable control tools. However, the IPM success is closely tied to the accuracy of pest monitoring itself (Ferreira Lima et al., 2020). For instance, arthropod pest monitoring can be carried out by a remote-controlled camera-equipped trap, which can gather constant information about the plant status, and which is likely more accurate and reliable than a human eye (Preti et al., 2021).

From 0 to 100: how to develop a smart trap

In this framework, the entomology lab of the Department of Agriculture, Food and Environment, University of Pisa, in close cooperation with the Department of Computer Science, University of Pisa, and the section of Artificial Intelligence for Media and Humanities of CNR of Pisa, are developing a new automatic trap that will feature artificial intelligence. This trap will be able to automatically localize, recognize and count major insect tomato crop (i.e., whiteflies (Hemiptera: Aleyrodidae) and *Liriomyza* spp. (Diptera: Agromyzidae)) pests by analysing digital images of tomato crops and to communicate with different decision support systems (DSS). Of note, whiteflies, with special reference to *Bemisia tabaci* (Gennadius, 1889) and *Trialeurodes vaporariorum* (Westwood, 1856), are not only responsible for direct damage to plants, but also act as vectors of several tomato viruses, such as the tomato yellow leaf curl virus (TYLCV) (Tan et al., 2017; Ramasamy and Ravishankar, 2018). The training of the AI-based algorithm can be divided into two major steps. The first one is the collection and annotation of images representing whiteflies and *Liriomyza* spp. collected by common yellow sticky traps from which the algorithm can learn some knowledge. The second step is the training of the artificial intelligence performed by the AIMH

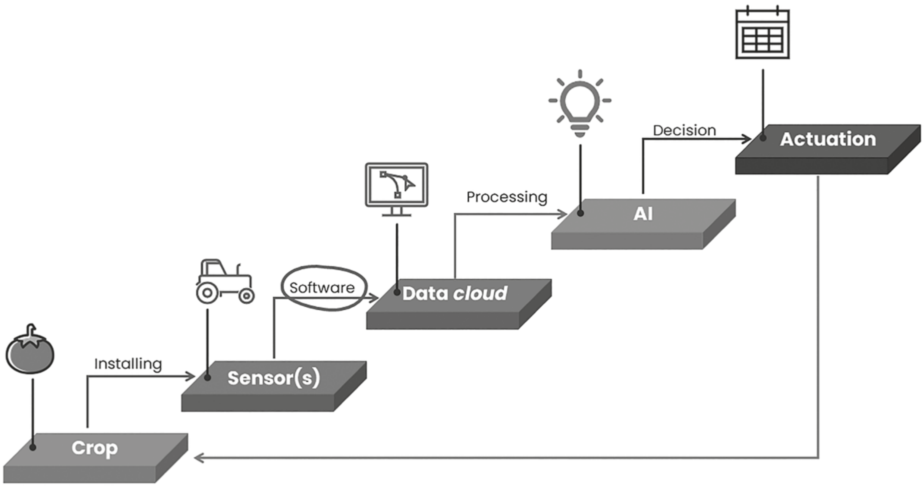

Fig. 1. The role of artificial intelligence (AI) in the agricultural management cycle. Using special sensors placed in the field, AI can obtain, transmit and process a big number of huge number of data and then AI can communicate real-time what is happening in the field to the farmer. This process enables farmers to make better decision and to intervene promptly if needed.

Fig. 2. LabelMe software. The image of yellow chromotropic trap with different bounding boxes. Each bounding boxes correspond to a particular coordinate of the image itself.

group. Exploiting these collected data, the AI-based algorithm will learn to automatically localize and classify the two classes of insects present in the input images. Finally, an estimation of the insects present in the trap is performed by summing up the found detections.

Step one: a collection of images and modification of it
To date, many pictures of yellow chromotropic sticky traps (25 × 20 cm) (ColorTRAP G, BioPlanet, Cesena, Italy) have been taken using a Nikon D5300 digital camera. All photos have been taken outside, with natural light conditions over different times of the day, to have heterogeneous pics in terms of brightness. This aspect is fundamental because if the AI-based algorithm is trained with photos taken with artificial light, there is a higher chance that the machine, once put in natural conditions, will incur into errors (Preti et al., 2021). Once all the images are collected, they are exported as RGB, and then processed using the software LabelMe (MIT Computer Science and Artificial Intelligence Laboratory (CSAIL), Cambridge, Massachusetts, USA), which allows to manually create bounding boxes, i.e., rectangles localizing the insects inside the images (Fig. 2). Basically, the bounding boxes, referred to as labels, are exploited by the AI-based algorithm during the training phase to learn to localize and recognize the insects.

Step two: the training of the AI-based algorithm
The AI-based algorithm consists of a Convolutional Neural Network (CNN or ConvNet), a Deep Learning technique widely used to automatically infer some knowledge from digital images and applied to solve tasks in various fields, such as object detection, or speech, vehicle, and facial expression recognition (Indolia et al., 2018). CNNs are composed of multiple layers of artificial neurons. When an image is introduced in the network, a cascade effect occurs, so that each layer generates several activation functions that are passed onto the next layer (Indolia et al., 2018). The first layer usually extracts basic features such as horizontal or diagonal edges. This output is passed on to the next layer which detects more complex features such as corners or combinational edges. As we move deeper and deeper into the network it can identify even more complex features such as objects, faces, etc. Based on the activation map of the final convolution layer, the classification layer outputs a set of confidence scores (values between 0 and 1) that specify how likely the image is to belong to a "class." For instance, if you have a CCNs that distinguishes *Liriomyza* spp. from whiteflies, the output of the final layer

is the possibility that the input image contains any of those insects. Other layers are instead in charge of regressing the coordinates of the bounding boxes localizing the objects to consider and to count.

Conclusions

Overall, we are fully aware that much remains to be done and that this approach represents only a small step within the Agriculture 4.0 framework. The use of automated traps takes IPM programs to the next level. However, to achieve this goal, a great initial effort is required that must consider the need for a multidisciplinary approach, involving figures from different research fields such as entomologists and computer scientists. Future challenges will be integrating data collected from automated traps into “Big Data” systems or DSS together with other geographical and environmental parameters (e.g., climatic conditions, control techniques for pests and microorganisms, agricultural techniques, irrigation, etc). These “avant-garde” systems will allow to know and then exploit the spatial-temporal distributions of the pests (captured by the traps) to improve and optimize their control with a technology-driven approach in IPM programs in both protected and open field environments.

Acknowledgements

The authors are grateful to Dr. Marco Mosti (Bioplanet, Cesena, Italy) for providing the insect pest populations used in our smart trap development trials. We are grateful to Prof. Lucia Guidi and Prof. Giacomo Lorenzini (Department of Agriculture, Food and Environment, University of Pisa) for organizing the Conference “180 Years of Excellence in Agricultural Sciences in Pisa, the State of Research Today” celebrating 180 years since the establishment of the Agricultural School at the University of Pisa, where the present contribution has been presented.

Funding

Valeria Zeni is co-funded by the University of Pisa PhD program and the PRIMA iGUESS-MED Project (https://www.iguessmed.com/).

REFERENCES

Indolia S., Goswami A.K., Mishra S.P., Asopa P. (2018). Conceptual understanding of convolutional neural network – A deep learning approach. Proc. Comput. Sci. 132, 679-688.

Liakos K.G., Busato P., Moshou D., Pearson S., Bochtis D. (2018). Machine learning in agriculture: A review. Sensors 18, 2674.

Preti M., Verheggen F., Angeli S. (2021). Insect pest monitoring with camera-equipped traps: strengths and limitations. J. Pest Sci. 94, 203-217.

Ramasamy S., Ravishankar M. (2018). Integrated pest management strategies for tomato under protected structures. In *Sustainable Management of Arthropod Pests of Tomato* (W. Wakil, G.E. Brust, T.M. Perring, eds.). Academic Press, pp. 313-322.

Tan X.L., Chen J.L., Benelli G., Desneux N., Yang X.Q., Liu T.X. et al. (2017). Pre-infestation of tomato plants by aphids modulates transmission-acquisition relationship among whiteflies, tomato yellow leaf curl virus (TYLCV) and plants. Front. Plant Sci. 8, 1597.

Zhai Z., Martínez J.F., Beltran V., Martínez N.L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. Comput. Electron. Agric. 170, 105256.