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Editorial

Hardware and Software Support for Insect Pest Management

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In recent years, the achievements of machine learning (ML) have affected all areas of industry and it plays an increasingly important role in agriculture as well. However, for remote sensing purposes, ML-powered software need to be extended with the appropriate hardware background. ML-aided remote sensing devices can be seen as embedded systems dedicated to one pre-defined task. Finding the right controller unit and plug-in board(s) for these embedded devices can be challenging because developers need to take into consideration the sensing device's computational resources and power consumption. It is especially important when the ML software core incorporates a state-of-the-art object detector model such as the You Look Only Once (YOLO) or Faster Region-Based Convolutional Neural Network (R-CNN).

In all fields of agriculture, a general goal is to maintain or increase the crop yield year over year. Unfortunately, this is very difficult in our changing world. The global temperature increase caused by climate change influences insect population development. Temperature has a huge effect on the rate of population expansion for several insect species. Since crop yields are affected by insect pests (that may damage crops), farmers apply different strategies for crop protection [1]. These strategies are more important than ever because the abrupt insect population growth causes an increase in their consumption of crops when the temperature rises.

Even though there are more crop protection approaches against different insect species, fertilization is one of the most effective methods. Since fertilization is costly and time consuming, an important question is how farmers can plan the spraying as optimally as possible. This is just one of the several questions where ML-aided sensing devices could help us find answers. However, in order for ML models to be successful, we need information (data) about the insect population. This is where sensing devices come into play.

A specific example of a sensing device is the automated insect trap which is used in pest management. Automated traps are essential for keeping track of insect activity and are frequently used in pest population forecasting [2]. Images taken by the traps carry a huge amount of data and sophisticated data analysis methods are needed to extract the necessary information which can be used for decision making.

The goal of the "Hardware and Software Support for Insect Pest Management" Special Issue (SI) published in *Agriculture* was to present how ML and modern integrated circuit technology can help plant growers to protect their crops against harmful pests. Three of the papers published in this SI are focused on codling moth (*Cydia pomonella*) monitoring which is the most harmful pest in apple orchards. The author of [3] presented a novel sensing device (plug-in board plus controller unit) for automatic insect pest counting in the field. In this paper, all major components of the devices have been presented, supported by schematics. The operation of this sensing unit has been tested with a deep network-based insect counting algorithm and the results showed that the device is able to operate for a long period with or without solar charging and its operating temperature remains below the safe limit even in a closed waterproof house.

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The aim of [4] was to develop an automatic monitoring system (smart trap and a detector model) for codling moths where the insect detector uses a deep neural network (DNN). The core of the detector model is the EfficientDet-4 which achieved an average precision (AP) of 0.93 with a 0.5 intersection over union (IoU) threshold. Beyond the insect detector model, the key features of their smart trap are also presented in the article.

Finally, the third article [5] is a review where the author presents the current image capture devices and insect counter algorithms which have been developed for codling moth monitoring. In this review, the reader can find the main features, advantages, and disadvantages of several prototype and commercial smart traps. Moreover, the efficiency of previously developed insect counting methods are also presented along with their various performance metrics.

Due to the high number of well-known object detectors (e.g., Faster R-CNN, YOLO, SSD) and their scalability, there are many possibilities for detector model development where the target object is the same (pre-defined insect species). In [6], the authors used the YOLOv5 (including its subversions) algorithm from the famous YOLO family. Their results showed out that YOLOv5 has high insect localization precision if a large amount of data is available for training. However, such an object detector requires many floating-point calculations and a large amount of physical memory. In the case of embedded systems, those requirements are challenging due to the limited hardware resource of controller devices. Based on my experience, the inference time of the YOLOv3 model is approximately 1 s on a computer with an AMD Ryzen (5000 series) CPU (Santa Clara, CA, USA) and Nvidia Geforce RTX GPU card (Santa Clara, CA, USA) while its inference time on a Raspberry Pi Zero W (Raspberry Pi Foundation, Cambridge, UK) is more than 10 min. This is a huge difference which makes the well-known object detector models unusable in many embedded system-based applications. Fortunately, the long image processing time is not a significant issue in insect monitoring because only one image is taken a day.

The last article [7] of the SI is also focusing on model-based predictions and its aim is to predict the evolution of spider mite population dynamics. This information can be used to control the pest population on a regular basis to promote high yield and high quality in dry bean production. As a part of a decision support system, the predictive model can help in the comprehensive and early season fight against the spider mite pest.

All contributors of the SI hope that the presented results in the published papers will contribute to more efficient crop protection against insect pests and subsequently to economic growth.

Conflicts of Interest: The author declares no conflict of interest.

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