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Developing a smart trap prototype equipped with camera for tortricid pests remote monitoring

Michele PRETI[1,2], Christian MORETTI[2], Gabriele SCARTON[3], Giovanni GIANNOTTA[3], Sergio ANGELI[1]
[1]*Faculty of Science and Technology, Free University of Bozen-Bolzano, Italy*
[2]*ASTRA Innovazione e Sviluppo Test Facility, Faenza, Italy*
[3]*FOS S.p.A., Bolzano, Italy*

Abstract

The effectiveness of insect pest management programs depends on the availability of reliable and updated information about the pest infestation status. Action thresholds derived by captures in monitoring traps are a pillar of modern integrated pest management programs to trigger and optimize the timing and usage of insecticide sprays. However, weekly trap inspections in field may lead to a delayed intervention and imply a certain labour cost. Such issues have led to some early adoption of automatic trap-based monitoring exploiting new technology. This work aimed to develop an innovative 'smart' trap prototype capable to monitor by remote insect pests, selecting codling moth, *Cydia pomonella* (L.), in pome fruit crops as case study. Smart trap components (hardware) were chosen considering the environmental sustainability and an economic evaluation of the trap prototype cost is provided together with the cost-benefit analysis of the remote pest monitoring. A detection algorithm (software) to automatically identify and count codling moth was developed by using open-source programs. The smart trap prototype was evaluated in field experiments. Qualitative parameters related to automatic pest identification such as accuracy, sensitivity and precision were calculated according to both false positive and false negative counts. This work describes the different steps necessary to develop smart traps for insect pests monitoring, showing the preliminary field results obtained with the proposed prototype. The smart trap efficiency in capturing codling moth was similar to a standard monitoring trap and the pictures provided a sufficient resolution to manually validate moth captures observing the images by remote. Nevertheless, the detection algorithm failed to automatically provide a trustworthy capture count data by remote because, using deep learning technique, thousands of pictures are usually required for the algorithm training towards the target species in order to reach a sufficient level of reliability. This work provides the basis for a further wider development of such smart trap prototypes worldwide.

Key words: *Cydia pomonella*, codling moth, electronic trap, automatic trap, automatic pest detection.

Introduction

Among the insect species causing economic losses in pome fruit crops, codling moth *Cydia pomonella* (L.) (Lepidoptera Tortricidae) is one of the major key pests. In fact, if not properly managed with complementary and integrate practices including chemical, mechanical and (micro)biological control, together with population suppression techniques such as mating disruption (MD) or sterile insect, codling moth infestations can severely impact pome fruit productions (Knight *et al.*, 2019a; Kadoić Balaško *et al.*, 2020). According to its biological requirements and to the climatic and environmental parameters reported in different geographical areas, it has been demonstrated that all the continents (with the exception of Antarctica) are suitable for codling moth development and its actual distribution covers the main pome fruit crops productive areas worldwide (Jiang *et al.*, 2018). The severity and global importance of this tortricid species have driven uncountable research studies on its management, with a turning point 50 years ago thanks to the identification of the major component of female codling moth sex pheromone, (*E*,*E*)-8,10-dodecadien-1-ol (commonly known as codlemone) (Roelofs *et al.*, 1971). Nowadays codlemone is largely utilized in orchards to: (*i*) record the male flight activity through monitoring trap captures; (*ii*) disrupt the adult behaviours by interfering with the frequency and timing of mating through the use of MD (Witzgall *et al.*, 2008; 2010).

A reliable codling moth monitoring is essential to properly and timely counteract the infestations, and usually trap counts are used both to determine the need to spray and to optimize spray timings. In orchards not treated with MD, the codlemone is usually applied alone to track the males population and indirectly females and offspring information are calculated, exploiting phenology models (Jones *et al.*, 2013). Nowadays a wide knowledge has been achieved regarding codlemone usage for monitoring. For instance, recent studies evaluated the behaviourally effective plume reach of a standard sex pheromone-baited trap (< 5 m), the trapping area of a single trap (ca. 21 ha) and provided data to convert relative pest captures into absolute pest densities (1 adult trap^{-1} corresponds approximately to 5 adults ha^{-1}) (Adam *et al.*, 2017). On the other hand, in orchards treated with the sex pheromone to perform MD, for monitoring purposes the codlemone is usually combined with other attractive volatile organic compounds acting as kairomones, to overcome the MD interference. The major compound practically applied since its discovery is the pear-derived kairomone (*E*,*Z*)-2,4-ethyl decadienoate (commonly known as pear ester) (Light *et al.*, 2001). Pear ester attracts both codling moth sexes and the microbial volatile acetic acid proved to be a potent synergistic for moth attraction in several studies (Knight *et al.*, 2018). Therefore, to date there are effective options to monitor this target pest, considering both sexes and regardless the application of MD.

Nevertheless, a limit of the traditional insect pest monitoring is due to the low spatial and temporal resolution that is usually achieved with standard monitoring traps.

Due to labour cost issues and required field visits to check insect pest captures, traps are usually deployed in accessible locations and in limited numbers. Thanks to the advent of new technologies (including remote sensing, electronics and informatics), the panorama of tools available has largely improved offering a variety of systems to automatically detect and monitor insect pests (Cardim Ferreira Lima *et al.*, 2020). Among such tools, a recent review by Preti *et al.* (2021a) extensively discusses the use of camera-equipped traps for insect pest monitoring. Smart traps that take pictures and exploit images to provide count data can be classified according to the level of trap automatization in semi-automated or fully automated systems, as described in Sciarretta and Calabrese (2019). Semi-automated traps require a manual count of the captures by human operator in remote, as reported in Guarnieri *et al.* (2011) for codling moth and in Ünlü *et al.* (2019) for European grapevine moth, *Lobesia botrana* (Denis et Schiffermuller). Automated traps can rely on detection algorithm capable of automatically identify and count the captured insects by means of image processing analyses, as reported by Lucchi *et al.* (2018) for European grapevine moth, by Doitsidis *et al.* (2017) for olive fruit fly, *Bactrocera oleae* (Rossi), and by Shaked *et al.* (2018) for other fruit flies species. To date, these devices are increasing in interest since they allow improving both spatial and temporal resolution in insect pest monitoring, creating the condition for a digital implementation of the management programs within the Internet of Things and the Big Data framework (Preti *et al.*, 2021a).

This work aimed to develop an innovative smart trap prototype equipped with a camera to perform a remote pest monitoring, selecting codling moth in pome fruit crops as 'case study'. Assembling materials and electronic components have been selected considering the environmental sustainability and reporting the relevant economic cost evaluations. A brand-new detection algorithm for captures identification and count has been developed and qualitative identification parameters such as accuracy, precision and sensitivity have been considered for this smart trap prototype.

Materials and methods

Construction of the smart trap prototype

The smart trap prototype developed was composed of a hardware part, including the trap chassis, the power supply system, the sensors including the camera and any related electronics (figure 1), and by a software to service the remote monitoring, including the image transmission, the image analyser and the operator interfaces (figure 2).

The chassis structure was composed of three major parts: (*i*) the upper cap, which contained all electric and electronic parts; (*ii*) the brim, which was designed to offer coverage and protection for the sticky liner and the lure towards the atmospheric events; and (*iii*) the base, which included four columns and a removable bulkhead used to place the sticky liner on the base (figure 3). The upper cap box (111.2 mm of length × 91.5 mm of width × 65.0 mm of height) was compact, resistant and waterproof. The trap brim had a pyramid trunk shape and presented holes for placing the anchoring systems to the plant and to the trap base. The base was rectangular-shaped (210.8 mm × 198.6 mm) and had holes to drain the water that may enter due to rain events. The trap chassis

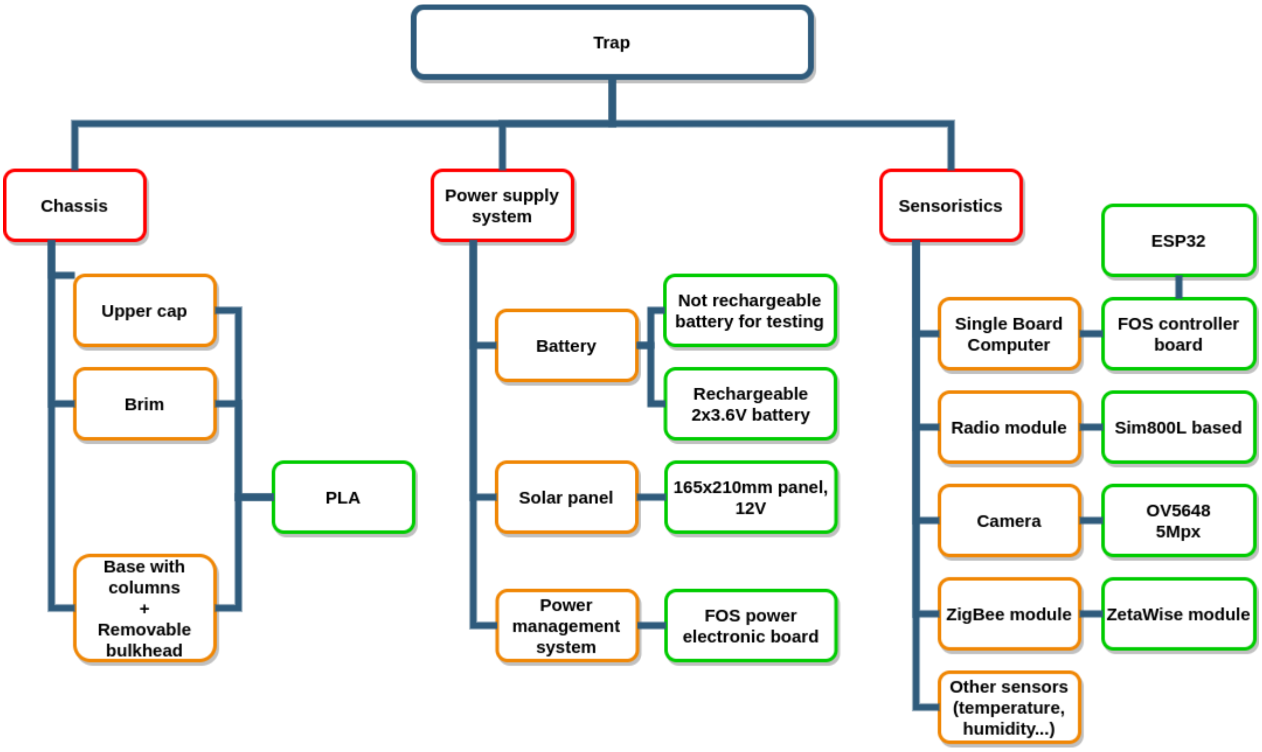


Figure 1. Schematic diagram of the smart trap prototype main components: the trap chassis, the power supply system and the electronics and sensors, including the camera for picture acquisition, represent the hardware part of the trap.

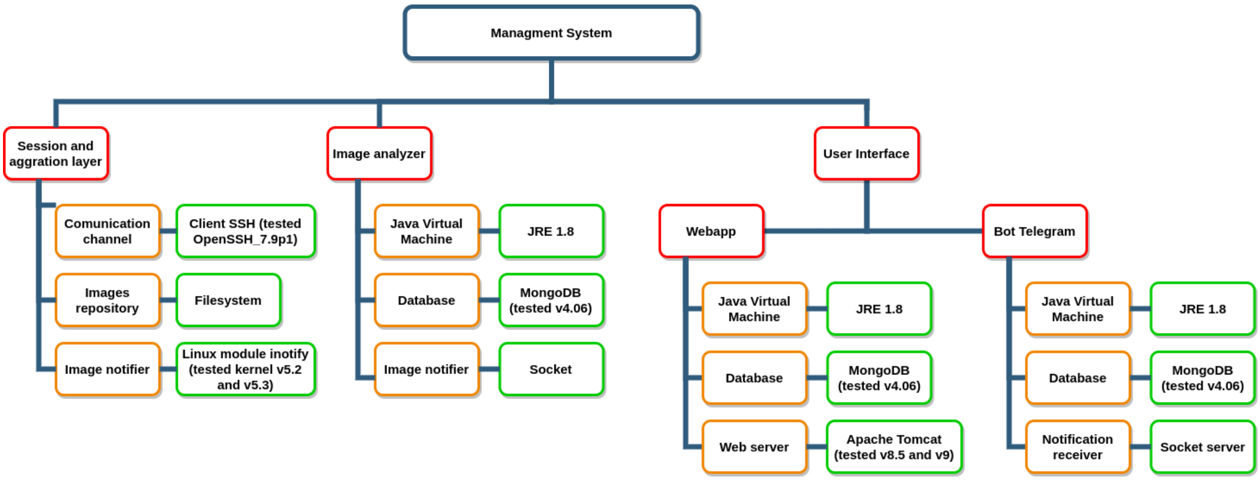


Figure 2. Schematic diagram of the software to service by remote the smart trap prototype: images transmission system, image analyser and operator interface.

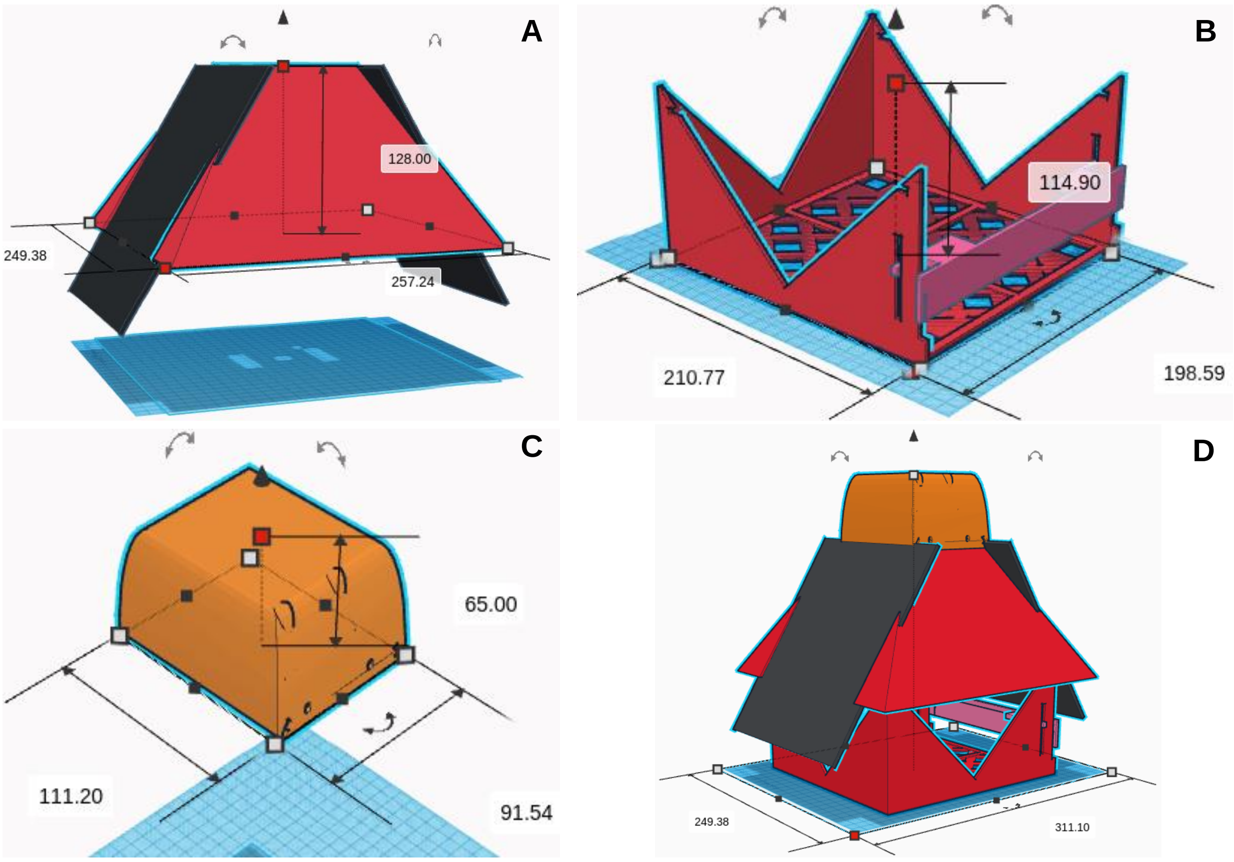


Figure 3. Smart trap prototype design showing the chassis structure (measures in mm). **A** = trap brim (solar panels in black); **B** = trap base with the removable bulkhead to insert the sticky liner; **C** = upper cap containing the electronic box and the camera; **D** = trap prototype assembled.

construction material was polylactic acid (PLA), a polyester bioplastic produced from renewable resources and biodegradable (Su *et al.*, 2019; Siakeng *et al.*, 2019). Polylactic acid has a better ecological impact than other printable materials by using Fused Deposition Modeling (FDM) method (Faludi *et al.*, 2015). A professional FDM 3D printer Ultimaker S5 was used to produce the trap structure using the PLA filament. Per each trap device, 653 g of PLA filament were used. A red PLA filament was selected since this colour does not impact negatively the codling moth captures and has no or little effect on the chromotropic attraction of beneficials and other non-targets (Clare *et al.*, 2000; Knight and Miliczky, 2003; Barros-Prada *et al.*, 2013).

The core of the electronic system was the ultra-low power EXPRESSIF microcontroller ESP 32, which managed all the peripherals and the power system. This microcontroller was a hybrid Wi-Fi & Bluetooth programmable chip with high level of integration; it managed and provided a communication stack to the peripherals through its SPI/SDIO or I2C/UART interfaces; it was based on Xtensa 32-bit LX6 microprocessor and the model used had just one core to maximize the low energy consumption. One of the relevant characteristics in the electronic system is the ultra-low power co-processor, which allowed the Analogic and Digital signal Conversions (ADC), the computation and to manage the level thresholds during the deep sleep mode; it was equipped by 448 MB of Read Only Memory (ROM) and 520 MB of Static Random Access Memory (SRAM). The activation timing was managed by a Real-Time Clock (RTC) and needed 0.01 mA s^{-1} of current in deep sleep mode. The connected photo camera was an Omnivision OV5648 with a resolution of 5 Mpixel (retrieving up to 2592 pixel × 1944 pixels of resolution). The minimum requirement of image sharpness for codling moth remote identification was defined according to what reported in Guarnieri *et al*. (2011). In the present work, the requested focus distance of the camera from the trap base was 22 cm. The cone of vision covered an elliptic projection of 17 × 19 cm, overlapping completely the whole size of the sticky liner (17 × 17 cm). In addition to the embedded communication systems, a GSM module was connected by UART interface. The GSM component was the SIMCom SIM800 chip. The electronic board needed to be powered by 5 V of voltage and 300 mA of current, in full working status.

Two photovoltaic modules (12 V, 2 W each) powered the electronic components of the smart trap and in low solar energy conditions, the power was granted by two lithium rechargeable graphene Panasonic NCR18650B batteries, which were connected in series. These batteries can supply 3500 mA as maximum current at 7.2 V (3.6 V each one) and need 8 V of charging voltage. The solar power was regulated by two monolithic integrated circuits LM2596 as step-down switching regulators (one per each voltage output). Since the battery temperature can increase due to external factors, such as the direct sun light overheat, or by charging cycle, the charging process was controlled by a battery management system (BMS). The BMS circuit helped the battery life as well. The two photovoltaic panels were installed directly on the trap brim (figure 3).

A GSM SIM card was used for sending data to the server by using GPRS connection. Pictures were univocally identified by a title reporting relevant information: each file was associated with a string reporting the monitoring field location and trap identification, and the day and time of picture acquisition. The electronic system was set to go in deep sleep mode for 5 minutes when the picture transmission system failed to send images for three consecutive times, and then it activates again to take another picture. This loop was set to be repeated twice and if picture sending failure persisted due for instance to poor or unstable connection, the system was set to go in deep sleep mode until the next scheduled timing for picture acquisition.

All acquired pictures were sent to the data server by using Secure Shell (SSH), which is a cryptographic network protocol to secure the operating services on the network. In the data server, the pictures were stored in a protected image repository where the detection algorithm executed the image analysis process. At the end of the image analyses, all pictures information and analyses results were stored permanently in the database (DB). The server application was database centric (figure 4). Thus, the database structure defined the subsystem working parameters and behaviour. All software subsystems (trap, analyser, webapp and Telegram bot) were dynamically driven by the database structure, such as the storage of the capture data information (figure 5), and the analyser learning parameters. Human operator can visualize capture pictures in two

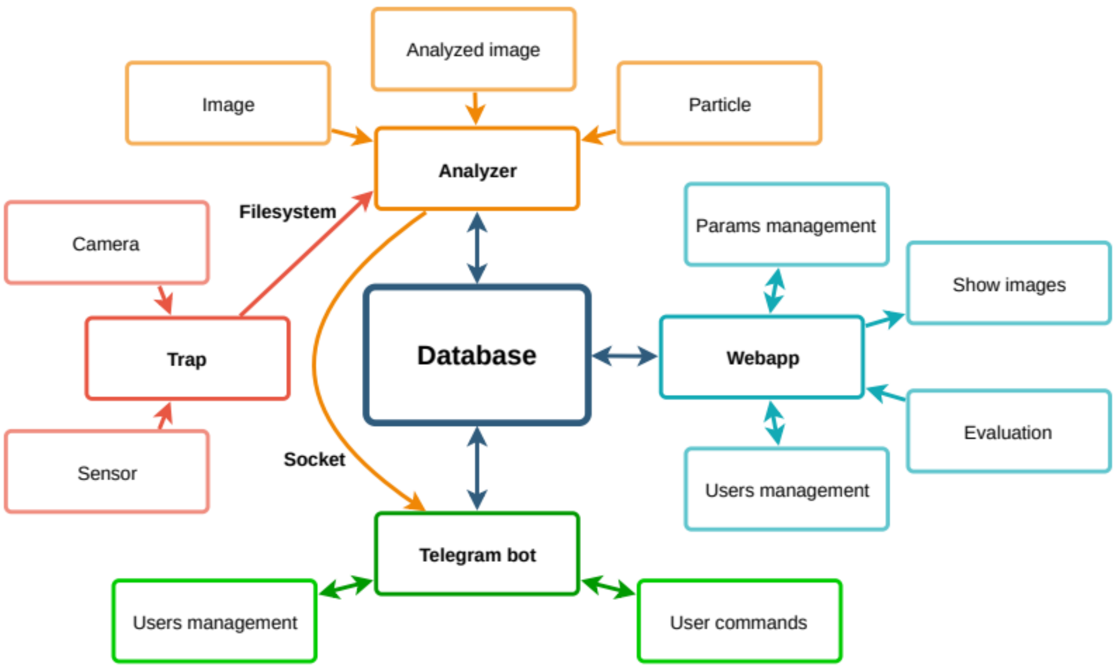


Figure 4. Data flow representation with the database as core part of the smart trap application architecture.

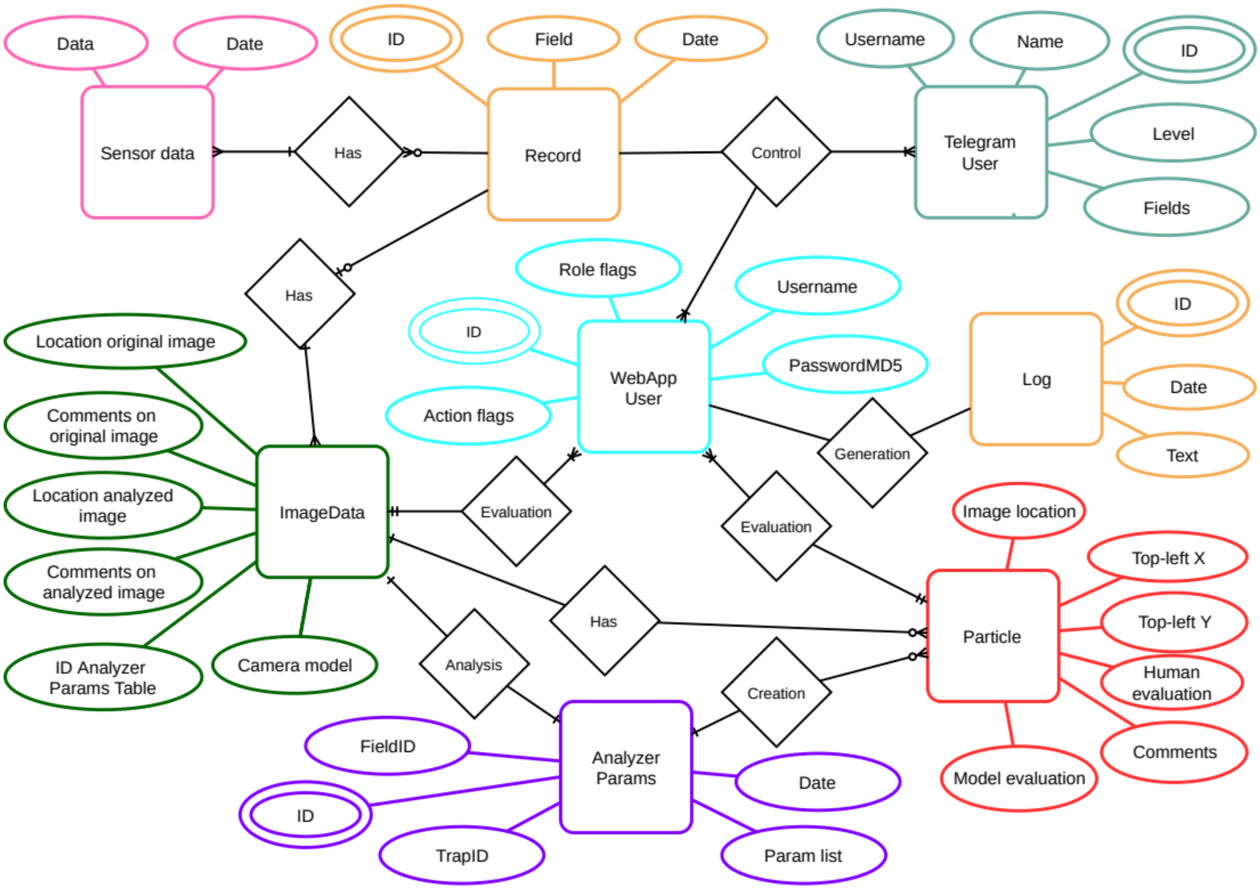


Figure 5. Data storage system of the smart trap prototype developed for codling moth remote monitoring.

forms: by using the Telegram bot in a smartphone and by using the webapp in a computer. The webapp used the stored information to display images with a user-friendly interface to allow the manual picture evaluation by user.

The software technologies used to develop the all server side components were based on both Java Development Kit 1.8, which is the development environment for building applications, applets, and components using the Java programming language, and Python as scripting program language (Java, 2020; Python, 2020). Java was used to develop the image analyser, webapp and Telegram bot software, Python 2.7 for all scripts to manage the session and aggregation layers. The firmware on the trap was developed by using C programming language. All data were stored in a MongoDB database system. MongoDB is a document database that stores the data in JSON-like documents (MongoDB, 2020). JSON (JavaScript Object Notation) is a lightweight data-interchange format. The webapp was published on Internet by using Apache Tomcat® (v8.5) web server. The Apache Tomcat® software is an open source implementation of the Java Servlet, JavaServer Pages, Java Expression Language and Java WebSocket technologies (Apache Tomcat, 2020). All software were developed by using Eclipse platform, which is an effective integrated development environment (desRivieres and Wiegend, 2004). The Java project management and comprehension software tool Apache Maven (versions 2018 and 2019) was used as repository and build environment for Java development (Apache Maven, 2020).

Detection algorithm for automatic pest identification and count

Automatic pest detection is a complex process divided in two main parts: (*i*) a preliminary image analysis performed by an image analyser program; and (*ii*) a subsequent automatic pest classification performed by an artificial intelligence algorithm.

The preliminary analyses of the images considered as input the pictures of the insect captures originated directly in field. After an image processing phase, the return output was a list of regions of interest, one for each possible target pest (in this case codling moth) occurring within the picture. Since the original photo was required to perform the human validation (checking for false negative and false positive results) and because computation and power resources on traps were limited, the analyses run on the server duplicating the picture, in order to have two adjacent and identical pictures: one unmodified and the other including the regions of interest marked by squares. In this work the preliminary image analysis process was based on ImageJ1, an open source image-processing program designed for scientific multidimensional images, specifically integrated in the server to run as soon as a new image arrived on the server (Schneider *et al.*, 2012; ImageJ, 2020). In order to reduce the effects of sun shadows and background interferences (in particular due to the glue of the sticky liners), the MorphoLibJ plugin was used for implementing a morphological filter (Maragos, 2005; Legland *et al.*, 2016). After the filtering, the images were analysed with ImageJ particles extractor to get the list of particles. The parameters of the extractor were based on preliminary test images taken in different light conditions and on target pest morphological characteristics provided by entomologist's data, such as pest shape, minimum and maximum size and dominant colour. These parameters depend not only on the type of pest to be detected but also on trap configuration, in particular the camera specification and the distance from the camera to the sticky liner. When the regions of interest were found, a watershed tool based on circularity divided overlapping pests to get a particle per each individual recognized as target pest. In the webapp, the human operator could validate manually each particle automatically recognized by the detection system within every single picture derived by the smart trap. Per each particle of each picture, the user was asked to answer whether the marked item was or not the target pest, including possible comments.

The output of this image analysis displayed on the web interface for human validation was therefore used as input for the automatic pest classification. The labelled images were used to create a Convolutional Neural Network (CNN), which is a state of the art regarding artificial intelligence process for image classification (Taylor and Nitschke, 2017; Ali *et al*., 2019). CNNs are inspired by biological processes such as the neural connectivity and they have the powerful feature to be independent from prior knowledge, making them suitable for a large variety of tasks. In this smart trap prototype, the development of the CNN model for pest classification is still in process, since this kind of powerful artificial intelligence framework requires many data to provide significant results. For instance, for deep learning insect pest recognitions other authors report the usage of large scale datasets with more than 75,000 images (Khalifa *et al*., 2020 and references therein). In order to maximize the use of data, some data augmentation techniques were also used: starting from a single image, eight different samples were created using rotation and mirroring functions (Mikołajczyk and Grochowski, 2018). Tilted images, zoomed images and cropped images were not used to preserve the proportion of the target pest. To implement this network and the data transformations, an open-source Java library, DeepLearning4j, was used, providing the environment to create a CNN and providing mechanisms to augment the data on the target pest. One of the features of DeepLearning4j is that the data augmentation happens 'on the fly': the different copies of the original classified image are created during the model creation/update and are not stored on disk. The classification model created by following this process was fixed and it was planned to update it manually with a new one tweaking the parameters as soon as new data validated by human operators were classified and there was a significant change in the performance. In this way, the improvements of the model were controlled by programmers and not automatic, with the possibility to make changes among consecutive model versions. As soon as the level of accuracy of the automatic detection algorithm is considered sufficient and the version of the model is stable, the model parameters will be adjusted automatically by using Deeplearning4j functions when new images validated by human operators will be produced. At the time of this work, validated data were in the order of hundreds. To provide a stable model, which automatically learns from human validations without overfitting, data in an order of thousand are required. Therefore, in this work the model was managed and modified directly by programmers due to the limited number of samples.

Economic evaluations: trap prototype cost and cost-benefit analysis

A trap cost estimation was calculated according to the actual expenses incurred to produce the smart trap prototype. The cost values, reported in euros, are referred to the purchase of the various hardware components in Italy and are updated to December 2020. Market value of such technologies is subject to fluctuation according to availability and demand, and it can be different across years and locations. Only the actual costs to make the smart trap prototype as described in this work were considered, without including the costs strictly related to a marketable product. Specifically, hardware components such as the PLA material, the camera, the electronic components, the power supply (batteries, solar panels and inverter), and the SIM card were all included in the economic evaluation, while other potential costs such as the fee to access the web application and the data traffic consumption were not included. In fact, the latter aspects are not considerable during the prototypal phase and can be calculated only on a finished product ready to be put on the market. For the trap construction, a forfait labour cost of 25.00 € was estimated for the components assemblage, considering that this cost varies according to the number of devices produced simultaneously. In this study, it was assumed that all the necessary hand tools needed for constructing and assembling were freely available.

Circumscribing the trap cost evaluation on the prototype version reported in this study, a cost-benefit analysis to monitor codling moth in pome fruit crops, in both apple and pear, by using either a conventional monitoring trap or the smart trap prototype was also estimated. To realize the cost-benefit analysis of the smart trap prototype, the following parameters were taken into account, referring specifically to Italy.

Usually, in Italy, codling moth flights last from mid April until mid September and therefore it can be assumed that the duration of its monitoring should be 5 months (from early April until the end of August) to cover the three flights in pear crop and 6 months (until the end of September) in apple crop. Therefore, a weekly trap check can imply 20 or 24 field visits in pear or apple crop, respectively. By using the smart trap, it was assumed to perform a minimum of 4 field visits for servicing the traps: one for trap set up, two for lures and liners replacements and one at the end of the season. In addition, it was assumed not to have the sticky liners frequently saturated by captures or debris and realistically 2 supplementary field visits of the smart traps to replace sticky liners were also included, for an estimated total use of five liners during the whole season. A distance of the monitoring site of 25 km from the office and a travelling costs of 0.40 € km^{-1} were considered, therefore each field visit resulted to cost 20.00 €. In addition, the travel time was estimated in 50 minutes roundtrip plus 10 minutes of trap check *in situ*, for a total of 1 hour of work. On the contrary, for the smart trap it was estimated to spend 10 minutes for the daily trap check in remote by using the web interfaces and 6 checks per week were considered, for a total of 1 hour of work per week. Using the remote monitoring was considered to exploit the advantage of a more frequent trap check, increasing the time resolution 6-fold compared to the weekly trap check *in situ* and maintaining the same man-hour usage. The labour cost was estimated in 10.00 € h^{-1} in all cases. Commercial standard monitoring traps, lures and liners costs were estimated specifically for codlemone-baited traps as average purchase costs from two different retailers and considering three different suppliers.

Field validation and data collection

Preliminary checks of the smart trap operativity, including its resistance towards atmospheric events, the power supply autonomy, the data acquisition and sending efficiency by remote, and the visualization of pictures in the on-line repository have been tested outdoor over two consecutive seasons (2018 and 2019, data not shown) before the final field validation performed in 2020 and reported in this work. Several prototype versions were realized according to the need of improvements and adjustments to satisfy the requirements reported in Preti *et al.* (2021a). Therefore, the latest prototype version of the smart trap corresponded to the minimum qualitative conditions defined prior to the trap development begin, specifically: (*i*) a compact, small-sized, robust and waterproof box containing all the electronics that work in autonomy and controlled by remote; (*ii*) a high resolution camera set at the proper distance from the sticky liner to obtain sharp pictures of the captures, with the target pest clearly recognizable by remote; (*iii*) a sufficient power supply to guarantee an operativity of the prototype for more than 4 weeks; (*iv*) a data transmission system capable to automatically acquire, send, store and analyse pictures; and (*v*) a low environmental footprint, considering low-cost recyclable assembling materials. Six identical devices of such smart trap prototype version were therefore produced for field evaluations.

Field experiments were conducted from July to October 2020 in both pear and apple organic orchards located in Emilia-Romagna Region (Italy) with known high infestation levels of the target pest. Since the selected orchards were treated with MD for codling moth, traps were baited with pheromone-kairomone blends, using Pherocon® CM-DA Combo-P (Trécé Inc., Adair, OK, USA), a new commercial binary lure comprised of a black PVC lure loaded with codlemone and pear ester and a white membrane cup loaded with acetic acid. This proprietary binary lure has been recently proved to enhance codling moth captures in disrupted orchards due to its PVC formulation in comparison to standard septa lure, both combined with an acetic acid membrane co-lure (Preti *et al.*, 2021b). The lures were placed directly on the stick liner in all traps. Traps were installed at 3 m of height inside the crop canopy and were placed at minimum 25 m from the orchard perimeter and apart. Traps were not rotated during field experiments and liners were not replaced.

To evaluate the smart trap prototype trapping efficiency, one trap comparison experiment was conducted in two pear orchards testing the automatic prototype and a standard monitoring orange delta-shaped traps, Pherocon® VI (Trécé Inc.). In each location three pairs of traps (smart *vs* delta) were compared from July 21 until August 18 recording the total codling moth captures per trap.

To evaluate both the power autonomy and the detection algorithm exactness, the same six smart trap prototypes used for the trap comparison experiment were kept in the field until September 14, for a total test duration of 55 days (first monitoring period). A second experiment to evaluate trap operativity in field condition was then run from September 16 until October 19 (35 days of test duration) in an apple orchard, with six replicates of the smart trap prototype (second monitoring period). Pictures acquisition was set at two shoots per day, specifically at 8:00 am and at 5:00 pm. Data on automatic counts (number of particles provided automatically by the detection algorithm as codling moth counts), manual counts (real number of codling moth captures provided by the human operator observing the pictures and confirmed by the direct trap check in field), number of false positives (misidentifications of codling moth wrongly provided by the detection algorithm) and number of false negatives (missed codling moth not recognized by the detection algorithm) were recorded per each picture over the whole monitoring period. Other non-target insect species captured, including for instance flies (Diptera Muscidae), were also recorded both during picture validation and direct field observation of the sticky liners, and their impact on the false positive counts was evaluated. At the end of each monitoring period, flies size was also measured to categorize this non-target according to its body length.

Capture data elaboration

Exploiting the automatic count, manual count, and number of false positive and false negative data per each picture collected, the following parameters were calculated: (1) False positive (%); (2) False negative (%); (3) Accuracy (%); (4) Sensitivity (%); and (5) Precision (%). The accuracy formula was adapted from Jiang *et al.* (2008 and 2013), while the sensitivity and precision formulas were adapted from Wen *et al.* (2015) and Ding and Taylor (2016).

$$(1)\ False\ positive\ (\%) = \frac{number\ of\ false\ positives}{number\ of\ automatic\ counts} \times 100$$

$$(2)\ False\ negative\ (\%) = \frac{number\ of\ false\ negatives}{number\ of\ manual\ counts} \times 100$$

$$(3)\ Accuracy\ (\%) = \frac{number\ of\ automatic\ counts}{number\ of\ manual\ counts} \times 100$$

$$(4)\ Sensitivity\ (\%) = \frac{number\ of\ true\ positives}{n.of\ true\ positives + n.of\ false\ negatives} \times 100$$

$$(5)\ Precision\ (\%) = \frac{number\ of\ true\ positives}{number\ of\ automatic\ counts} \times 100$$

Where the number of true positives is equal to the number of automatic counts minus the number of the false positive counts.

Regarding the interpretation of the automatic detection algorithm parameters, the percentages of both false positive and false negative allow to evaluate the exactness of the system for the target pest automatic identification and count. The detection algorithm is more reliable when both false positive and false negative percentages will be close to zero. An accuracy equal to 100% means that the number of items marked and counted automatically by the recognition algorithm corresponded to the number of target pest individuals present in the sticky liner (to be noted that also in case of simultaneous presence of equal numbers of false positive and false negative, the accuracy would be 100%). An accuracy lower than 100% means that there were target insects not recognized by the software, therefore the automatic identification and count underestimated the real pest occurrence. An accuracy higher than 100% means that there were non-target insects or other items counted as the target pest by the software, therefore the automatic identification and count overestimated the real pest occurrence (in this case, the false positives impact the accuracy overrating the effective codling moth numbers). Both values of sensitivity and precision can range between 0 and 100%. Values of sensitivity close to 100% mean that the occurrence of false negative is very low and therefore all the target pest individuals present are correctly detected by the automatic system (showing that the algorithm is sensible toward the target pest and it does not miss codling moths). Values of precision close to 100% mean that the occurrence of false positive is very low and therefore the total automatic detection corresponded to the correct codling moth detections (showing that the algorithm is precise and it does not mark non-target insects or other items).

Regarding the non-targets, specifically for muscid flies, the percentage of flies counted as false positive was calculated, together with the percentage of flies detected by the algorithm out of the total flies present in the sticky liners.

Statistical analyses

Statistical analyses were performed with R software version 4.0.3 (R Core Team, 2020), including the packages lme4 (Bates *et al*., 2015) and multcomp (Hothorn *et al*., 2008). AIC (Akaike's Information Criteria) parameter and the residual distributions were considered to select fitted models. In all the analyses, the level of significance was set at P = 0.05.

Captures data were found to fit normal distribution and therefore were analysed with a linear model (lm). In the trap comparison experiment, the two locations were considered together since there was no significant effect of the location on the moth captures (t value = 0.313; P = 0.761). To highlight differences between the smart trap prototype and the standard monitoring delta-shaped trap in terms of trapping efficiency, an ANOVA test was performed.

To test differences among smart trap prototypes in terms of automatic pest detection, accuracy, sensitivity and precision data were analysed by using a generalized linear mixed-effects model (glmer) from lme4 package, fitting a Poisson distribution. The trap ID was considered as predictor, together with the number of real codling moth counts and the number of flies counted, both added as controlling variable. The number of real counts was added as a model weight, while the trap ID was also included as random effect. A multiple comparison post-hoc test was performed on the fitted model (glht function from multcomp package).

The effect of the flies captured on the number of particles automatically detected was analysed by using a glmer with Poisson distribution. The number of true positive counts was added as controlling variable, while the trap ID was included as random effect.

Mean values are followed by Standard Error of the Mean (± SEM), unless otherwise specified.

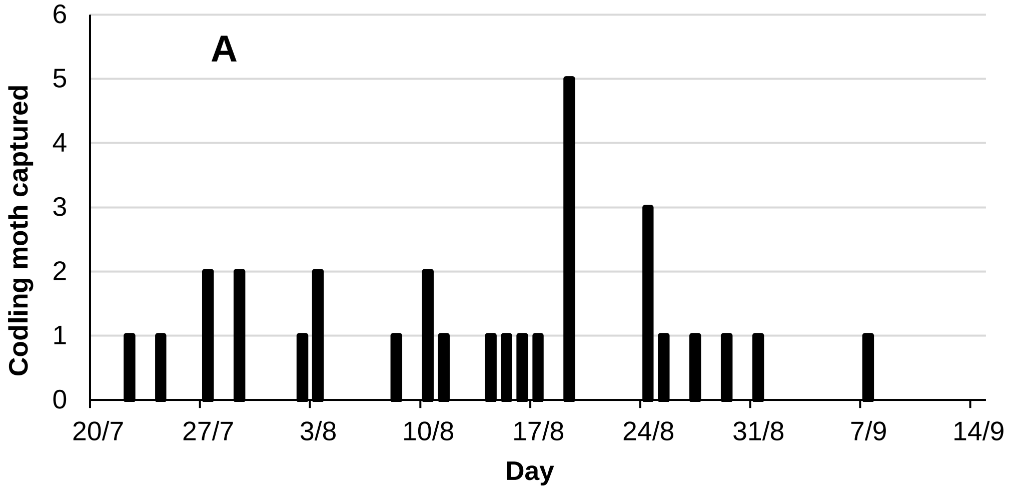
Results

The smart trap prototype developed in this study proved to be operative in field condition, with an external structure robust and resistant to the atmospheric events. The power autonomy varied among the tested devices, resulting in a variable number of pictures provided. In fact, some devices were still active sending pictures for a few days after the field experiments ceased, showing an operation lasting up to 8 consecutive weeks, while other devices interrupted the picture sending prior to the end of each experiment. The failure in sending pictures that occurred in some devices was likely due to connectivity issues and in these cases the battery discharged rapidly, not allowing the remote validation of the captures for the whole monitoring period. During the first monitoring period (July-September), three out of six devices interrupted picture transmission after 5 days of operation or less, and therefore were excluded from data analysis on the detection algorithm exactness due to the reduced samples size. All six devices tested during this first monitoring period were instead considered for capture data analysis since all traps captured codling moth. During the second monitoring period (September-October), all traps were operative for minimum 4 weeks.

The smart traps trapping efficiency was comparable to the one provided by standard monitoring delta-shaped traps, with no significant effect of the trap design (df = 2, 9; F = 0.427; P = 0.665). Over the 4 weeks of field testing for trap design comparison, the smart traps captured on average 17.7 ± 3.1 codling moth, while the standard delta traps captured 13.5 ± 3.4 codling moth.

The codling moth captures in the smart trap prototypes were clearly recognizable by human operator due to the high resolution of the camera (5 Mpixel) and the manual check of the images allowed to describe the codling moth capture trend by using the smart traps data, as exemplified in figure 6. However, the automatic counts provided by the detection algorithm did not match with the manual counts provided by the human operator. Accuracy, precision and sensitivity of the detection algorithm under development are reported in table 1 for the two monitoring periods. All three parameters were significantly different (P < 0.001) among traps in both monitoring periods. Accuracy was higher than 100%, overestimating 1.5-3-fold the real captures count. Sensitivity was inferior to 30%, showing that several codling moth captures were missed by the automatic pest detection system, while the low precision reflected the abundance of false positive misidentifications.

During the first monitoring period, a total of 352 pictures derived from three smart trap prototypes were analysed. The average number of particles recognized



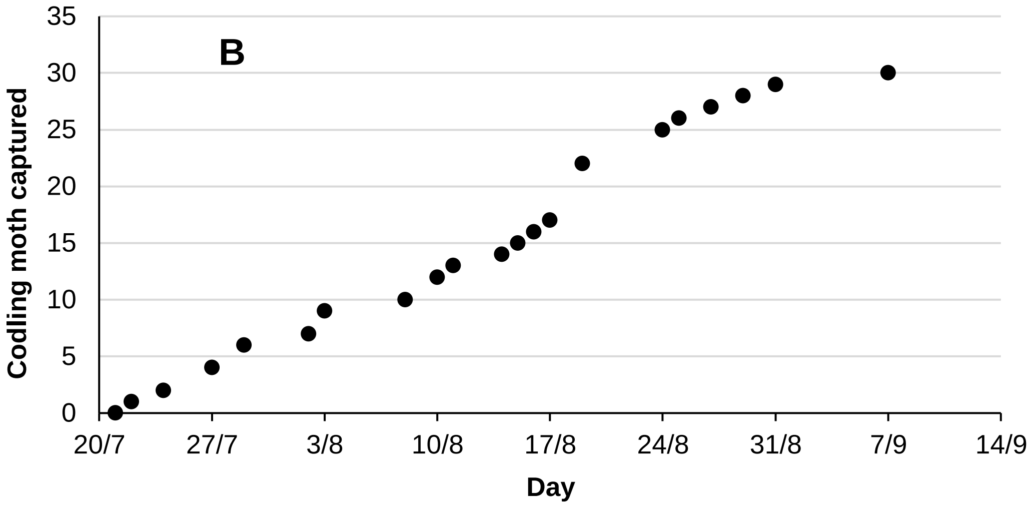


Figure 6. Codling moth captures reported as an example by one smart trap over the monitoring period July 21 - September 14 in a pear organic orchard treated with mating disruption. **A** = new daily captures; **B** = cumulative captures.

Table 1. Exactness of the automatic detection algorithm at early stage development for codling moth. Accuracy, sensitivity and precision of the algorithm were calculated on a limited sample dataset (pictures number into brackets).

Monitoring period (total number of analysed pictures)	Mean values (± SEM) Accuracy (%)	Sensitivity (%)	Precision (%)
July-September [a] (352)	156.7 ± 6.2	28.1 ± 1.0	21.0 ± 0.7
September-October [b] (332)	302.2 ± 20.0	26.5 ± 2.8	9.4 ± 1.2

[a] Data resulting from three smart traps prototypes; [b] Data resulting from six smart trap prototypes.

Table 2. Major non-targets represented by flies (Diptera Muscidae) that impacted negatively the exactness of the automatic detection algorithm developed for codling moth.

Monitoring period (total number of flies captured)	Mean values (± SEM) Number of flies captured	Number of flies counted by the algorithm	Flies counted out of the total present (%)	False positive represented by flies (%)
July-September [a] (38)	7.4 ± 0.3	4.2 ± 0.2	59.1 ± 1.7	30.6 ± 1.3
September-October [b] (34)	1.4 ± 0.1	0.8 ± 0.1	59.3 ± 2.8	33.7 ± 2.3

[a] Data resulting from three smart traps prototypes; [b] Data resulting from six smart trap prototypes.

automatically by the detection algorithm was 17.0 ± 0.6, while the real codling moth counts were on average 13.4 ± 0.5 per picture. The automatic counts included 79.0% ± 0.7 of false positives, while the false negatives were 72.2% ± 1.1. In the first period, over more than 6,000 particles automatically marked and counted, about 4,600 particles were false positives. These misidentifications included a small portion (8.2%) of double counts, i.e., codling moth individuals counted twice due to wings expanded. The rest of false positives were represented mainly by shadows in the sticky liners, in a few cases by the lures, and by muscid flies. A total of 66 codling moth individuals and 38 flies were caught in three smart traps during the first monitoring period. The non-targets, measured to be classified according to their size, were mostly the same size of codling moth: 71.1% of captured flies had a body length comprised between 0.5 and 1.0 cm, while 15.8% had a size smaller than 0.5 cm and 13.2% had a size comprised between 1.0 and 1.5 cm. On average, almost 60% of the flies captured in the smart traps were misidentified as codling moth and flies represented about 30% of false positive counts (table 2).

During the second monitoring period, a total of 332 pictures collected from 6 smart trap prototypes were analysed. The detection algorithm automatically recognized on average 3.3 particles per picture, while there were on average 0.9 ± 0.1 codling moth individuals per trap. False positive misidentifications accounted for 90.7% ± 1.2 of the automatic counts, while the false negatives were 72.8% ± 2.9. In the second period, over about than 1,100 particles automatically marked and counted, about 1,000 particles were false positives. Similarly, to the first period, the majority of misidentification were due to shadows and flies, while the codling moths double counts were 2.4% of the false positive counts. In the second monitoring period, a total of 15 codling moth individuals and 34 flies were captured in the six smart traps. Flies body size was inferior to 0.5 cm for 14.7% of the captured flies, while 64.7% had a size comprised between 0.5 and 1.0 cm and 20.6% had a size comprised between 1.0 and 1.5 cm. Percentages of flies misidentified were similar in the two monitoring periods (table 2). The total number of flies captured had a significant effect on the automatic counts both during the first and the second monitoring period (df = 348, z value = 11.95, $P < 0.001$ and df = 328, z value = 14.45, $P < 0.001$, respectively).

Table 3. Hardware components and labour costs to produce a smart trap prototype equipped with camera for tortricid pests remote monitoring.

Cost item	Cost (€)
Trap chassis [a]	50.00
Controller board [b]	200.00
Power supply - 2 batteries	15.00
Power supply - 2 solar panels	30.00
Power supply - 1 inverter	20.00
Camera Omnivision OV5648	25.00
SIM card	10.00
Labour for construction [c]	25.00
Total	375.00

[a] Trap chassis cost includes the plastic material used per one device (at 25.00 € kg^{-1} of PLA) and the 3D printing expenses; [b] The controller board includes all the electronic components; [c] Forfait cost considering the components assemblage executed by a trained person.

The economic evaluation of the smart trap prototype construction is reported in table 3, while the cost comparison of the classic monitoring with the remote monitoring is reported in table 4. The production of one smart trap prototype costed in total 375.00 €. When the smart trap is used in pear crop, monitoring codling moth for 5 months, the overall remote monitoring cost estimated is 1.2-fold higher compared to the classic monitoring *in situ*. When the smart trap is used in apple crop, for a longer monitoring period (6 months), the cost of the remote monitoring is 1.1-fold higher than the classic one. An even longer monitoring period, increasing the number of field visits, can result in comparable costs. In both simulations, the remote monitoring compared to the classic monitoring *in situ* allows a 6-fold time resolution (i.e., 6 weekly data in comparison to the single direct trap check data in field).

Discussion and conclusions

Insect pest monitoring is crucial to predict when and where an insect pest will cause damage to a crop in order to prevent and counteract the pest infestations. It needs to be both efficient and reliable, and considering the limited

Table 4. Costs of codling moth remote monitoring in pome fruit crops by using a smart trap prototype in comparison to a standard monitoring trap to be checked weekly in field.

Cost item	Cost (€)			
	Pear		Apple	
	Smart trap prototype	Standard monitoring trap	Smart trap prototype	Standard monitoring trap
Trap device	375.00	15.00	375.00	15.00
Lure and liners	15.00	15.00	15.00	15.00
Field visits [a]	180.00	600.00	180.00	720.00
Remote monitoring [b]	200.00	-	240.00	-
Total	770.00	630.00	810.00	750.00

[a] Trap set up, lures and liners replacements, trap removal at the end of the season, and all the trap checks *in situ* are included in this cost voice; [b] Six weekly checks by remote location for the whole codling moth flight season are considered in this cost voice.

resources available for direct field, scouting can be optimized by using new technologies. The main advantages of using camera-equipped traps are the less time spent in field and the possibility to obtain a higher temporal resolution data on the pest population dynamics. The remote monitoring offers the opportunity to avoid unnecessary field visits, limiting them to locations and periods that strictly require a direct scouting. In addition, it provides precise information about the timing of insecticide applications, delivering data on a daily basis in comparison to the weekly trap check, and allows to better exploit and implement the insect phenology forecasting models (Preti *et al*., 2021a). However, the remote monitoring with smart traps cannot replace completely the in-field scouting: a few field visits are required to install the smart traps and service them, replacing for instance lures and liners. Growers can potentially implement their pest monitoring and management programs by means of such technologies. Nevertheless, an effort to promote the smart traps development and adoption is required. In fact, to date the costs and partial knowledge of the advantages derived by the smart trap usage limit their potential use among growers. This work proposes the development of a brand-new smart trap prototype starting from the construction materials and considering both environmental and economic sustainability; open-source programs were used to develop the automatic detection algorithm; the first results of the trap prototype field validation were provided in the early stage of its development and a cost-benefit analysis was also considered to address the remote monitoring cost matter.

One issue encountered during the field validation was the limited power autonomy of some devices due to repeated failures in sending data. As reported in López *et al*. (2012), the highest power consumption of a smart trap is usually due to data transmission. In the present work, the poor or unstable connection of some devices affected negatively the operational life, rapidly discharging the battery due to multiple sending of pictures. However, in this study it was proved that with no data sending errors smart traps were operative for a minimum of 2 months. The power issue was caused by both not good network coverage on the tested field locations by all Italian GSM operators and not optimized cellular network technologies for the Internet of Things (IoT) and Mobile Edge Computing (MEC) (Giannotta *et al*., 2019). IoT consists of smart devices that communicate with each other (Al-Sarawi *et al*., 2017), while MEC is an emergent architecture, where cloud-computing services are extended to the edge of networks leveraging mobile base stations (Abbas *et al*., 2018). To reduce the encountered problems, a feasible solution would be to implement an image compression algorithm that works on the very low power microcontroller. Also increasing the energy power of the system using very low-cost components (more accumulators and more performant solar panels) can be a practical and effective solution to ensure a longer operational life of the smart trap. In addition, the new 5G mobile technology, which is designed to support the IoT devices to be permanently linked to the network with low energy consumption (Giannotta *et al*., 2019), could help to solve the connectivity issues.

Regarding the smart trap trapping efficiency, in a preliminary 4-week duration trial the tested design was capable of capturing the target pest codling moth in comparable numbers to standard monitoring traps. Extensive field evaluations of the proposed prototype design are required to further demonstrate the consistency in captures of the smart trap in comparison to a standard monitoring designs (usually the delta-shaped traps) to trigger control interventions at a given threshold. As reported in literature (Guarnieri *et al*., 2011; Knight and Light, 2005; Knight *et al*., 2019b), different factors can affect moth captures, including structural elements (such as trap shape and opening width, trapping surface size and adhesive material) and operative decisions (such as trap position within the canopy and its proximity to fruits). All these aspects need to be considered both for a further improvement of the smart trap design and for a correct deployment of the monitoring traps in field.

Despite the smart trap captured codling moth and pictures collected provided a sufficiently high image resolution to manually validated moth captures by remote, the detection algorithm failed to automatically provide a trustworthy capture data. Deep learning validation with further pictures data is likely necessary to reach a sufficient level of reliability in the automatic detection and count system. Similar studies on insect detection carried on with the same deep learning approach exploiting the CNN algorithm and few hundreds of pictures in the dataset concluded that one possible way to solve the target detection error was to augment the size of the dataset (Xia *et al*., 2018). In fact, a theoretical calculation proved that the error in the CNN algorithms class is correlated to the dataset size (Du *et al*., 2018). This study considered three qualitative parameters related to pest identification exactness (i.e., accuracy, sensitivity and precision) in order to assess the status of the automatic detection algorithm. The obtained result were expected to be not satisfactory, since the smart trap was evaluated in an early stage of its development and the algorithm still needs to be alimented with more data to work properly. This evaluation basis will be useful for further validation of this prototype in the future and for comparison among prototypes and commercial smart traps.

The percentage of either false positive or false negative allows to evaluate the exactness of the system for codling moth automatic identification and count. The detection algorithm can be judged reliable when both false positive and false negative percentages are close to zero. In fact, the abundance of false positive implicates overestimations of the real captures, triggering control actions when not needed. On the contrary, the occurrence of false negative (i.e., underestimation of real pest pressure) can delay or miss a necessary intervention involving a lower or lack of control. The algorithm outputs included a high number of both false positive and false negative counts, suggesting that adjustments of the detection algorithm are required. The flies automatically detected were similar in size to codling moth, which has a forewing length of 6.5-11.0 mm (TortAI, 2020). Therefore, additional parameters should be considered to better discriminate between codling moth and flies, such as an improved analysis of the light conditions when the picture is taken. This is not a trivial process, as shadows and sunlight deeply change the colour perception from a machine point of view. To solve this issue, a build-it flash light could likely be exploited to improve the standardization of light conditions during picture acquisition as successfully proposed and adopted in previous related works (Selby *et al.*, 2014; Rassati *et al.*, 2016).

Regarding the smart trap cost-benefit analysis, the economic calculation demonstrated that despite a slightly higher cost (1.1-1.2-fold) of the remote monitoring compared to the classic monitoring, it was possible to increase of 6-fold the time resolution, providing daily pictures of the pest captures. This aspect is not negligible since a better optimization of the management practices, including a more efficient usage of insecticides, may imply the grower incomes increase due to the reduced losses. Other authors described the convenience of smart trap usage. For instance, Ünlü *et al.* (2019) reported that the remote monitoring of tortricid pest in Turkish vineyards allowed to save money and time, with the smart trap cost recovery by avoiding just two field visits in isolated and distant locations (125 $ of weekly field survey compared to 250 $ of smart trap production cost). Selby *et al.* (2014) demonstrated that the usage of a smart trap for research purposes to collect data on the daily insect pest activity over the 24 hours costed 78% less than employing a human observer and despite the initial cost of a smart trap was more expensive, its usage over time would amortize the cost compared to the man-powdered monitoring. Also in the present study, a longer use of the smart trap would widen the difference between the classic and remote monitoring, emphasizing the suitability of the latter one to reduce costs and improve quality. However, the cost-benefit analysis of this work considered a prototypal trap cost. Usually, a commercialized product includes also other cost items, such as the fee that a company applies for the access in the web application. In addition, a prototype cost evaluation has not considered variable costs depending on the data traffic consumption, the technical assistance and the training offered as services for a commercial smart trap, plus other extra features such as the inclusion of weather sensors and weather data availability in the trap device. A future economic evaluation including these parameters should consider commercial smart traps. In particular, considering either the purchase of a smart trap or the seasonal rent of this service.

In conclusion, this study reports the process of a smart trap prototype development using the most updated technologies and including its preliminary field validation. A further improvement of such prototype needs to consider both the optimization of the data transmission related to the power autonomy, to ensure a complete operability over the entire monitoring season, and a refinement of the automatic detection algorithm, in order to allow a reliable machine-based count data delivery. In this case study it was proved that with a slight increase of the monitoring cost, the smart trap system was able to provide a consistently higher temporal resolution of the capture data information compared to the standard monitoring. Camera-based insect pest monitoring is a different discipline than the area-wide remote sensing in entomology performed with airborne techniques based on spectral features (Riley, 1989; Nansen and Elliott, 2016). Nevertheless, deploying smart traps in multiple locations to create a trap network (Potamitis *et al.*, 2017), the remote monitoring with smart traps becomes area-wide and can be considered as a complementary approach to the remote sensing provided by satellite and aerial images. Data derived from both smart traps, placed locally *in situ*, and from remote images covering wider geographical areas (Abd El-Ghany *et al.*, 2020) can be combined for a multidisciplinary detection, forecasting, and management of a number of insect pests and diseases in agricultural crops and forestry.

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Authors' addresses: Sergio ANGELI (corresponding author: sergio.angeli@unibz.it), Michele PRETI (michele.preti@natec.unibz.it), Faculty of Science and Technology, Free University of Bozen-Bolzano, piazza Università 5, 39100 Bolzano, Italy; Michele PRETI (michele.preti@astrainnovazione.it), Christian MORETTI (christian.moretti@astrainnovazione.it), ASTRA Innovazione e Sviluppo Test Facility, via Tebano 45, 48018 Faenza, Italy; Gabriele SCARTON (gabriele.scarton@fos.it), Giovanni GIANNOTTA (giovanni.giannotta@fos.it), FOS S.p.A., via Alessandro Volta 13/a, 39100 Bolzano, Italy.

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