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Development of an autonomous smart trap for precision monitoring of hematophagous flies on cattle

Gaspare Santaera [a,b], Valeria Zeni [c], Gianluca Manduca [a,b], Angelo Canale [c,d], Marcello Mele [c,d], Giovanni Benelli [c,d], Cesare Stefanini [a,b], Donato Romano [a,b,*]

[a] The BioRobotics Institute, Sant'Anna School of Advanced Studies, Viale Rinaldo Piaggio 34, Pontedera, Pisa 56025, Italy
[b] Department of Excellence in Robotics and AI, Sant'Anna School of Advanced Studies, Piazza Martiri della Libertà 33, Pisa 56127, Italy
[c] Department of Agriculture, Food and Environment, University of Pisa, Via del Borghetto 80, Pisa 56124, Italy
[d] Centro di Ricerche Agro-ambientali "E. Avanzi", University of Pisa, via Vecchia di Marina, 6, 56122, San Piero a Grado (PI), Italy

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ABSTRACT

Hematophagous flies pose a significant threat to livestock health and productivity. Traditional pest control methods, which heavily rely on chemical insecticides, present risks such as resistance development and environmental harm. This study presents a novel smart trap for real-time monitoring and identification of Tabanidae, Hippoboscidae (i.e., *Hippobosca equina* L.), and Muscidae (i.e., *Stomoxys calcitrans* (L.)) on cattle. The system includes a microcontroller for managing various sensors (light, temperature, humidity, and gas) and power management. The control unit is complemented by a microprocessor responsible for managing and processing images from a camera. The system integrates high-resolution imaging, a convolutional neural network (CNN) for species recognition, and environmental sensors to monitor factors affecting insect behavior. On the test set, the CNN achieved an overall precision of 0.96 and recall of 0.98 in detecting instances, with an overall classification accuracy of 0.96. Equipped, also, by lithium-ion battery and by communication module, the trap can operate autonomously and transmit data, becoming suitable for large-scale deployments. Overall, the tool developed here offers a practical and cheap solution for sustainable and accurate pest monitoring of hematophagous flies attacking cattle in pasture and feedlot.

Introduction

Hematophagous insects represent a threat to livestock health and welfare in agricultural systems [1]. Among them, several Diptera species are both pests and vectors of various pathogens of veterinary importance [2–4]. The resulting economic implications are important, encompassing direct losses due to decreased animal productivity, and indirect costs associated with veterinary care and pest management interventions [5]. Traditionally, the management of these pests predominantly relied on chemical insecticides, which, although effective in the short term, present substantial risks such as the development of insecticide resistance, and non-target effects on human health and the environment [6,7]. Thus, developing sustainable pest management strategies that incorporate early detection and accurate monitoring of hematophagous flies is essential.

Precision pest management is increasingly being recognized as a promising approach to address these challenges [8–10]. Central to this approach is the ability to monitor pest populations with high accuracy and in real time, enabling targeted interventions that minimize the use of chemical products [11]. Recent advances in artificial intelligence (AI) and automation have the potential to revolutionize pest monitoring systems by providing the technological foundation for precision agriculture [12,13]. AI-driven technologies, particularly those employing machine learning algorithms, can facilitate the automatic detection, identification, and quantification of pest species, thereby enhancing the efficiency and effectiveness of pest management practices [14–18].

Significant progress has been made toward the development of automated systems (e.g., smart pest traps) that integrate advanced sensing, imaging, and data processing capabilities [19,20]. These systems are designed to continuously monitor insect populations, providing valuable data that can inform pest control decisions. For instance, several studies have reported the successful deployment of smart traps that exploit high-resolution cameras coupled with machine learning algorithms to identify and classify insect species based on morphological

* Corresponding author.
E-mail address: donato.romano@santannapisa.it (D. Romano).

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characteristics [21–24]. Such systems are capable of working autonomously in various environmental conditions, offering real-time data collection and analysis [25]. Despite these advancements, existing smart traps often face limitations related to scalability, environmental adaptability, and the accuracy of species identification in diverse field conditions. Furthermore, the integration of environmental sensors to monitor factors such as temperature, humidity, and light, which influence insect behavior and population dynamics, remains underexplored in the context of smart traps [7].

Considering these challenges, herein we have developed an innovative smart trap prototype aimed at the identification and monitoring of various hematophagous flies attacking cattle in pasture and feedlot, specifically fly species belonging to the family Tabanidae, as well as *Hippobosca equina* L. (Diptera: Hippoboscidae) and the stable fly *Stomoxys calcitrans* (L.) (Diptera: Muscidae). These species cause direct harm on animals, which is typically intensity-dependent, but more significantly, they can contribute to indirect damage by facilitating the spread of pathogens like filarial nematodes and various viruses [26,27].

This study details the design, development, and initial field testing of our smart trap, highlighting its potential to improve the sustainable management of haematophagous fly populations in livestock stables. By combining high-resolution imaging, advanced machine learning algorithms, and comprehensive environmental monitoring, this smart trap aims at offering a robust and scalable solution for monitoring flies attacking cattle in pasture and feedlot. Our research contributes to the growing body of literature on precision agriculture and underscores the importance of integrating AI and automation in the development of sustainable pest and vector management technologies. Fig. 1 presents the workflow of the proposed approach.

Materials and methods

Species collection and identification

Three families of flies attacking cattle on pasture or confined rearing area, were studied i.e. Tabanidae, Hippoboscidae (*H. equina*), and Muscidae (*S. calcitrans*). Part of the hematophagous flies were sampled at the experimental farm of Centro di Ricerche Agro-Ambientali "Enrico Avanzi" (CiRAA), University of Pisa (Italy); the farm is composed by 500 hectares of arable land, and two stables, where nearly 100 dairy cattle and 50 beef cattle are reared.

Stomoxys calcitrans specimens were sampled indoor during milking sessions in the dairy cattle barn using an entomological net and an aspirator. Tabanids were gathered using the Tabanus Trap (VOSS. farming) positioned in three hotspots at CiRAA (spot 1: 43.681218, 10.340477; spot 2: 43.682560, 10.339620; spot 3: 43.662785, 10.29131). This type of trap uses solar heat to deceive female tabanids into locating the trap, which can be detected by the warmth emitted by an inflated black ball suspended underneath a plastic hood. Upon landing on the black sphere, the females ascend into the collecting chamber from which they cannot free themselves. Species identification was conducted based on the descriptions and keys provided by Chvála et al. [28], Walker [29], and [30]. *Hippobosca equina* individuals and some additional specimens of *S. calcitrans* and Tabanidae from the entomological collection at the Entomology Section of the Department of Agriculture, Food and Environment, University of Pisa, were utilized for the training.

Smart trap design

The smart trap was designed with a robust plastic enclosure that houses all the electronic components, including a camera for image acquisition. This enclosure is mounted on a white Plexiglas board, which

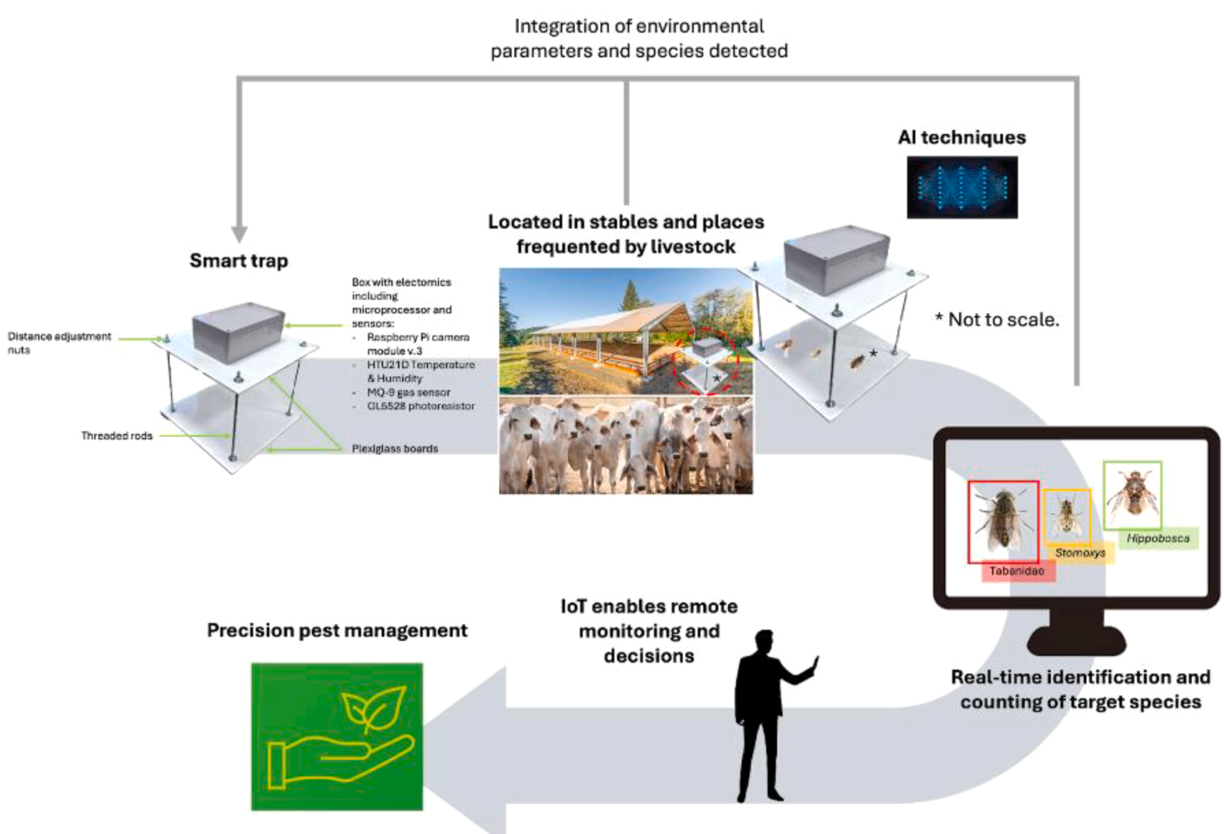

Fig. 1. Workflow of the proposed approach.

serves as the base, while a second Plexiglas board, positioned parallel to the first, forms the visual background of the trap. These two boards are connected by four threaded rods, allowing for adjustable distance regulation between the camera and the background (Fig. 2). Chromotropic or olfactory cues are incorporated within the trap to attract target insect species.

Hardware components

The smart trap hardware includes a Raspberry Pi 4 microprocessor board, an ESP32-based microcontroller board (LilyGO-T-7670), a variety of sensors, and a high-resolution camera (Raspberry Pi Camera Module v.3). To facilitate remote data transmission and location tracking, a GSM/GPS module is integrated into the system (Fig. 3).

To monitor environmental conditions, a digital sensor known as HTU21D was employed for its reliability in measuring temperature and humidity, which are critical factors influencing insect biology and behavior. Given the operational environment within livestock stables, where high concentrations of cattle are present, the MQ-9 gas sensor was selected for its capability to detect gasses such as carbon monoxide, methane, and LPG, which are essential for monitoring air quality and assessing environmental safety.

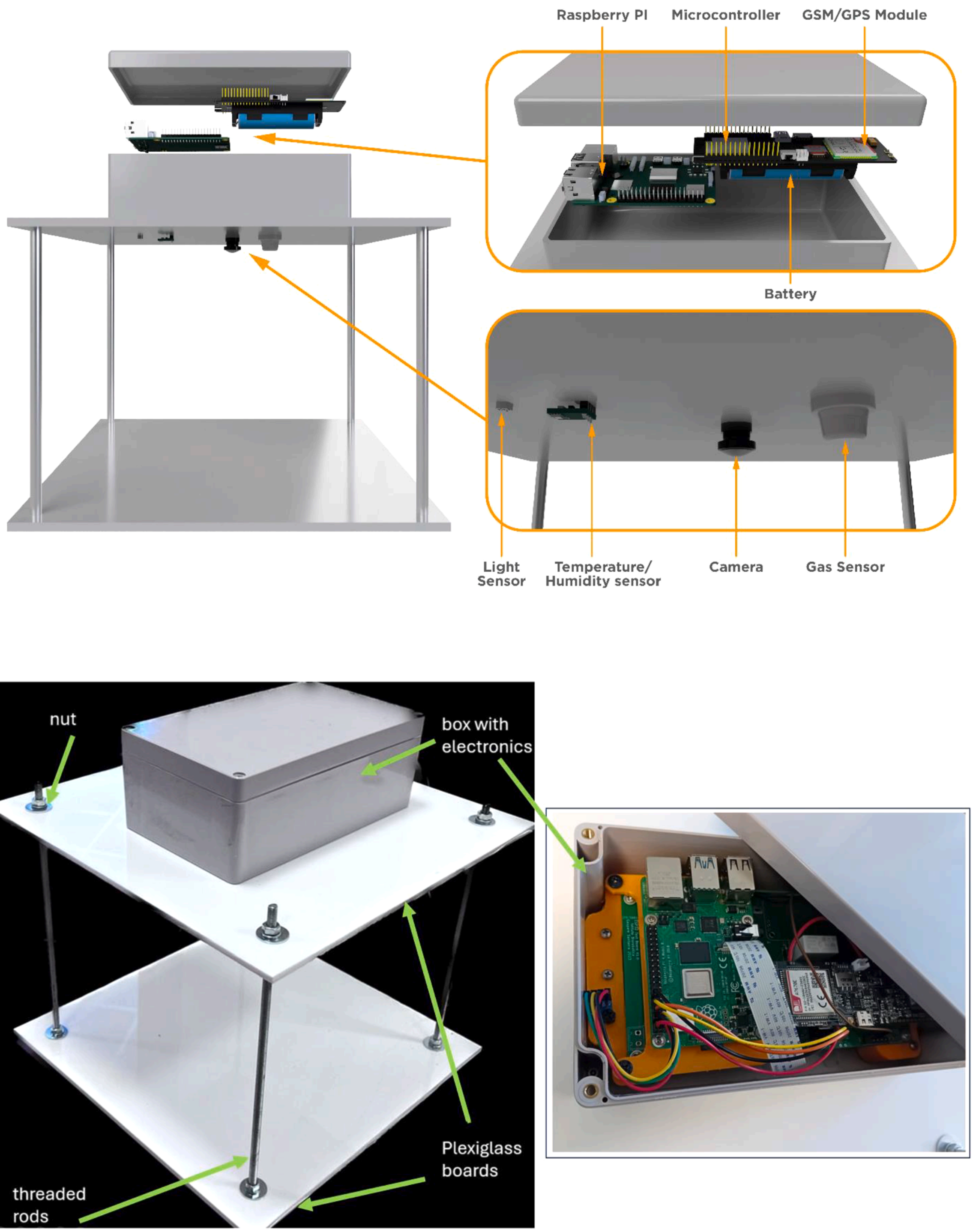

Fig. 2. Schematic representation of the smart trap structure, along with the assembled version, including its components description.

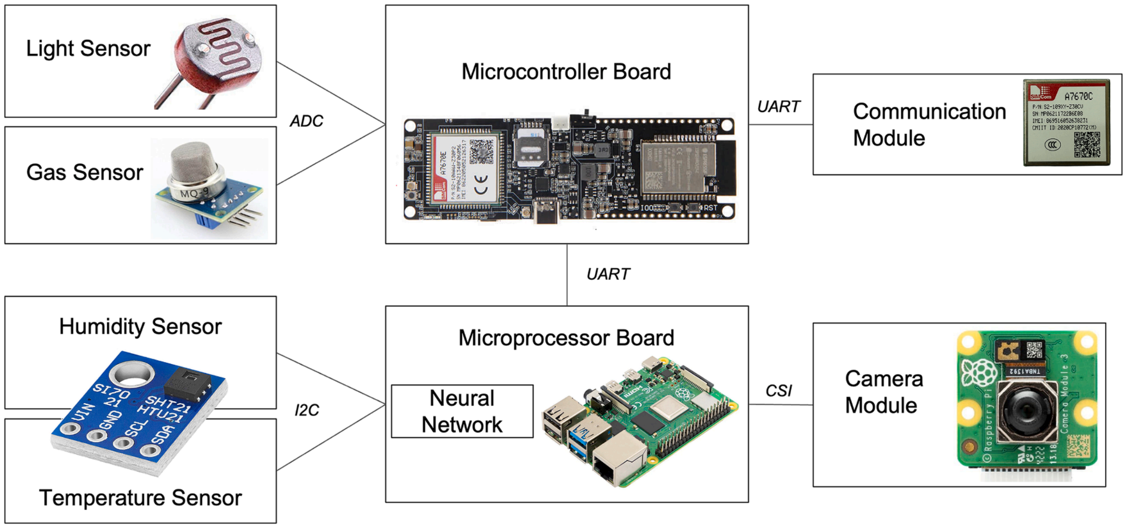

Fig. 3. Architecture of the hardware inside the smart trap including the microprocessor, microcontroller, camera, sensors, and communication module.

In addition to these sensors, the trap includes a GL5528 photoresistor to measure ambient light levels. The varying conductance of this sensor, depending on luminance, provides valuable data for correlating insect activity with light conditions. The primary tool for fly identification is the high-resolution Raspberry Pi Camera Module v.3, which captures images processed in real-time by a convolutional neural network (CNN) trained to classify various fly species.

The smart trap's functionality is governed by two main processing units: the Raspberry Pi 4 microprocessor and the ESP32-based microcontroller. The microcontroller is tasked with low-level operations, such as analog-to-digital conversions, sensor data acquisition, and power management, while the microprocessor handles more complex tasks, including running the neural network for image processing and managing data storage and transmission.

The smart trap can perform remote monitoring and data transmission, made possible by the integrated GSM/GPS module (A7670). This module, supporting multiple communication protocols such as LTE-TDD, LTE-FDD, GSM, and GPRS, enables the smart trap to connect to the internet and send collected data, including insect counts and environmental parameters, to a remote server via email. In the event of power loss, the system seamlessly switches to a backup battery managed by the microcontroller. To conserve power, the microcontroller disables the microprocessor and reduces communication frequency, sending alarm notifications via SMS or email as needed. The microcontroller then enters a low-power sleep mode, periodically waking to check the system's status.

During normal operation, the smart trap autonomously collects and processes data continuously. Sensor readings are acquired every second and temporarily stored in arrays managed by the microcontroller. The microprocessor regularly requests data from the microcontroller, processes images from the camera, and uses the neural network to compute the desired outputs. These results, including the number and type of insects detected, are logged and transmitted daily to a remote server via email. A log file is attached in each email. When powered by a battery, the smart trap operates by activating the communication module only once a day to conserve energy. When powered by the electrical grid, however, the communication system can remain active continuously, allowing remote requests and commands to be sent via specific SMS messages or email.

The GSM/GPS module also provides geolocation capabilities with an accuracy of approximately three meters. While this feature may not be essential for traps that remain stationary within a single stall, it proves valuable for mobile deployments, enabling precise data correlation with specific locations during post-processing.

Automatic detection algorithm and dataset

For this study, the Ultralytics YOLOv8s model was chosen, building upon the YOLO (You Only Look Once) family of CNNs [31]. YOLO has proven to be highly effective in real-time object detection, notable for its ability to execute the task in a single pass through the network, making it computationally efficient. These networks have been successfully applied to a wide range of detection tasks, ranging from environmental applications [32], to medical [33] and industrial contexts [34]. YOLOv8 represents an advancement within the YOLO family, incorporating deep learning improvements for enhanced speed, accuracy, and ease of deployment. We opted to use the small version of YOLOv8 due to its lighter architecture, which offers faster processing times and reduced computational requirements while maintaining strong performance. This study gathered a total of 479 images, which were divided into three sets: 420 images for training, 40 images for validation, and 19 images for testing. The images were manually labeled using the online software Roboflow. The dataset includes three distinct object categories, Hippoboscidae, *Stomoxys*, and Tabanidae flies.

The number of instances per image ranges from 1 to 5, featuring various combinations of these categories within a single image. To reduce bias toward any dominant class, the instances were balanced across categories. The dataset was collected in a controlled environment throughout the entire day, specifically between 9:00 and 18:00, capturing images under varying lighting conditions to enhance the model's ability to generalize. To better replicate a natural setting, potential classifier disturbances commonly found in the wild, such as leaves, stones, and other environmental elements, were intentionally included in the background. Additionally, to further aid the classifier in generalization, images were captured against diverse backgrounds made of different materials and colors, including a gray polystyrene surface and a black cloth, in addition to a neutral backdrop. This approach ensures robustness to real-world variations and improves the model's ability to accurately distinguish the target species. To enhance model generalization, data augmentation techniques were applied. All images were resized to 640 $\times$ 640 pixels. The CNN model was fine-tuned using a pre-trained version of YOLOv8s, originally trained on the COCO dataset.

Results

The performance of the CNN model in object detection was evaluated, Fig. 4 presents key metrics recorded during both training and validation phases. During training, a common trend observed was the consistent decrease in loss metrics, which signaled the model's adaptive

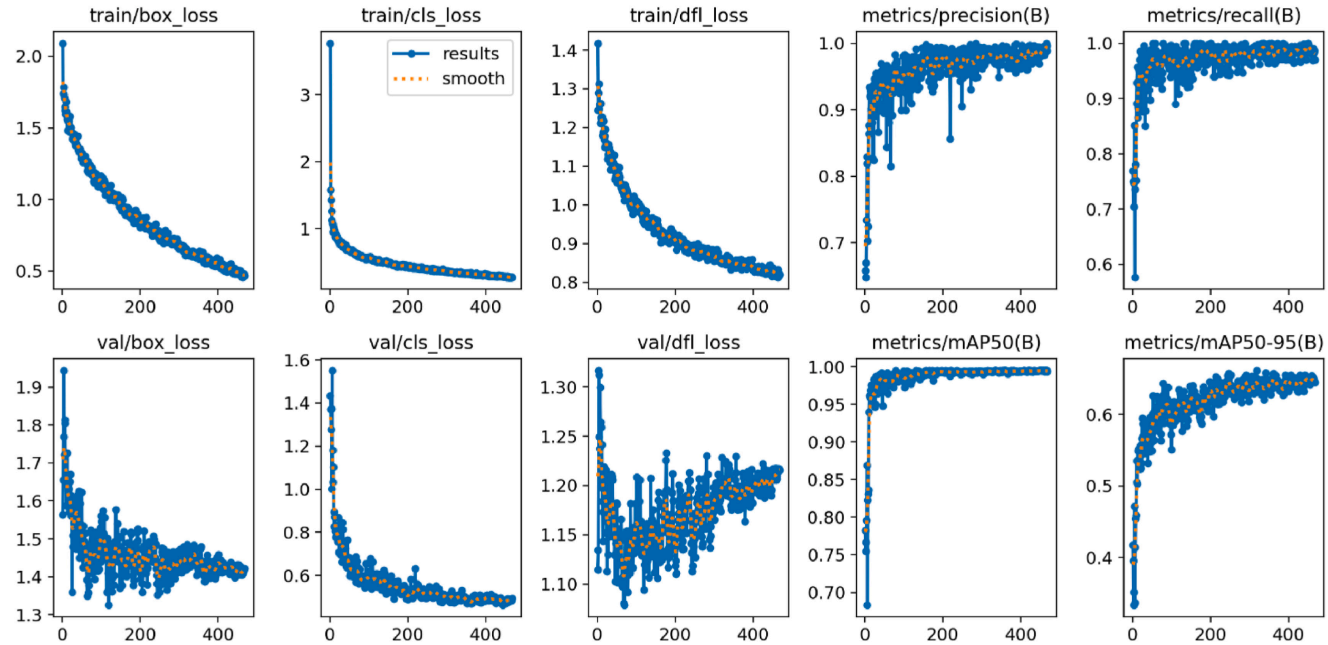

Fig. 4. Key metrics illustrating model's performance in object detection during both training and validation phases.

learning and its capability to iteratively fine-tune parameters, thereby enhancing its accuracy in identifying complex patterns within the dataset. The model's precision, recall, and mean Average Precision (mAP) improved across epochs, eventually stabilizing after the epoch 300. Training was stopped early since no further improvements were detected in the final 150 epochs. Overall, the CNN achieved 0.99 precision, 0.98 recall, and a mean average precision at a 0.5 threshold (mAP@0.5) of 0.99 on the validation set. The network exhibited an overall precision of 1.0 at a confidence threshold of 0.9, and an overall recall of 1.0 at a confidence threshold of 0.0. The overall F1-score reached its peak of 0.99 at a confidence threshold of 0.737. The overall classification accuracy was 0.94.

On the test set, the best model configuration achieved, overall, 0.96 precision, 0.98 recall, and 0.995 mAP@0.5. The precision was 1.0 at a confidence threshold of 0.912, and the recall 1.0 at a confidence threshold of 0.0. Fig. 5 shows the F1-confidence curves generated from the test results, including individual curves for each class and an overall curve representing all classes. These curves, displaying the F1-score at various confidence thresholds, demonstrate that the model has achieved an optimal balance between precision (accuracy of positive predictions) and recall (ability to retrieve all positive instances). This balance highlights the overall effectiveness of the model in object detection and its ability to distinguish positive from negative instances. The overall F1-score reached a value of 0.97 at a confidence threshold of 0.122. These test results were consistent with those from the validation set, demonstrating that the network has effectively generalized and had not suffered from overfitting during training. Fig. 6 displays sample detections from the test set, demonstrating the model's accuracy in

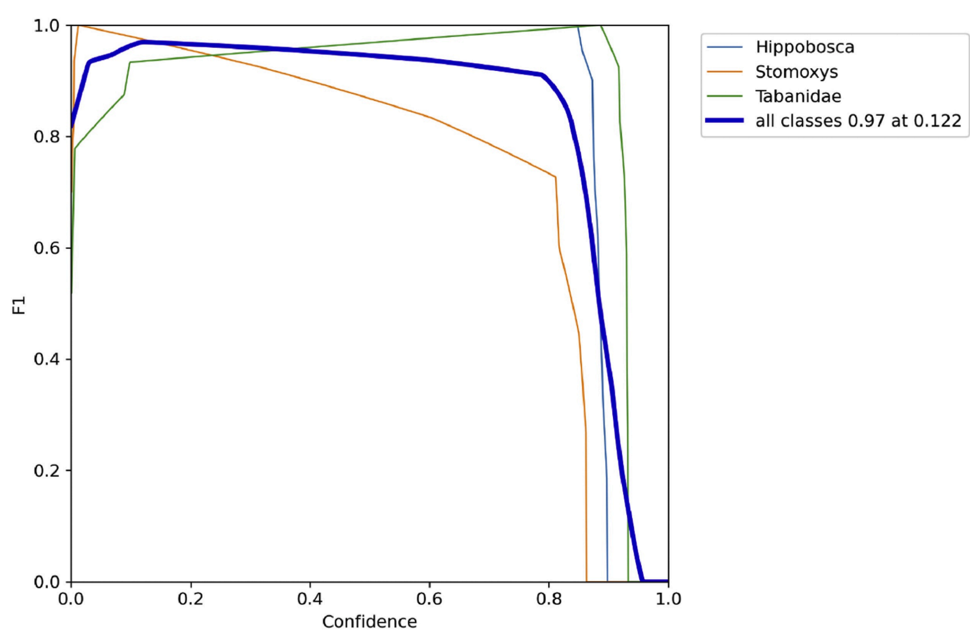

Fig. 5. F1-confidence curves.

identifying key features across various instances in unseen data. These examples underscore the detection algorithm's robustness and its ability to generalize effectively across new samples.

Fig. 7 illustrates the normalized confusion matrix. Overall, the confusion matrix suggests that the model performed well in classifying the different classes in the test set, with minor errors. The CNN achieved an overall classification accuracy of 0.96.

Discussion

This study introduces a new device for monitoring the population of tabanid, hippoboscid, and muscid flies attacking cattle. The present low-cost tool can allow the assessment of several key parameters, including the measurement of environmental factors that may influence flies' population dynamics. The system is designed as an open platform, enabling the integration of additional sensors to enhance research capabilities, as well as to adapt the trap for studying other insect species. Connection to standard communication networks facilitates programmable message transmission, real-time data transfer, and remote control and avoids the presence of an operator, who might affect the environment during measurements. Of note, the developed AI system not only delivers effective insect recognition, but also supports the training of new neural networks, enabling identification of different insect species and making the smart trap adaptable to diverse applications. Laboratory tests with sample species have confirmed the tool's effectiveness. Future research will aim at achieving real-time insect identification in the field, with targeted mechanical or chemical capture actions limited to designated areas of interest. Significant progress has been made in developing automated systems like smart pest traps, which integrate advanced sensing, imaging, and data-processing technologies [19,20]. These advanced systems enable continuous surveillance of insect populations, providing critical data to support and refine pest control strategies. A growing number of studies highlight successful implementations of smart traps equipped with high-resolution cameras and machine learning algorithms that can identify and classify insect species based on distinctive morphological features. Preti et al. [35] developed a smart trap prototype for remote monitoring of codling moths in pome fruit crops, aiming to reduce the labor and delays associated with traditional trap inspections. Brunelli et al. [36] presented an ultra-low power smart camera for detecting and recognizing codling moths in apple orchards, aiming to enable early pest detection and long-range wireless alarms. The smart trap developed by Wang & Bu [24] was designed for monitoring codling moths in apple orchards, uses advanced sensors and machine learning to provide continuous, real-time pest detection. Our prototype represents a significant advancement in the field of pest management by integrating several cutting-edge technologies into a single, cohesive system. The smart trap is equipped with a high-resolution camera capable of capturing detailed images of insects as they enter the trap. These images are processed in real-time using a CNN, which has been trained to identify various species, particularly the above-mentioned flies those within the Diptera order, which are of primary veterinary importance.

The hardware architecture of the smart trap is centered around a microprocessor, which serves as the processing unit for image data and controls the operation of integrated environmental sensors. These sensors include temperature, humidity, and light sensors, which monitor the environmental conditions within the stable, providing contextual data that may influence insect activity. The trap includes a methane sensor to detect harmful gas emissions, for monitoring air quality conditions [37–40].

The entire system is enclosed within a robust plastic housing that protects the electronic components from environmental factors while allowing for efficient image acquisition.

One of the key innovations of our smart trap is its ability to function autonomously with minimal maintenance. Power is supplied through a combination of a power supply and lithium-ion batteries, ensuring continuous operation even in remote or off-grid locations. The trap is also equipped with a communication module that facilitates real-time data transmission via Wi-Fi or cellular networks, enabling remote monitoring and data analysis. This feature is particularly valuable for large-scale deployments where constant human oversight is impractical.

In several studies [41–43], insect captures were manually verified from images accessed remotely via computer or smartphone, requiring a trained observer at the control station to accurately identify species. While this method eliminates the need for field visits, it is still time-consuming and depends heavily on human expertise. In contrast, our smart trap leverages deep learning techniques for autonomous, in-device data processing, avoiding the need for manual identification. Designed with minimal maintenance requirements, it provides ready-to-use, processed data and enables long-term deployment even in remote or off-grid locations, significantly reducing both labor and operational time.

According to Selby et al. [44], using wireless technology, such as Wi-Fi or cellular signals, for trap monitoring may reduce visit

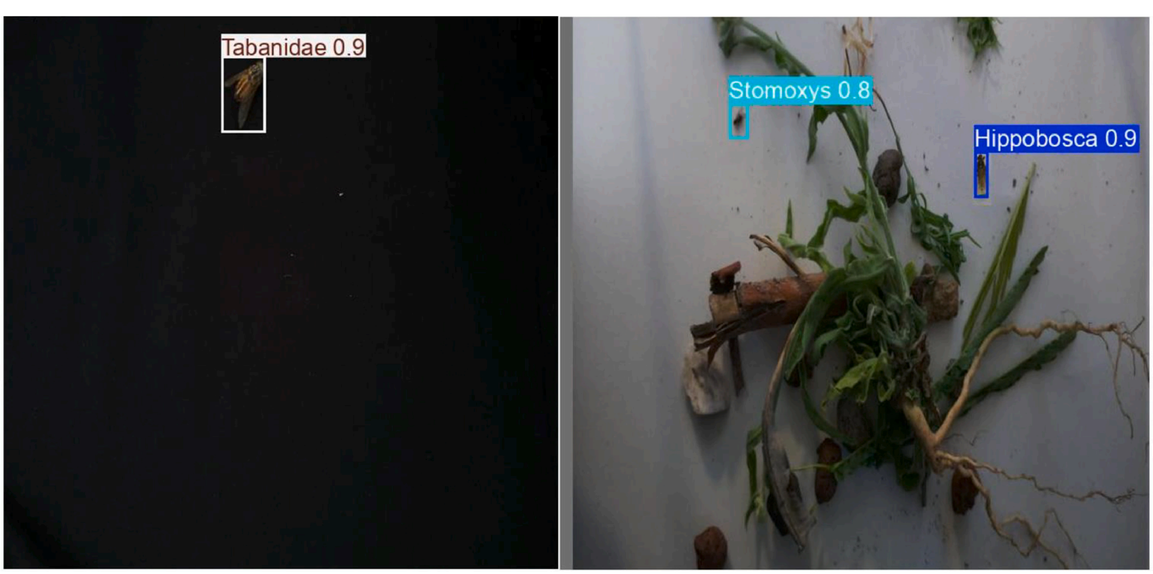

Fig. 6. Sample detections from the test set: two representative images from the test set demonstrating the model's detection capabilities, highlighting its accuracy and consistency.

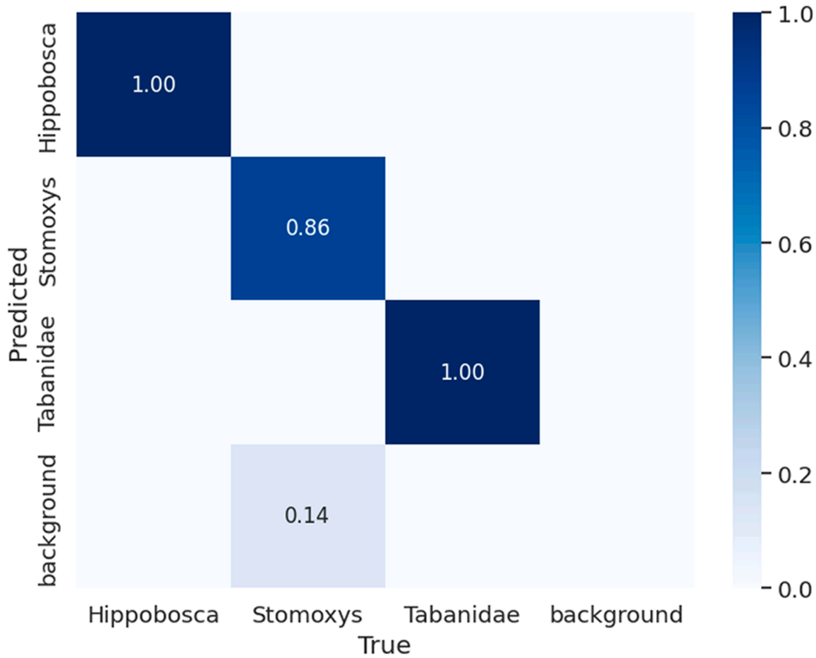

Fig. 7. Normalized confusion matrix.

requirements by facilitating real-time access to trap data, status, settings, and data processing from distant locations. This feature is particularly useful for large-scale deployments where frequent on-site inspections would be impractical and resource-intensive. In this direction, Our smart trap integrates a communication module that allows for real-time data transmission through Wi-Fi or cellular networks, enabling remote monitoring and prompt data analysis. By providing real-time updates on pest activity, the system allows for more timely decision-making and targeted pest control interventions.

Earlier research on smart monitoring mostly focused on agriculture [15,41] and urban pests [45]. For instance, Eliopoulos et al. [45] created an IoT-compatible gadget for the automated identification and reporting of crawling insects in urban environments, effectively integrating with smart buildings. Ünlü et al. [42] developed a system to monitor the European grapevine moth, *Lobesia botrana* Denis & Schifermüller (Lepidoptera: Tortricidae), in vineyard environments. On the other hand, our advanced smart trap is designed for the surveillance of hematophagous flies attacking beef and dairy cattle in diverse environments addressing a vital need in animal health and management. This application is particularly important as these insects pose significant health risks to livestock, potentially transmitting diseases and affecting animal welfare [46,47]. By utilizing our system in this context, we aim to provide a targeted, automated solution for monitoring and managing these insects, offering a more efficient and scalable approach compared to traditional methods.

A further advantage is represented by the integration of advanced image processing and classification algorithms directly within the trap, eliminating much of the need for external data processing. This system can autonomously detect and classify insects on-site, delivering instant results and enabling faster responses to infestations. This on-site processing capability not only accelerates pest management decisions, but also reduces operational costs by limiting the need for manual intervention and off-site data analysis. The system is highly scalable, allowing for the integration of future network updates and the addition of new algorithms enhancing the trap's ability to monitor the pest populations.

The system developed in this study combines energy autonomy, real-time communication, and efficient on-device data processing to offer a sustainable, cost-effective solution for large-scale pest monitoring. These innovations enhance the practicality and scalability of smart traps in agricultural settings, where continuous pest surveillance is essential but labor-intensive.

This work contributes to the expanding field of precision agriculture, highlighting the essential role of AI and automation in advancing sustainable pest management technologies. By incorporating these technologies, we aim to improve the efficiency and effectiveness of pest control methods, supporting the development of more intelligent, resource-efficient agricultural practices that address the increasing challenges in pest and vector management, while minimizing environmental impact.

Ethics Statement

Not applicable: This manuscript does not include human or animal research.

If this manuscript involves research on animals or humans, it is imperative to disclose all approval details.

If Yes, please provide your text here:

No permissions were required, as the work was based on the automatic recognition of insect pests.

CRediT authorship contribution statement

Gaspare Santaera: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Valeria Zeni:** Writing – review & editing, Investigation, Data curation. **Gianluca Manduca:** Writing – review & editing, Methodology, Investigation, Data curation. **Angelo Canale:** Writing – review & editing, Resources, Project administration. **Marcello Mele:** Writing – review & editing, Resources, Project administration, Methodology. **Giovanni Benelli:** Writing – review & editing, Project administration, Methodology, Funding acquisition. **Cesare Stefanini:** Writing – review & editing, Resources, Methodology, Data curation. **Donato Romano:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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