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Advancing social insect research through the development of an automated yellowjacket nest activity monitoring station using deep learning

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Abstract

1. We describe the development and validation of an autonomous monitoring station that identifies and records the movement of social insects into and out of the colony.
2. The hardware consists of an illuminated channel and a fixed camera to capture the wasps' activities. An ad hoc post-processing software was developed to identify the direction of movement and caste of the recorded individuals.
3. Validation results indicate that the model can detect with high levels of accuracy the presence of workers, drones and gynes, whereas direction of movement is accurate only for workers and drones, but not for gynes. Further development of the software and hardware should enable higher levels of accuracy, especially in terms of the direction of movement of reproductive individuals.
4. This innovative tool holds immense potential for advancing ecological and behavioural research by providing researchers with rapid and easily accessible data.
5. Understanding the activity patterns of individual wasps within the colony can yield valuable insights into factors influencing their growth, foraging patterns and the behaviour of reproductive individuals. Ultimately, this information can be incorporated into effective management plans for controlling harmful social insect populations in both ecological and productive systems.

KEYWORDS
automatic caste recognition, automation, big data, machine learning, neural network, pest, social insects

INTRODUCTION

The problem posed by invasive species in new environments, both in ecological and productive systems, is widely recognized. Insects are arguably the most significant pests to humans worldwide, and particularly, eusocial insects have the remarkable capacity to invade new territories (Beggs et al., 2011; Fowler et al., 2019; Moller, 1996) and because of the difficulty in managing them, can cause severe damage in crops and other activities (Bertelsmeier, 2021; Foster & Harris, 1997). Eusocial insects are those that live in colonies with overlapping generations, cooperative brood care and division of labour, making them a rare but highly ecologically successful form of life (Manfredini et al., 2019). For instance, ants have become one of the main pest organisms for agricultural and forestry production in South America (Della Lucia et al., 2014; Fowler et al., 2019; Montoya-Lerma et al., 2012) while social wasps represent in many parts of the world threats to the primary sector, such as the health of livestock and apiculture that can be severely affected (Lester & Beggs, 2019;

Andres Martínez and Maite Masciocchi contributed equally to this work.

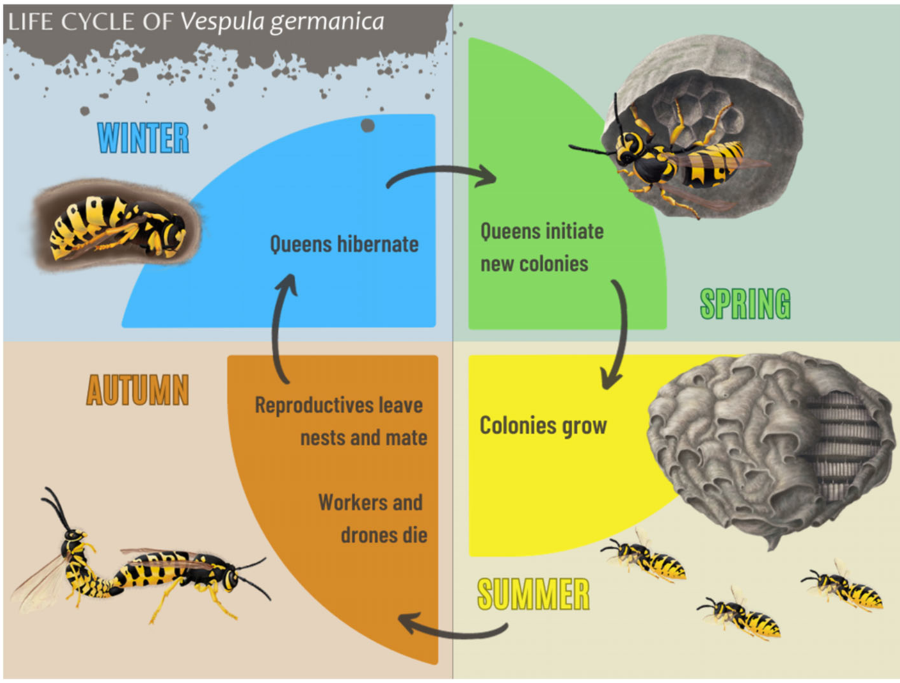

FIGURE 1 Key moments in the life cycle of *Vespula* spp. Queens initiate new nests during spring with the number of workers increasing until autumn. Then, reproductive individuals emerge from nests and mate. Later in autumn, drones (i.e., males) and workers die and queens hibernate in sheltered places. With the warmer days in spring, queens found the new colonies, and these grow until autumn. Image credits: wasp and nest illustrations Julia Rouaux and Irene Behrens.

Macintyre & Hellstrom, 2015). In this context, the development of environmentally sustainable tools for sound management of social insect populations requires solid knowledge of their behaviour and ecology.

Within the family Vespidae (Hymenoptera), eusociality has independently evolved twice, giving rise to 23 species within the eusocial genus *Vespula* (Hymenoptera: Vespidae). Notably, two of these species have become significant pests and established themselves outside their native habitats. The German wasp (*Vespula germanica*) (Hymenoptera: Vespidae) and the common wasp (*Vespula vulgaris*) (Hymenoptera: Vespidae) have been present for more than a decade in Argentina: *V. germanica* since the 1980s (Beggs et al., 2011; Lester & Beggs, 2019) and *V. vulgaris* since 2010 (Masciocchi et al., 2010). Both species represent a serious problem for a variety of human and economic activities due to their venomous sting, high population growth rate, behavioural plasticity and a generalist diet, in addition to their negative ecological impacts. The negative impact that *Vespula* wasps have on various productive and urban activities is significant. Given its generalist diet and predatory behaviour, attacks on beehives or adult honeybees are common, adversely affecting up to 10% of the hives (Clapperton et al., 1989). In addition to beekeeping, both livestock and forestry activities are impacted by the invasive wasp, sometimes resulting in significant economic losses due to reduced quantity and quality of milk and interference with forestry operations (Macintyre & Hellstrom, 2015; Yeruham et al., 2002). Additionally, *Vespula* species can damage fruits, reduce productivity in vineyards, chew on the sores or scabs of cattle and contribute to the spread of plant diseases (Lester & Beggs, 2019). Also, wasps can have a significant impact on human health due to their venomous stings, leading to allergic reactions and accidents.

Although their painful sting is noteworthy, another problem with these wasps arises from their feeding and characteristic biology, which exert a substantial influence on human activities. Their diet primarily comprises protein and carbohydrates, with variations throughout the year. Typically, proteins (i.e., insects, meat, etc.) are transported back to the nest by worker wasps to nourish the larvae, whereas carbohydrates (i.e., fruits, flowers, honeydew, etc.) are commonly utilized to meet the energy needs of workers and other members within the nest (Spradbery, 1973). In temperate regions that have been invaded by these wasps, their annual cycle involves queens (mated gynes) overwintering. In spring, new colonies are established and begin to develop. The population reaches its peak in late summer, with colonies growing to include thousands of individuals (Figure 1). This period poses a significant threat. Despite their pest status, options for managing their populations remain limited. Currently, the primary strategies employed worldwide are the use of toxic baits targeted at workers and manual nest destruction (Dimarco et al., 2017; Lester & Beggs, 2019).

Understanding in detail the activity patterns of *Vespula* spp. colonies could yield valuable insights of the factors that could affect their biology such as colony growth, foraging behaviour and activity patterns of reproductive individuals. However, fieldwork can be challenging, especially when cryptic behaviours exhibited by venomous social insects are involved. *Vespula* spp. can display aggressiveness in the proximity of their colony, making it risky to record behaviours with minimal disturbance and risk to the observer. Even though some studies in the genus have been conducted on colony-related aspects involving labour-intensive methodologies (Malham et al., 1991), an opportunity lies in developing precise and easy-to-use equipment by taking advantage of technological methods.

The evolution of big data and computer vision applications in biology has been made possible by the use of artificial intelligence and new technologies, offering significant advantages in understanding the ecology and behaviour of insects. The process of computer vision encompasses capturing images, transforming light into numerical representations, extracting data using diverse techniques, employing software for quantification tasks and concluding with the analysis of the data within the framework of a pre-established hypothesis for interpretation (Manoukis & Collier, 2019). Additionally, the substantial reduction in the cost of essential hardware components, including cameras and other electronic parts, has played a crucial role. This cost-effectiveness has been further augmented by the accessibility and versatility offered by three-dimensional (3D) printing technology, which facilitates the design and construction of lightweight yet durable pieces at a fraction of traditional manufacturing costs. The affordability of 3D printing has not only enhanced the overall cost-effectiveness of developing computer vision systems but has also spurred innovation in the creation of customized, intricate components tailored to specific research needs. Furthermore, the proliferation of deep neural networks and computer vision has optimized real-time data collection, enabling continuous and accurate monitoring of insect behaviours. These advanced tools not only enhance the efficiency and accuracy of research but also open new perspectives for the discovery and understanding of previously unexplored phenomena (Blair et al., 2024; Dell et al., 2014; Plum et al., 2023), making these technologies increasingly accessible for a wide range of applications and contributing to the continued advancement of computer vision in various scientific domains.

In this context, our objective was to develop a monitoring tool to facilitate detailed studies of incoming and outgoing individuals of social insect colonies throughout the season. Specifically, we designed hardware that can be positioned at the entrance of an experimental wasp colony (i.e., natural nest removed from its natural location and relocated in an artificial enclosure). The hardware is equipped with a camera and sensors while specially developed software, trained through deep learning, detects workers, drones (i.e., males) and gynes, under the assumption that morphological differences between castes could be used to identify them.

METHODS

Nest removal and rearing

The colony of this invasive social wasp used in this study was obtained by excavating an active *V. germanica* nest in the vicinity of San Carlos de Bariloche, Argentina (41°08′ S and 71°18′ W) on 15 February 2023. The subterranean nest was anaesthetized with ethyl ether (98% purity; Sigma Aldrich, St. Louis, MO, USA) and then excavated. The procedure was carried out before dawn to retain the highest number of individuals as possible within the nest. Once removed, it was carefully placed in a nest box and transported to the field station at IFAB (Instituto de Investigaciones Forestales y Agropecuarias Bariloche, Rio Negro, Argentina), where it was maintained without food resources (i.e., natural feeding regime). The nest box (Figure 2) consisted of a cubic aluminium container (sides 35 cm) with a connecting polyvinyl chloride (PVC) pipe (length = 30 cm, ⌀ = 2.5 cm) that communicated to the monitoring station (Figure 3). A valve was fitted mid-way through the PVC pipe to momentarily prevent wasps from exiting the nest when manipulation was required such as installing the monitoring station. The top side of the square box was covered with a lid, with a glass panel fitted below for direct colony observation. The bottom and side walls were isolated with high-density Styrofoam (thickness = 2.5 cm) for thermal insulation. One of the sides had a circular ventilation grid (⌀ = 2.5 cm). Preliminary studies indicated that wasps continued their normal activities under these controlled conditions (Martínez et al., 2021) (Figure 2).

Monitoring station

The monitoring station (23 cm tall × 19 cm wide × 16 cm deep) consisted of five 3D-printed parts and an assortment of electronic parts (Figure 3). 3D printouts were made with black filament (polylactic acid, ⌀ = 2.85 mm), which served as the support and housing for the electronic components in addition to an acrylic walkway (11 × 7.5 × 0.7 cm) through which wasps entered and exited the colony while being recorded. Electronic parts consisted of a minicomputer (NVIDIA Jetson Nano Developer Kit B-01) fitted with a 500 GB external mini-SD card. A digital camera with a wide field of vision (Sony IMX219-130, 8MP, 130° FOV camera for NVIDIA JETSONecs, max resolution 3280 × 2464 pixels, focal length 1.88 mm), centred above (at 10.8 cm) the walkway. Two USB ports, an ethernet port, a 12 V power supply inlet, a thermo-hygrometer (DHT-22), a 24 LED white light source (LED strip 5050, 10 sections), a heatsink (aluminium, 10 × 7.5 × 2.5 cm, 15 fins) and a cooler fan (⌀ = 12 cm) were also fitted in the station. The equipment was connected to a 12 V power outlet, which in turn was connected to a normal power outlet (220 V) via a transformer (12–220 V). Both walkway and housing were designed and constructed so that wasps could not gain access to the electronic parts inside the equipment. The housing had ventilation holes that permitted the flow of air.

Given the prototype status of the monitoring station, it was not expected to be watertight, therefore it was placed below a small roof of a shed (Figure 4), so that it would be protected from the elements, with the colony placed inside the shed with no artificial heating or cooling. The exit of the colony was through a pipe that connected the nest to the station placed in the exterior through a hole in the wall.

FIGURE 2 Left: *Vespula germanica* colony, placed inside the artificial nest box (newspaper sheets are carefully placed inside the box for easily accessible material for wasp nest construction). Right: Wasp activity and a portion of the nest can be observed through the protective glass of the box. Image credits: Nicolás Mazzola.

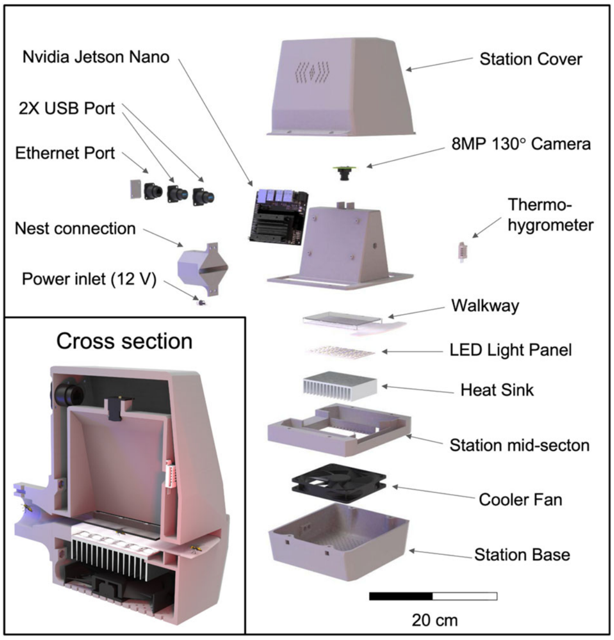

FIGURE 3 Electronic components and their placement in the monitoring station. The station consisted of an assortment of electronic parts and five 3D-printed sections that conformed to the housing and support of the electronic components. The entrance of the station for the wasps is through the right side of the walkway, where they pass below the camera and move onto the nest connection and later into the nest. Image credits: Pierre Marcotoulli.

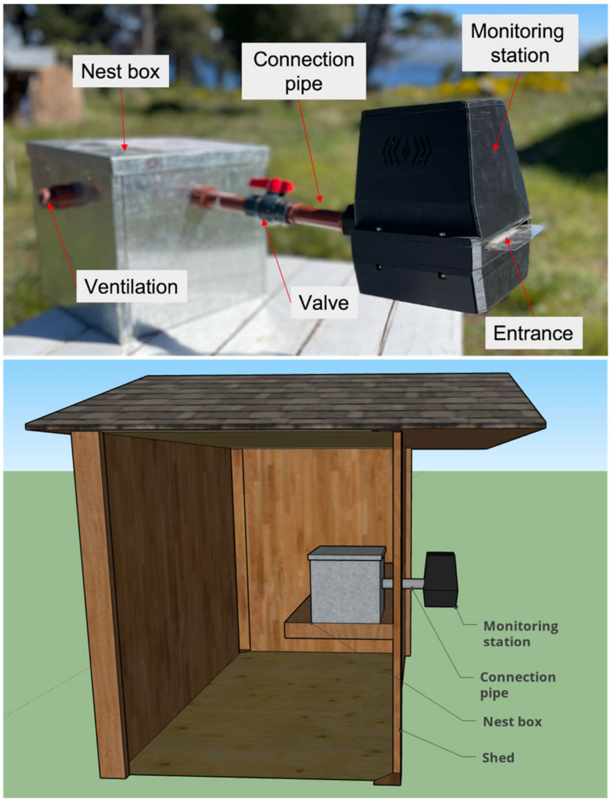

FIGURE 4 Top: Nest box used to rear a colony under semi-controlled conditions that allowed attachment of the automated monitoring station. Bottom: Illustrative showing the placement of the monitoring unit attached to the nest box inside the shed. Image credits: Andrés S. Martínez.

Video acquisition

The monitoring station was attached to the nest box entrance between 17 March and 10 June 2023 (i.e., late summer to mid-autumn) with traffic recorded on most days between 7 AM and 8 PM at 10 frames per second. Under exceptional circumstances, recordings were halted due to power cuts. In order not to create excessively large video files, filming was split into 15-min intervals and stored H.264 files on the SD

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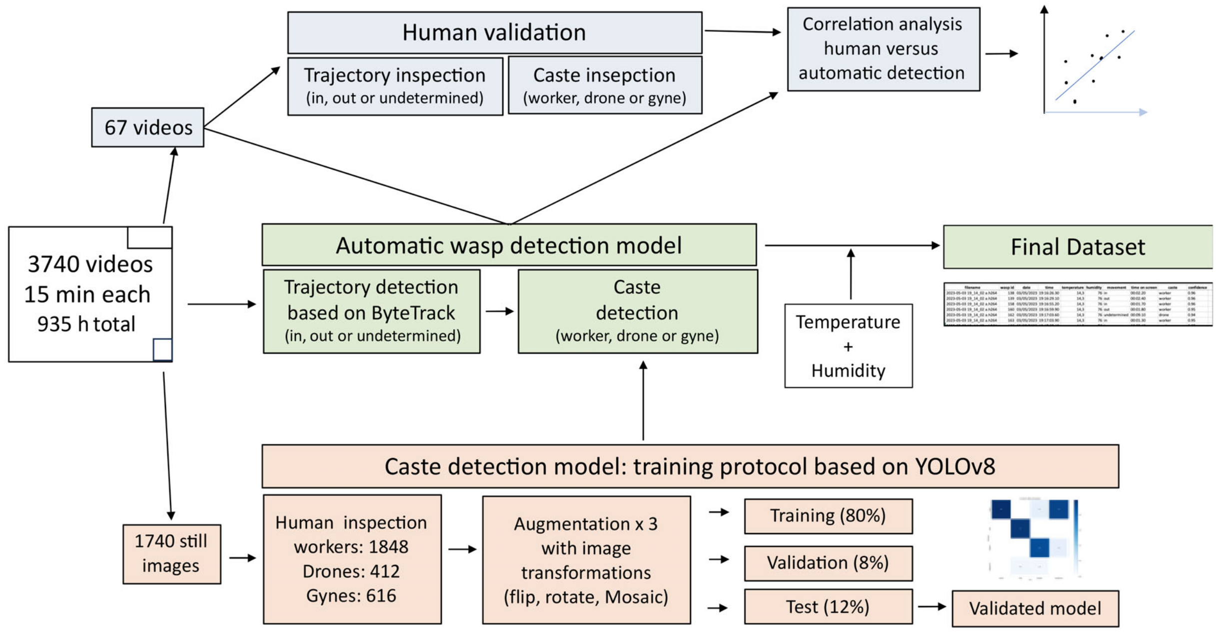

FIGURE 5 Summary of the steps accomplished to obtain the validated automatic detection model. We recorded 3740 videos about 15 min-long. Still images were extracted from videos to validate the caste-detection model based on YOLOv8. This algorithm was then incorporated into the trajectory detection algorithm based on the ByteTrack platform. This final model was then validated via the human inspection of 67 videos and contrasting the detections made by the algorithm through correlation analysis.

card installed in the Nvidia Jetson Nano. A total of 79 days were recorded registering 935 h of the nest activity in 3740 video files (some hours were lost due to powercuts). Files were named using the year, month, date, hour, minutes and seconds (yyyymmddhhmmss). Additional .txt file was created with temperature and humidity data sampled at 5 min intervals. The recording of video files and storage of climatic variables were carried out based on ad hoc Python instructions (Python Language Reference, version 3.12.0; Van Rossum & Drake, 1995).

Rationale for algorithm development and validation

The development of the final recognition model involved a series of steps (Figure 5): First, we trained and validated the caste-detection algorithm using as a base the YOLOv8 platform (Xu et al., 2022) in which 1740 still images (augmented to 5220 images) extracted from our video set were used to train, validate and test the model (Figure 5, pink boxes). Once validated, this model was incorporated into a second algorithm based on the ByteTrack algorithm (Zhang et al., 2022) used to detect individual wasps and their trajectories (Figure 5, green boxes). To validate this final algorithm, a single observer inspected 67 videos selected at random and contrasted with the automatic wasp detection algorithm by means of correlation analysis (Figure 5, blue boxes).

Caste-detection training and validation

At the end of the wasp flight season, once no wasps were observed arriving or leaving the nest entrance, videos were downloaded and inspected. An image dataset was then generated by manually annotating 1740 still frames randomly picked from a subset of the captured videos during the season, with workers, gynes and drones. The dataset contained the bounding boxes for 1848 instances of workers, 616 of gynes and 412 of drones that were visually inspected and annotated according to their caste (Figure 6). To augment the dataset, we added image transformations which included rotating them 90° and 180°, flipping them vertically and mosaic combinations. For each image, we generated three new ones by randomly applying these transformations, thus augmenting the dataset threefold. Images were divided into three subsets: images for model training (Training = 80%), images for validating the performance of the model (Validation = 8%) and images for testing how the model performed (Test = 12%). The object detection was approached by training a YOLOv8 neural network architecture, provided by Ultralytics (learning rate = 0.015, epochs = 100, image size: 640) (Xu et al., 2022).

Automatic trajectory detection

The movement patterns of detected individuals were classified according to their position relative to the walkway during the 15 min videos, comparing the first and last tracked frame (array and matrix code based on OpenCV 4.8.1.78 and numpy 1.23.5, available at https://pypi.org). We used the ByteTrack tracking algorithm (Zhang et al., 2022) already integrated into the Ultralytics detection pipeline to associate the detections from one frame to another, providing identity consistency in the arrays of detections and enabling the creation of a trajectory for every single wasp. The trajectory of each individual

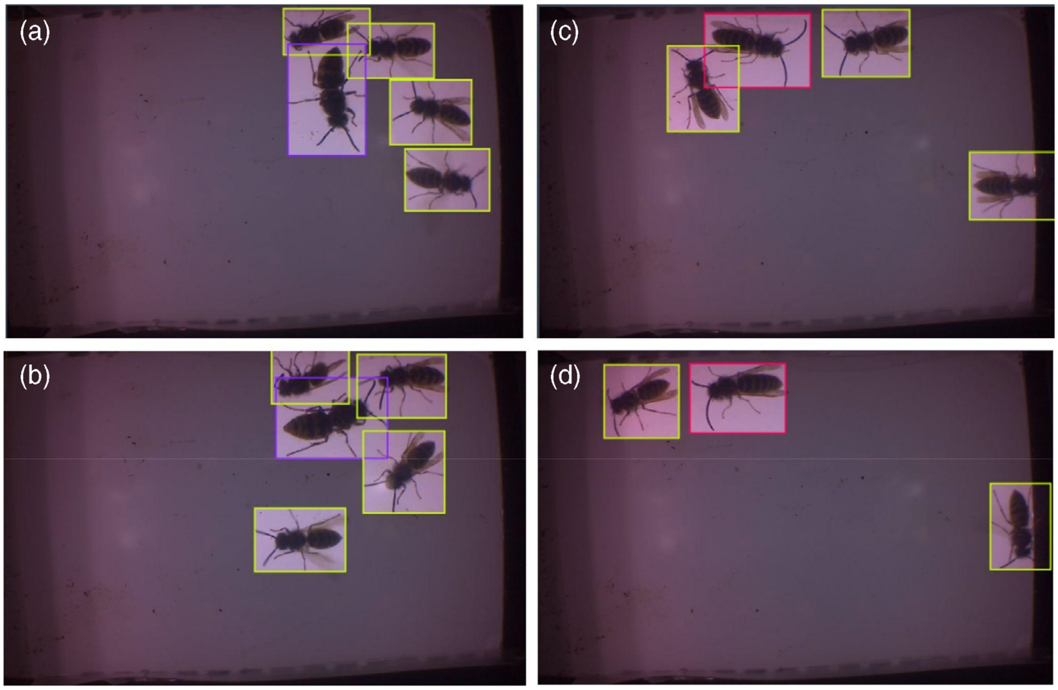

FIGURE 6 The training was done by manually annotating castes to the observed workers (yellow), drones (red) and gynes (violet) on 1740 images taken at random from frames (a–d) from the videos captured during the season. These images contained a total of 1848 workers, 616 gynes and 412 drones, which were used to train the vision model. Colour coding of bounding boxes: yellow = workers, red = drones and violet = gynes.

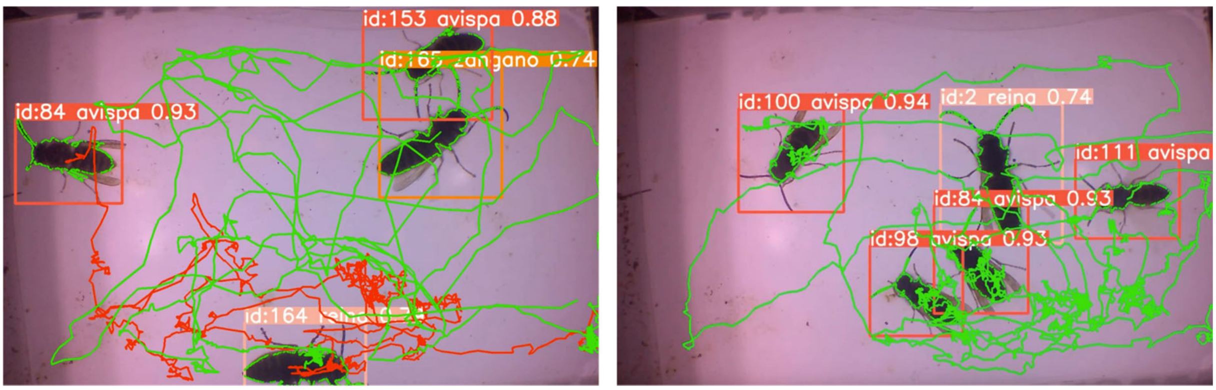

FIGURE 7 Example of wasp detection and tracking after training the YOLOv8 model for caste-detection. For each 15 min video, each individual was assigned a trajectory (ByteTrack tracking algorithm) with a unique identification number (id), and a caste (avispa = worker, zangano = drone and reina = gyne) associated with a probability (0.00–1.00, e.g., 0.93 for id: 84) of belonging to that particular caste.

was classified either as 'In' (appearing from the left and disappearing on the right, assuming entry into the nest), 'Out' (appearing from the right and disappearing on the left, assuming to be leaving the nest) or 'Undetermined' (appearing and disappearing on the same side or not leaving the walkway), with speed and duration of trajectory included into the database, together with temperature and humidity.

Integration of automatic trajectory and caste detection

For each individual tracked, the caste was predicted by the YOLOv8 model, producing a list of predictions from every frame in which the tracked individual was visible (Figure 7). To do so, the model, first, assigned to any given individual at each frame, a bounding box (position) and a partial probability (partial*p*) of belonging ($p = 1$) or not ($p = 0$) to one of the three castes (partial*p*_worker, partial*p*_drone and partial*p*_gyne) since caste assignment could vary along the detected trajectory of an individual (due to events such as wasp collisions or morphology variations while moving). Second, a caste probability ('*p*_worker', '*p*_drone' and '*p*_gyne') was calculated based on the overall probability of belonging to each of the three castes: this was done by obtaining the summation of all the occurrences of belonging to one caste, divided by the summation of all the probabilities for the three the castes:

$$p\_\text{worker} = \sum \text{partial}p\_\text{worker} / \left(\sum \text{partial}p\_\text{worker} + \sum \text{partial}p\_\text{drone} + \sum \text{partial}p\_\text{gyne} \right);$$

$$p\_\text{drone} = \sum \text{partial}p\_\text{drone} / \left(\sum \text{partial}p\_\text{worker} + \sum \text{partial}p\_\text{drone} + \sum \text{partial}p\_\text{gyne} \right);$$

$$p\_\text{gyne} = \sum \text{partial}p\_\text{gyne} / \left(\sum \text{partial}p\_\text{worker} + \sum \text{partial}p\_\text{drone} + \sum \text{partial}p\_\text{gyne} \right).$$

Lastly, acknowledging that workers were significantly overrepresented in the dataset (remember a normal *Vespula* colony generally consists of thousands of workers and a few hundred drones and gynes coexisting; Martínez et al., 2021), a threshold ($p = 0.25$) was introduced for the final prediction, resulting in a wasp being assigned the caste of gyne or drone for p_drone or p_gyne ≥0.25 and worker when p_drone or p_gyne <0.25.

Human validation

To validate the data obtained from the automatic identification software, 67 unlabelled videos (15 min in length each) were selected at random, visually inspected and annotated manually by a single expert observer. Videos were categorized into those that human inspection detected workers only, those with workers and reproductives and videos with no wasps at all (Nothing). Furthermore, wasp movement was classified into nine categories according to the direction of movement ('in', 'out' or 'undetermined'—this last category refers to wasps staying within the walkway throughout the period that were identified) and caste ('worker', 'drone' or 'gyne'). In case no wasps were detected throughout the video, a count of 0 was assigned to each category for that video file. Software-labelled annotations were compared with the human-labelled annotations using linear regression analysis.

Data analysis

Caste detection

The accuracy of the caste-detection algorithm was evaluated using the mainstream evaluation metrics normally employed for machine learning protocols. Human annotated images (actual observations) are compared to the counts for each class (caste) made by the model (predicted observations). Therefore, a value of 1 is representative of the highest level of accuracy, whereas a value of 0, represents no correspondence at all. The test was carried out with 12% of the total generated images, which were not included in the training nor validation steps. A fourth level is added, 'Background', to represent those instances where no wasp was observed by the human inspection, but the algorithm has a positive detection.

Human validation

For each video category ('Workers only', 'Workers and reproductives' and 'Nothing'), the count of individuals for each of the nine categories (direction of movement and caste) estimated by visual inspection and by computerized counts, were contrasted using the root mean square error (RMSE) to evaluate correlation performance within each caste. An RMSE of 0 indicates a perfect fit, whereas larger numbers indicate deviation between observed and expected values. It is important to note that RMSE values are scale-dependent and therefore should only be used to make comparisons within the same caste category, since counts between castes varied. We also used the R^2 of the linear regression to compare the performance of the model between castes. Please note that statistics are not reported for comparisons where no individuals were observed by human or computational inspection. All analyses were performed using R software v.4.3.1 (R Core Team, 2023).

RESULTS

Validation of caste-detection model

The caste-detection model predicted accurately workers with a confidence level of 99%, drones with 88% and gynes with 96% accuracy, with an F1 score of 0.94 (Figure 8). It is worth mentioning that the algorithm miss-detected some castes: four workers mistaken for drones, six drones mistaken for workers and two with the background for gynes. Additionally, miss-detections included detecting an individual instead of the background (2 drones and 22 workers).

Human validation

From the 67 videos used for validation, 24 had only workers, 18 had workers and reproductive individuals and 25 had no wasps. Videos for which human detection detected no wasp activity, computational detection coincided in all of them, with no individuals detected in all of them. Linear regressions indicate that videos with workers only (i.e., without reproductive individuals), algorithm performance was high. First, computational analysis coincided with human inspection at not detecting reproductive individuals. Furthermore, for inbound wasps (In: $\text{RMSE} = 2.63$; $R^2 = 1.00$), outbound wasps (Out: $\text{RMSE} = 2.96$; $R^2 = 1.00$) and those not moving in nor out (Undetermined: $\text{RMSE} = 3.28$; $R^2 = 0.90$), correlations were high. In videos with simultaneous appearance of both workers and reproductive individuals, the performance of the detection algorithm was high

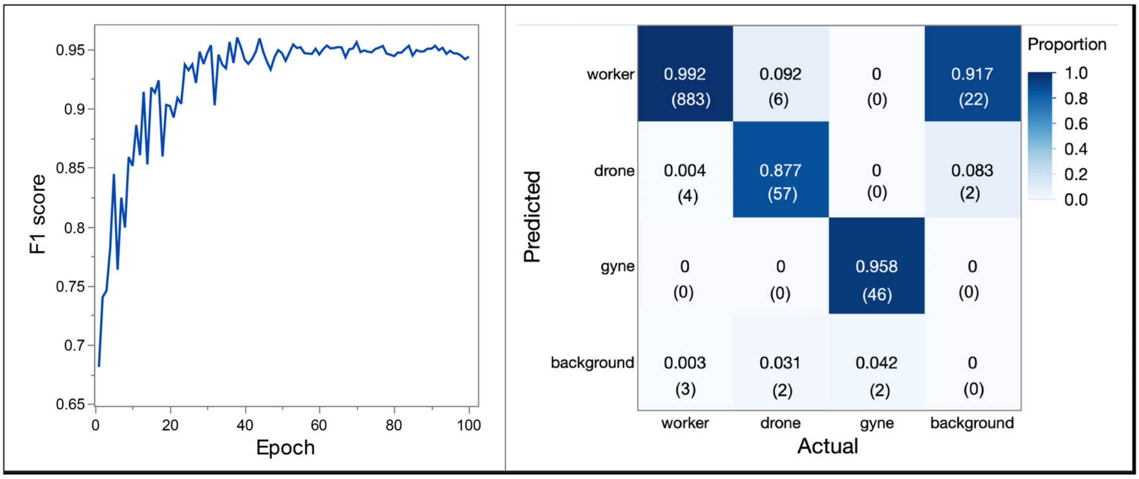

FIGURE 8 Model performance according to the F1 Score (left) and confusion matrix (right). Accuracy levels of wasp detections belonging to three different castes (worker, drones and gynes) showing the YOLOv8 automatic caste-detection algorithm (Predicted) compared with human inspection (Actual). The proportions of correspondence between the predicted and actual counts of the different castes are shown in the centre of the box while the counts of the algorithm analysis are shown between brackets. A fourth level is added, 'Background', to represent those instances where no wasp was observed by the human inspection, but the algorithm has a positive detection.

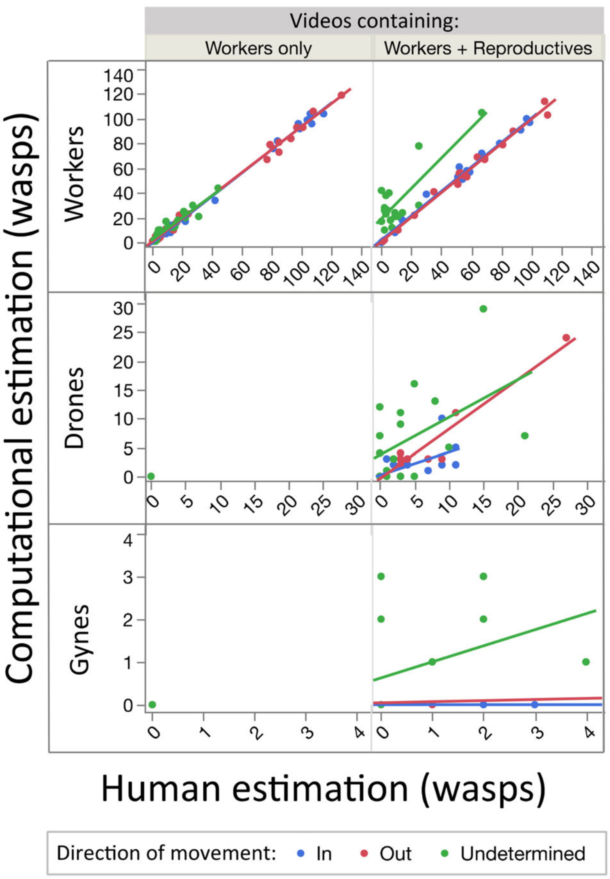

FIGURE 9 Linear correlations of wasps counted by human inspection compared to the computational algorithm considering their direction of movement (into the nest [in], exiting the nest [out] or undetermined direction [undetermined]) and caste (workers, drones or gynes) in videos exclusively with workers (workers only), workers and reproductives (workers + reproductives).

for inbound (In: RMSE = 3.70; $R^2 = 0.99$) and outbound workers (Out: RMSE = 3.70; $R^2 = 0.99$) but lowered its detection performance for workers not moving in nor out (Undetermined: RMSE = 13.93; $R^2 = 0.67$). The detection accuracy of drones was low for those moving inward (In: RMSE = 1.99; $R^2 = 0.42$), whereas it was higher for those drones classified as moving outbound (Out: RMSE = 1.60; $R^2 = 0.93$) and lowest for drones not moving in or out (Undetermined: RMSE = 6.87; $R^2 = 0.25$). In the case of gynes, a low overall number (33 gynes) was detected with human inspection, while only 48.5% (16 gynes) were detected by computational detection. Upon closer inspection, the performance of the model was low, especially for those gynes classified with an inbound movement since no gynes were detected by the computational method, while 16 were classified by humans (Out: RMSE = na; R^2 = na). The model had low performance at detecting gynes going out (Out: RMSE = 0.24; $R^2 = 0.02$), whereas for those not going in nor out, the detection was better (Undetermined: RMSE = 1.05; $R^2 = 0.14$) (Figure 9; Table A1).

DISCUSSION

Eusocial insects exhibit a distinctly organized colonial lifestyle marked by well-coordinated social structures, making them some of the most severe pests known to humans. Characteristics such as elevated reproductive rates, high dispersal capabilities and superior competitive prowess compared with solitary insects, in addition to high levels of plasticity, contribute to their adeptness in affecting human environments (Lester & Beggs, 2019; Manfredini et al., 2019). The challenge these species pose to sustainable management of their populations requires a profound knowledge of their behaviour and ecology. Increasingly, researchers are developing technological equipment to monitor the behaviour of insects. Images produced through computer vision, obtained from real world, align well with the quantitative understanding of insect behaviour. For example, a system for detecting locomotion, equipped with automatic trajectory tracking and data analysis, as developed to assess insect jumping, which has broad applicability in measuring both jumping behaviour and endurance in locomotion of insects (Zhou et al., 2020). Other applications include tools for determining the attractiveness of a trap by assessing the abundance of attracted insects (Manoukis & Collier, 2019), real-time counting and automatic identification of insects in field traps (Chen et al., 2014) or simply a synthetic data generator designed to run on consumer-grade hardware, producing thousands of annotated images per hour (Plum et al., 2023).

Here, we report the development of a station designed for monitoring the movement of social vespids as they enter and exit their parental nest, with its associated software developed with deep learning, being able to identify up to a certain level of accuracy the direction of movement and caste. This equipment has the potential to advance ecological and behavioural research by providing easy-to-obtain data with high levels of accuracy at a relatively low cost. In social insects, which live in colonies composed of hundreds to thousands of individuals, conducting experiments near the nest entrances is a challenging task. First, because under disturbance, the typical defensive response of these insects is to attack posing serious threats to the observer. Such is the case of *V. germanica* workers, which can deliver a painful and dangerous sting; hundreds of workers can attack simultaneously, potentially affecting human health. Second, to obtain results using more traditional methods such as direct human observation (e.g., Malham et al., 1991; Martínez et al., 2021; Ruxton et al., 2001), would require many hours of observations to record, for example, daily patterns or the effect of climatic variables on the daily dynamics of insects and, in turn, hours to compile the data table.

Vespula germanica is a polymorphic wasp (Blackith, 1958), in which caste differentiation is primarily based on dimensions, specifically the length-to-width ratio, in addition to the length of the antennae which is longer in drones. The caste-detection model trained with annotated still images resulted in high levels of accuracy, with workers and gynes being detected accurately in >95% of the cases, whereas drone detection had lower levels of precision (88%), with the system assigning drones as workers or vice versa. Notably, we found instances of misdetections where the algorithm assigned the category of worker when there should have been no detection at all (i.e., background detections). Inter- and intra-caste variation (along the season) is a source of variability that could reduce the levels of certainty in the caste identification process determination. When caste-data prediction is incorporated into the whole trajectory of an insect, through the final model (trajectory detection model and caste-detection model), high accuracy was found for workers and drones, while less robust for gynes. The confidence of prediction was high for workers including inward, outward and undetermined movement, if there were no reproductive individuals in the walkway. However, when reproductive individuals were present in the field of vision of the camera, the accuracy decreased for workers, especially for those that stayed in the walkway (i.e., 'Undetermined'; undetermined workers in videos with workers only: $\mathrm{RMSE} = 3.28$, $R^2 = 0.9$; undetermined workers in videos with workers and reproductives: $\mathrm{RMSE} = 13.93$, $R^2 = 0.67$).

This lower accuracy could be attributed on one hand, to the particular behaviour when reproductives appear on the camera field of vision: individuals (of all castes) tend to stay in the walkway and form tight groups (clustering). Clustering results in the edges of the bodies merging, lead to potential misdetections. These individuals also tend to stay in the walkway for long periods (>15 min), leading to errors, given that videos are 15 min long, lacking the desired continuity. Another behavioural pattern that represents a challenge is that when reproductives are in the walkway, some workers intensely 'patrol' (patrolling) the walkway, leading to collisions with the groups, something that can also lead to tracking errors. Additionally, human error could contribute to the loss of accuracy since individuals on videos with heavy traffic, tight groups with high collision rates, can be difficult to follow by the human eye. This lower-than-expected accuracy could be improved in future versions of the algorithm by increasing the framerate of the recordings (e.g. 10–15 frames/second) and further training of the caste-detection algorithm (i.e. addition of annotated images of gynes and drones). It is also important to mention that in the longer run, the detection software is expected to run live, something that could improve accuracy by not having the cuts of the relatively short videos used at this stage of development. Even though detection accuracy for drones and gynes was high when inferred from still images (i.e., caste-detection algorithm), the overall accuracy lowered when predictions were made from videos. The reason for this could be due to the same grouping and patrolling behaviour mentioned above, resulting in tracking and caste-detection errors. Another source of error could have been that, given the natural proportion found in *Vespula* spp. colonies, gynes and drones were underrepresented compared with workers in the training dataset of our caste-detection model. Future video captures of new colonies will enable building up our annotated image dataset to improve the trained algorithm.

Despite the higher detection errors for drones and especially gynes, our automatic detection device is still valuable, even at a relatively early development stage where the accuracy for gyne detection needs to be improved. The possibility of detecting with high accuracy worker activity throughout the colony growth period offers promising prospects. Once installed in the nest, this device automatically records insect activity, storing the data in a simple format suitable for subsequent data analysis. The addition of meteorological sensors allows each record to be correlated with temperature and humidity data. All this information could permit inferences about growth rates, possible drivers for the observed growth, daily and/or seasonal activity and nest-leaving patterns of reproductives once the algorithm is perfected (Figure 10). Gaining insights into these aspects of wasp biology could be an important input to management practices that involve behavioural manipulation (Foster & Harris, 1997; Rodriguez-Saona & Stelinski, 2009). For instance, knowledge of climatic triggers of nest departure for reproductive individuals could be incorporated into methods that encompass behavioural manipulation of reproductive

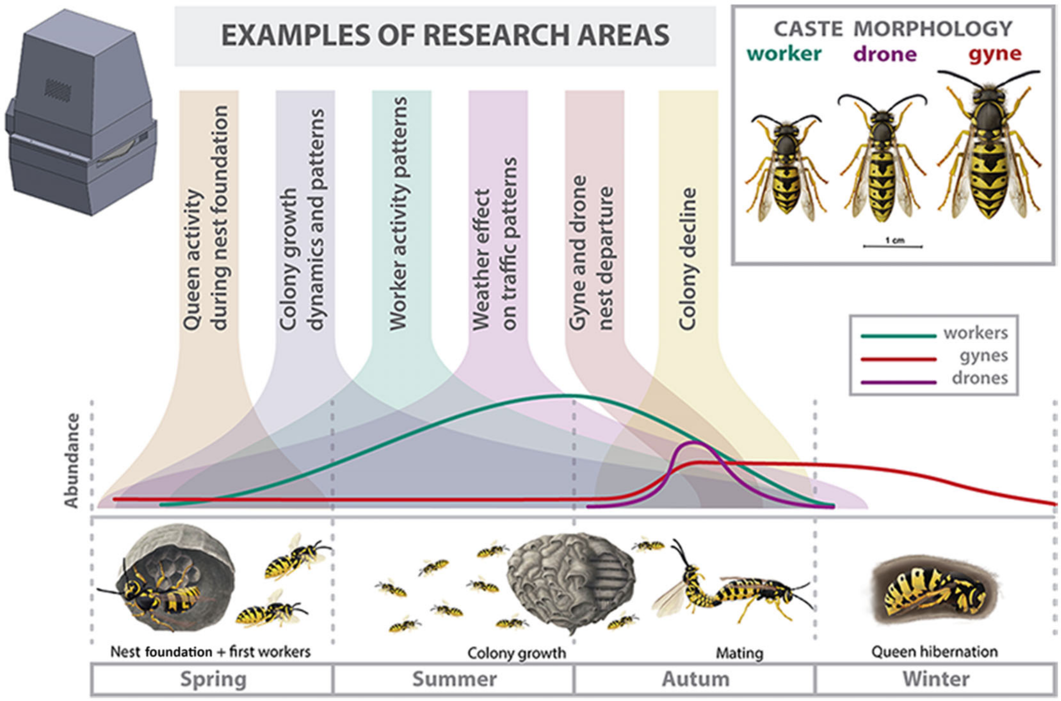

FIGURE 10 Possible research areas that can be addressed during the cycle of a *Vespula* spp. colony using the monitoring station. The autonomous station could be used to study gyne activity during nest foundation at the beginning of the colony growth process until the emergence of reproductive individuals of the parental nest. The autonomous station recognizes castes based on their different morphology. Image credits Julia Rouaux and Irene Behrens.

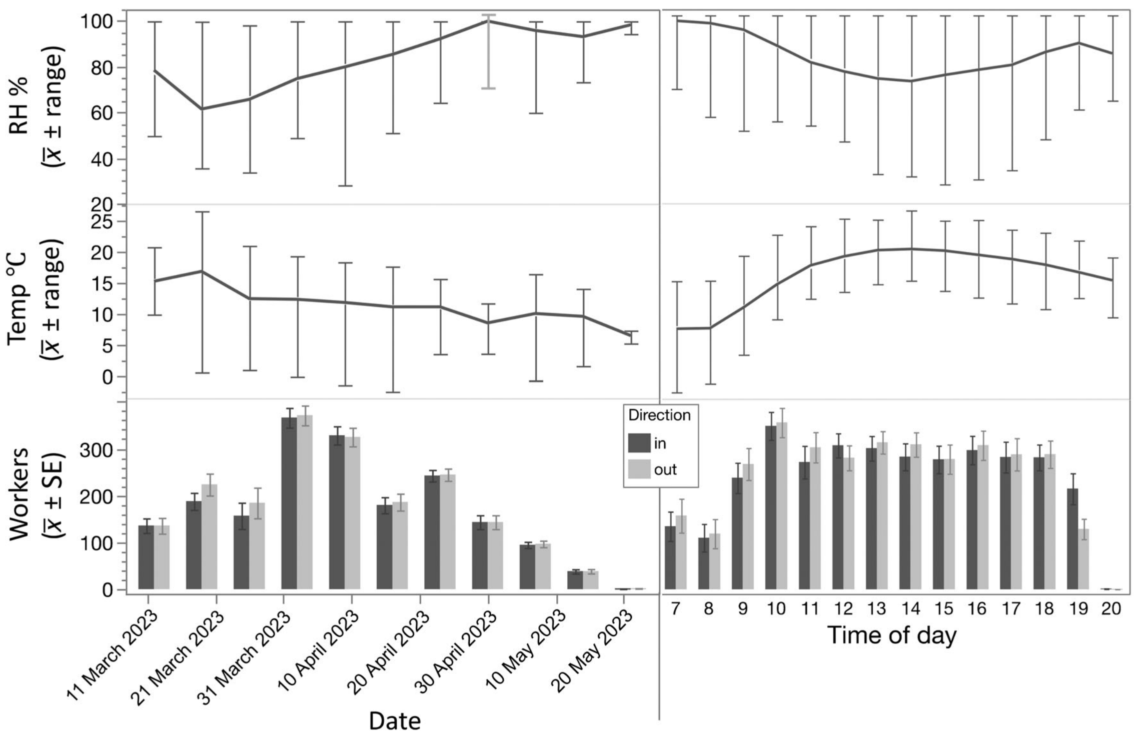

FIGURE 11 Examples of worker inward and outward traffic combined with weather data during the period the station was active. Left: Mean number of worker wasps entering and exiting the nest during part of the period tested with mean temperature (Temp) and relative humidity (RH) acquired by the dedicated sensors incorporated to the station. Right: Mean number of worker wasps entering and exiting the nest during the recorded time frame (7–20 h) at the peak of the recorded period (2–28 April). Temperature and relative humidity data acquired by the dedicated sensors in the station are also included.

individuals. Furthermore, the principles (rationale, hardware, software) presented here can be adapted to different biological interests and with the correct training to other social insect species.

Data collected by the automatic detection station enables to easily extract information (Figure 11). For instance, data on workers can be rapidly processed at different time scales, which can be plotted contemplating the whole sampling period for inbound and outbound traffic levels and contrasted with temperature and humidity. Additionally, data permits to observe traffic levels during the day, while contrasting it with temperature and humidity for that particular time frame.

Even though detection levels are robust for workers and drones, not differing substantially from human inspection, there are some aspects of the detection that need to be improved, especially that related to the detection of gynes. The monitoring station should benefit from further development of the software and the structure. For instance, on one hand, further training of the caste-detection algorithm, encompassing individuals from different colonies and especially more reproductives would help represent the variability between individuals. Additionally, recording at a higher frame rate and increasing video length, could enable better tracking capabilities. On the other hand, we envision the adaptation of the hardware for placement in natural nests with all the necessary protection required for outdoor exposure. As mentioned, *V. germanica* nests are underground and have an entry tunnel connecting to the outside through one aperture at ground level through which wasps enter and exit. The aforementioned improvements should enable higher accuracy levels in gyne recognition; nevertheless, the current state of development of the equipment still offers auspicious results at this stage, by offering the possibility to detect worker and drone movement patterns.

AUTHOR CONTRIBUTIONS

Andrés S. Martínez: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft; writing – review and editing. **Carola Dreidemie:** Funding acquisition; project administration; resources; supervision; visualization; writing – review and editing. **Fernan Inchaurza:** Data curation; investigation; software. **Agustin Cucurull:** Data curation; investigation; software; visualization. **Marian Basti:** Data curation; formal analysis; investigation; methodology; software; validation; visualization; writing – review and editing. **Maité Masciocchi:** Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

All data, algorithms and the 3D model of the station are available upon request.

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REFERENCES

Beggs, J.R., Brockerhoff, E.G., Corley, J.C., Kenis, M., Masciocchi, M., Muller, F. et al. (2011) Ecological effects and management of invasive alien Vespidae. *BioControl*, 56, 505–526. Available from: https://doi.org/10.1007/s10526-011-9389-z

Bertelsmeier, C. (2021) Globalization and the anthropogenic spread of invasive social insects. *Current Opinion in Insect Science*, 46, 16–23. Available from: https://doi.org/10.1016/j.cois.2021.01.006

Blackith, R.E. (1958) An analysis of polymorphism in social wasps. *Insectes Sociaux*, 5, 263–272. Available from: https://doi.org/10.1007/BF02223936

Blair, J.D., Gaynor, K.M., Palmer, M.S. & Marshall, K.E. (2024) A gentle introduction to computer vision-based specimen classification in ecological datasets. *The Journal of Animal Ecology*, 93, 147–158. Available from: https://doi.org/10.1111/1365-2656.14042

Chen, Y., Why, A., Batista, G., Mafra-Neto, A. & Keogh, E. (2014) Flying insect classification with inexpensive sensors. *Journal of Insect Behavior*, 27, 657–677.

Clapperton, B.K., Alspach, P.A., Moller, H. & Matheson, A.G. (1989) The impact of common and German wasps (Hymenoptera: Vespidae) on the New Zealand beekeeping industry. *New Zealand Journal of Zoology*, 16, 325–332.

Dell, A.I., Bender, J.A., Branson, K., Couzin, I.D., de Polavieja, G.G., Noldus, L.P.J.J. et al. (2014) Automated image-based tracking and its application in ecology. *Trends in Ecology & Evolution*, 29, 417–428. Available from: https://doi.org/10.1016/j.tree.2014.05.004

Della Lucia, T.M., Gandra, L.C. & Guedes, R.N. (2014) Managing leaf-cutting ants: peculiarities, trends and challenges. *Pest Management Science*, 70, 14–23. Available from: https://doi.org/10.1002/ps.3660

Dimarco, R.D., Masciocchi, M. & Corley, J.C. (2017) Managing nuisance social insects in urban environments: an overview. *International Journal of Pest Management*, 63, 251–265. Available from: https://doi.org/10.1080/09670874.2017.1329566

Foster, S.P. & Harris, M.O. (1997) Behavioral manipulation methods for insect pest-management. *Annual Review of Entomology*, 42, 123–146. Available from: https://doi.org/10.1146/annurev.ento.42.1.123

Fowler, H., Bernardi, J., Delabie, J., Forti, L. & Pereira-da-Silva, V. (2019) Major ant problems of South America. In: *Applied Myrmecology*. Boca Raton: CRC Press, pp. 3–14.

Lester, P.J. & Beggs, J.R. (2019) Invasion success and management strategies for social *Vespula* wasps. *Annual Review of Entomology*, 64, 51–71. Available from: https://doi.org/10.1146/annurev-ento-011118-111812

Macintyre, P. & Hellstrom, J. (2015) *An evaluation of the costs of pest wasps in New Zealand*. Wellington, NZ: Department of Conservation and Ministry for Primary Industries.

Malham, J.P., Rees, J.S., Alspach, P.A., Beggs, J.R. & Moller, H. (1991) Traffic rate as an index of colony size in *Vespula* wasps. *New Zealand Journal of Zoology*, 18, 105–109. Available from: https://doi.org/10.1080/03014223.1991.10757956

Manfredini, F., Arbetman, M. & Toth, A.L. (2019) A potential role for phenotypic plasticity in invasions and declines of social insects. *Frontiers in Ecology and Evolution*, 7, 375.

Manoukis, N.C. & Collier, T.C. (2019) Computer vision to enhance behavioral research on insects. *Annals of the Entomological Society of America*, 112, 227–235.

Martínez, A.S., Rousselot, N., Corley, J.C. & Masciocchi, M. (2021) Nest-departure behaviour of gynes and drones in the invasive yellowjacket *Vespula germanica* (Hymenoptera: Vespidae). *Bulletin of Entomological Research*, 111, 174–181. Available from: https://doi.org/10.1017/S0007485320000462

Masciocchi, M., Beggs, J.R., Carpenter, J.M. & Corley, J.C. (2010) Primer registro de *Vespula vulgaris* (Hymenoptera: Vespidae) en la Argentina. *Revista de la Sociedad Entomológica Argentina*, 69, 373–380.

Moller, H. (1996) Lessons for invasion theory from social insects. *Biological Conservation*, 78, 125–142.

Montoya-Lerma, J., Giraldo-Echeverri, C., Armbrecht, I., Farji-Brener, A. & Calle, Z. (2012) Leaf-cutting ants revisited: towards rational management and control. *International Journal of Pest Management*, 58, 225–247.

Plum, F., Bulla, R., Beck, H.K., Imirzian, N. & Labonte, D. (2023) replicAnt: a pipeline for generating annotated images of animals in complex environments using unreal engine. *Nature Communications*, 14, 7195. Available from: https://doi.org/10.1038/s41467-023-42898-9

R Core Team. (2023) *R: a language and environment for statistical computing* R Version 4.3.1. Vienna, Austria: R Foundation for Statistical Computing.

Rodriguez-Saona, C.R. & Stelinski, L.L. (2009) Behavior-modifying strategies in IPM: theory and practice. In: Peshin, R. & Dhawan, A.K. (Eds.) *Integrated pest management: innovation-development process*, Vol. 1. Dordrecht: Springer, pp. 263–315.

Ruxton, G.D., Lee, J. & Hansell, M.H. (2001) Wasps enter and leave their nest at regular intervals. *Insectes Sociaux*, 48, 363–365. Available from: https://doi.org/10.1007/PL00001792

Spradbery, J.P. (1973) *Wasps. An account of the biology and natural history of social and solitary wasps, with particular reference to those of the British Isles*, 1st edition. Seattle: University of Washington Press.

Van Rossum, G. & Drake, F.L. (1995) *Python reference manual*. Amsterdam: Centrum voor Wiskunde en Informatica.

Xu, S., Guo, Z., Liu, Y., Fan, J. & Liu, X. (2022) An improved lightweight yolov5 model based on attention mechanism for face mask detection. *Presented at the International Conference on Artificial Neural Networks*, Springer. pp. 531–543.

Yeruham, I., Schwimmer, A. & Brami, Y. (2002) Epidemiological and bacteriological aspects of mastitis associated with yellow-jacket wasps (*Vespula germanica*) in a dairy cattle herd. *Journal of Veterinary Medicine Series B*, 49, 461–463. Available from: https://doi.org/10.1046/j.1439-0450.2002.00487.x

Zhang, Y., Sun, P., Jiang, Y., Yu, D., Weng, F., Yuan, Z. et al. (2022) Byte-track: multi-object tracking by associating every detection box. *Presented at the European Conference on Computer Vision*, Springer. pp. 1–21.

Zhou, F., Kang, L. & Wang, X.-H. (2020) JumpDetector: an automated monitoring equipment for the locomotion of jumping insects. *Insect Sci*, 27, 613–624. Available from: https://doi.org/10.1111/1744-7917.12668

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APPENDIX A

TABLE A1 Wasp counted by human and computational estimations in videos with only workers, and videos with workers and reproductives, with respective RMSE and R^2 for each comparison.

Videos containing	Number of videos analysed	Caste	Direction of movement	Wasp count: Human estimation	Wasp count: Computational estimation	RMSE	R^2
Workers only	24	Workers	In	939	878	2.63	1.00
			Out	965	916	2.96	1.00
			Undetermined	296	319	3.28	0.90
		Drones	In	0	0	0.00	
			Out	0	0	0.00	
			Undetermined	0	0	0.00	
		Gynes	In	0	0	0.00	
			Out	0	0	0.00	
			Undetermined	0	0	0.00	
Workers + reproductives	18	Workers	In	929	949	3.70	0.99
			Out	980	981	3.70	0.99
			Undetermined	194	583	13.93	0.67
		Drones	In	60	27	1.99	0.42
			Out	71	53	1.60	0.93
			Undetermined	78	117	6.87	0.25
		Gynes	In	16	0	0.00	
			Out	7	1	0.24	0.02
			Undetermined	10	15	1.05	0.14

Abbreviation: RMSE, root mean square error.