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Developing a prototype smart monitoring tool for improved vine weevil monitoring in soft-fruit and ornamental crops

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1. Abstract

Vine weevil, *Otiorhynchus sulcatus* F. (Coleoptera: Curculionidae), is an economically important pest of soft-fruit and ornamental crops globally. Managing this pest historically relied on broad-spectrum synthetic insecticides, but has shifted toward integrated pest management compatible methods such as entomopathogenic nematodes and fungi to target soil-dwelling larvae. These methods require reliable pest monitoring tools to be truly effective, however existing tools have been demonstrated to be largely unreliable and time-consuming to implement. This project aimed to develop a protype monitoring tool that could automatically identify adult vine weevil. Results presented here indicate that pre-trained machine learning models can reliably identify adult vine weevil in laboratory and semi-field environments as well as demonstrating that retrofitting existing monitoring tools with low-cost electronic components enhances functionality without negatively impacting insect-monitoring tool interactions. This is the first report of such technologies being specifically developed for vine weevil and demonstrates the feasibility of an automated monitoring approach, which could benefit growers going forward as it will provide greater information about pest populations in their crops and better inform management decisions. Further development of the prototype monitoring tool is required before commercial deployment would be possible.

2. Introduction

Vine weevil, *Otiorhynchus sulcatus* Fabricius 1775 (Coleoptera: Curculionidae), is an economically important insect pest of soft fruit and ornamental crops (Pope and Roberts, 2022). Once considered a sporadic glasshouse pest across Europe and North America (Gill *et al.*, 2001), this species has become one of the most serious horticultural crop pests throughout its geographical range during the last five decades. Increased economic importance is most often attributed to significant growth of the horticultural sector alongside adoption of new growing practices (*e.g.*, use of black polythene mulches). These changes unintentionally benefited vine weevil development and reproduction by reducing insecticide efficacy while also providing a protective environment from unfavourable climatic conditions (Penman and Scott, 1976; van Tol *et al.*, 2012).

Approaches to vine weevil control have largely shifted from a reliance on persistent broad-spectrum insecticides to using entomopathogenic nematodes (EPNs) and fungi (EPFs) that target the soil-dwelling larvae (Blackshaw, 1986; Bruck, 2007; Bruck and Donahue, 2007; Ansari, Shah and Butt, 2010). Alternative larval control measures based on entomopathogens represents an important step toward a more sustainable, integrated approach to vine weevil management. This approach, like all integrated pest management (IPM) programmes, relies on pest monitoring within crops to reduce grower reliance on synthetic chemical insecticide applications (Kogan, 1998; Dara, 2019). Early detection of vine weevil within crops is essential for successful management of this pest. Ineffective monitoring often leads to growers being unaware of an economically damaging pest population until after significant crop losses have been inflicted (Li, Fitzpatrick and Henderson, 1995). Vine weevil monitoring efforts are complicated by the nocturnal feeding behaviour of adults as well as the subterranean lifestyles of both larvae and pupae (van Tol *et al.*, 2012). Developing true IPM programmes for vine weevil has been limited by ineffective monitoring techniques (Fezza *et al.*, 2022; Pope and Roberts, 2022).

Monitoring vine weevil predominantly focuses on adults because larval monitoring typically involves root sampling, which are both time consuming and potentially damaging to crop plants (Mankin and Fisher, 2002). Visual assessments, where growers either search for characteristic leaf notching caused by feeding or dislodge individuals from the plant through gentle shaking at night (Li, Fitzpatrick and Henderson, 1995), are the most widely used monitoring techniques for adults (Gordon *et al.*, 2003). Assessments of leaf notching are thought to be reliable early in the growing season, but over time newer notches become difficult to distinguish from older ones while shaking risks dislodging fruits or leaves. Indirectly monitoring vine weevil presence through leaf notch assessments can also lead to delays in detection, allowing oviposition to occur before control measures can be applied (van Tol *et al.*, 2012). Due to the impractical nature of night-time crop assessments, more effective monitoring methods are urgently needed. While attempts have been made to develop acoustic detection of the subterranean larval stages (Mankin and Fisher, 2002), most research in this area has focused on the use of artificial refuges (*i.e.*, individuals can enter and leave) or traps (*i.e.*, individuals can enter but not leave) for adults. Throughout this report, artificial refuges and traps are collectively referred to as monitoring tools.

Monitoring tools aim to the exploit negative phototaxis behaviour exhibited by adults, causing individuals to seek shelter during daylight (Roberts *et al.*, 2020; Fezza *et al.*, 2022). A range of monitoring tool designs have previously been investigated, including: grooved wooden boards placed on the ground (Maier, 1983; Li, Fitzpatrick and Henderson, 1995; Gordon *et al.*, 2003), pitfall traps (Hanula, 1990), corrugated cardboard wrapped around plant stems or rolls placed on the ground (Phillips, 1989; Hanula, 1990), traps marketed for other insect pest species (Pope *et al.*, 2018), and a purpose-designed vine weevil trap (Roberts *et al.*, 2020). Please see Roberts et al. (2020) for a comprehensive overview of these different monitoring tools and an assessment of their efficacy. Although monitoring tools are regularly deployed in the field, there is some debate and uncertainty regarding their efficacy and reliability. Factors such as size, colour, shape, and entrance number may all play a crucial role in monitoring tool efficacy (Fezza *et al.*, 2022).

Assessment of six monitoring tool designs in a simple semi-field environment demonstrated that, while all designs can detect the presence of vine weevils, the number of weevils found within each monitoring tool was incredibly variable (Roberts *et al.*, 2020). The worst performing designs were grooved wooden boards and corrugated cardboard rolls, while the best was a purpose-designed vine weevil trap that is black and conical. As grooved wooden boards and cardboard rolls are amongst the most widely used monitoring tools used by growers (Hanula, 1990; Gordon *et al.*, 2003), alternative designs should be developed and promoted to help improve monitoring efficacy and reliability. While it is not fully understood what characteristics make the worst performing traps ineffective (Fezza *et al.*, 2022), it is speculated that their inability to trap individuals (*i.e.*, they can enter and leave) may be a contributing factor as many growers do not check monitoring tools frequently. As demonstrated for other weevil species, monitoring tool efficacy and reliability has the potential to be enhanced through inclusion of a semiochemical lure, typically using species-specific sex or aggregation pheromones to attract more individuals to the monitoring tool (*e.g.*, Cross et al., 2006). Despite vine weevil chemical ecology having been extensively studied over the past twenty-five years no effective attractants have been identified to date. Development of better night-time monitoring methods that do not rely on directly trapping individuals and frequent physical inspections is a priority objective to facilitate improved vine weevil management.

Monitoring methods that are quick to implement and automatically identify crop pests would provide an important tool that limits insecticide use through increased IPM adoption. One possible approach to developing such methods is to pair computer vision with machine learning models to recognise objects, images or videos and then apply an appropriate classification to enable identification. Similar approaches have been implemented for automated monitoring of crop pests (*e.g.*, Ding and Taylor, 2016; Li et al., 2020), though none have been developed for nocturnal beetle pests to the authors knowledge. This project set out to build and test a prototype ‘smart’ monitoring tool for vine weevil adults based on a commercially available monitoring tool, providing a proof-of-concept platform for future development and potential commercialisation.

3. Materials and methods

3.1. Insects

3.1.1. Vine Weevil Culture

Vine weevil, *Otiorhynchus sulcatus* (Coleoptera: Curculionidae) at various larval stages were collected from commercial strawberry (*Fragaria* × *ananassa* cv. Duchesne) crops grown in Staffordshire (UK) during autumn 2021. Larvae were maintained on strawberry (cv. Elsanta) plants housed within a 47.5 cm^3 white mesh cage (BugDorm-4S4545, MegaView Science Co. Ltd., Taichung, Taiwan) in a controlled environment room (20 °C; 60 % relative humidity; 16:8 photoperiod) (Fitotron, Weiss Technik, Ebbw Vale, Wales, UK). Resultant adults from this larval population were maintained under the previously stated environmental conditions using a standard method of placing the weevils in plastic terrariums (30 × 19.3 × 20.6 cm) containing yew (*Taxus baccata*) branches and moist paper towels that were replaced weekly (Shah *et al.*, 2007; Pope *et al.*, 2018; Roberts *et al.*, 2020). All adult weevils used in this study were at least one month old and had been confirmed to be reproductively active, ensuring that subsequent monitoring tool tests used a field-representative pest population.

3.1.2. Earwig Culture

Adult European earwigs, *Forficula auricularia* Linnaeus 1758 (Dermaptera: Forficulidae) were collected from an experimental polytunnel containing strawberry plants (cv. Elsanta) at Harper Adams University (Shropshire, UK) during January 2022. Individuals were combined into a single laboratory culture and maintained on strawberry leaves infested with potato aphids, *Macrosiphum euphorbiae* (Hemiptera: Aphididae) housed within a 47.5 cm^3 white mesh cage (BugDorm-4S4545 in a controlled environment room (20 °C; 60 % relative humidity; 16:8 photoperiod) (Fitotron). This population served as a non-vine weevil species for training a machine learning model.

3.2. Monitoring Tool

3.2.1. Design

The prototype monitoring tool developed during this project was based on an existing product commercially marketed for vine weevil monitoring (Fig. 1) (Chemtica, Heredia, Costa Rica). This product was selected as it has previously been shown to be moderately effective for vine weevil monitoring under semi-field conditions (Roberts *et al.*, 2020). Although this product has some desirable design features due to its dark colouration and height (Fezza *et al.*, 2022), it was determined that modification could further enhance monitoring efficacy. A clear acrylic disc (2 mm thickness) that was held 5 mm above the base of the monitoring tool on three feet equally spaced around the perimeter of the disc was inserted into the monitoring tool to provide an area for vine weevil adults to position themselves within when seeking refuge during daylight hours (Fig. 2). The addition of a clear acrylic base had three primary functions: (1) limit vine weevil orientation so that they could be accurately imaged, (2) facilitate entry and exit of vine weevil adults to transform the monitoring tool from a trap to a refuge and (3) exploit vine weevil thigmotactic behaviour to provide a 'preferred' refuge area (Roberts *et al.*, 2020).

Figure 1 Chemtica vine weevil trap (A) assembled for in-field deployment with entry location identified by (a) and (B) with top removed to showcase the internal structure.

A Raspberry Pi camera module (V2.1; PiHut, Haverhill, Suffolk) and light emitting diode (LED) ring light (PiHut) was internally mounted at the apex of the monitoring tool to capture images of vine weevil adults seeking refuge under the clear acrylic base. Initial testing of this setup identified imaging issues as the clear acrylic base reflected light back into the camera, essentially preventing it from capturing high-quality images. A circular 'window' (5 mm diameter) was cut into the clear acrylic base to minimise reflectance issues. A white base was also installed into the monitoring tool to act as a light-coloured backdrop for image capture and provide contrast against the dark coloured vine weevil adults. To make the modified monitoring tool 'smart' a Raspberry Pi Zero 2W microprocessor (PiHut) was externally mounted to the side of the monitoring tool. This is a relatively new Raspberry Pi model (launched January 2022) and was selected for this project due to its low power consumption requirements, excellent integration with various software libraries and broad range of connectivity options (WiFi, USB, mini-HDMI). Alongside executing Python scripts to delivery functionality, the Raspberry Pi 2W was fitted with a BME280 temperature / humidity sensor (AZ Delivery, Deggendorf, Germany) and BH1750FVI lux sensor (AZ Delivery) to record key environmental conditions during monitoring tool deployment. The 'smart' monitoring tool is, at present, mains powered. Due to the ongoing global silicon shortage having a negative impact on computer chip production, the project was only able to purchase a small number of Raspberry Pi Zero 2W units and this delayed 'smart' monitoring tool construction.

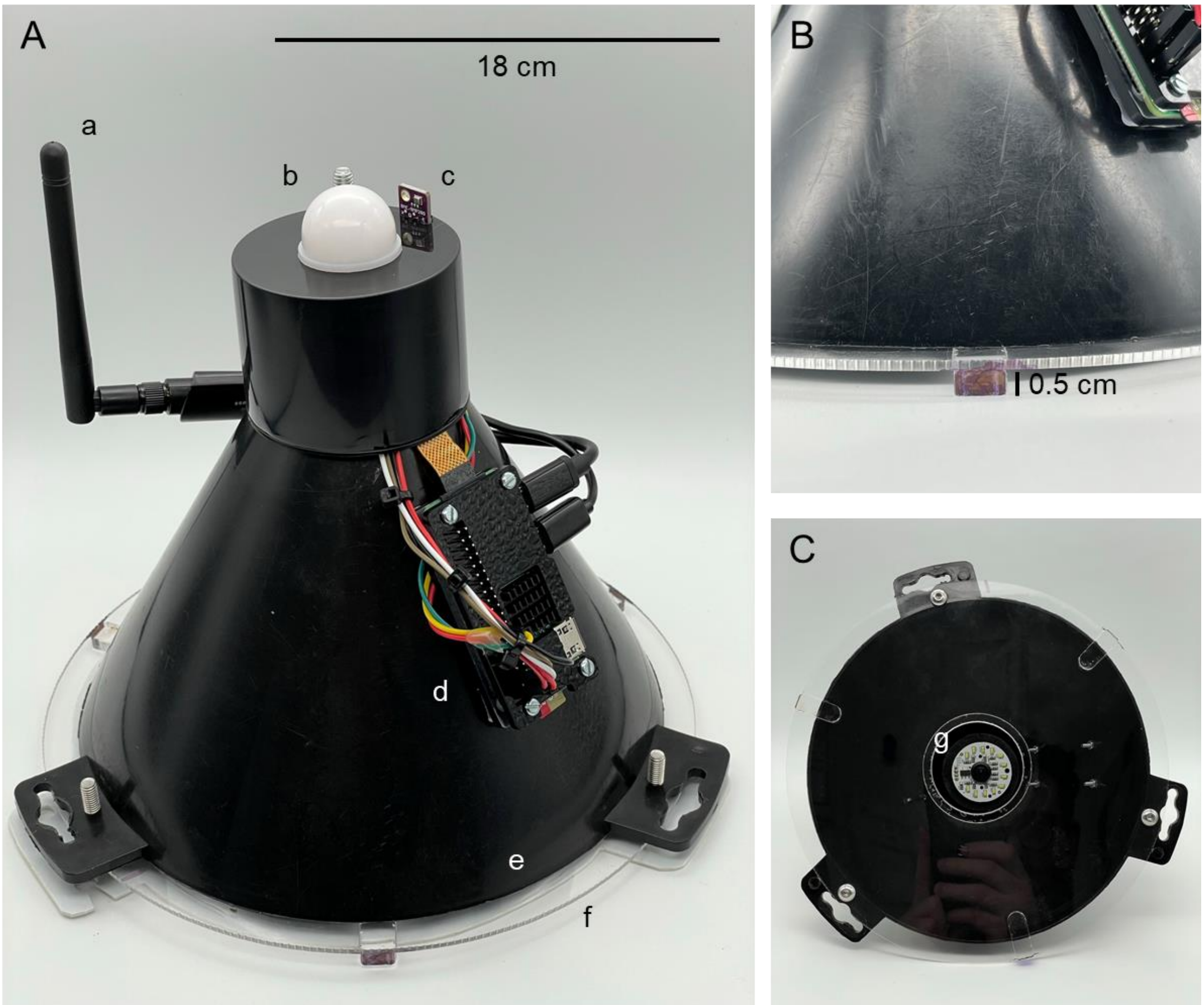

Figure 2 Modified Chemtica vine weevil trap to add smart features (A) assembled for in-field deployment with (a) Wi-Fi antenna, (b) BH1750FVI lux sensor, (c) BME280 temperature / humidity sensor, (d) Raspberry Pi

Zero 2W, (e) clear acrylic and (f) entry location, (B) close-up of entry location and 0.5 cm stand-offs and (C) internal view of the (g) LED ring light and camera.

3.2.2. Image Capture and Processing

Images from within the monitoring tool were captured every ten minutes to create a bespoke training data set for this project. The initial focus of capturing these images was to single out individual adult vine weevils so that they can be classified and counted. However, as adult vine weevils tended to group together due to their thigmotactic behaviour (Fig. 3), counting the total number of individuals within the trap was computationally challenging. An alternative approach was devised that looks for differences between subsequent images, which identified an insect arriving in a new location. It should be noted that it was not possible to determine whether an insect was counted more than once, only a general level of insect activity can be established using this method. This approach determined a region of interest (ROI) that contained an insect, with a sub-image (100 x 100 pixels) being cropped out from the ROI for labelling in preparation for training a machine learning model. To ensure that these sub-images contained a single centrally located insect, a threshold was applied to the image's moment of inertia (*i.e.*, to make the image centrally 'balanced') and then a second threshold was applied to the amount of white background (*i.e.*, to minimise empty space within an image). Processed images were uploaded to GitHub until required for use as a deep learning model training data set. Python scripts for imaging processing can be accessed here and are documented to contain all key information required to implement them on another Raspberry Pi system (*e.g.*, threshold values).

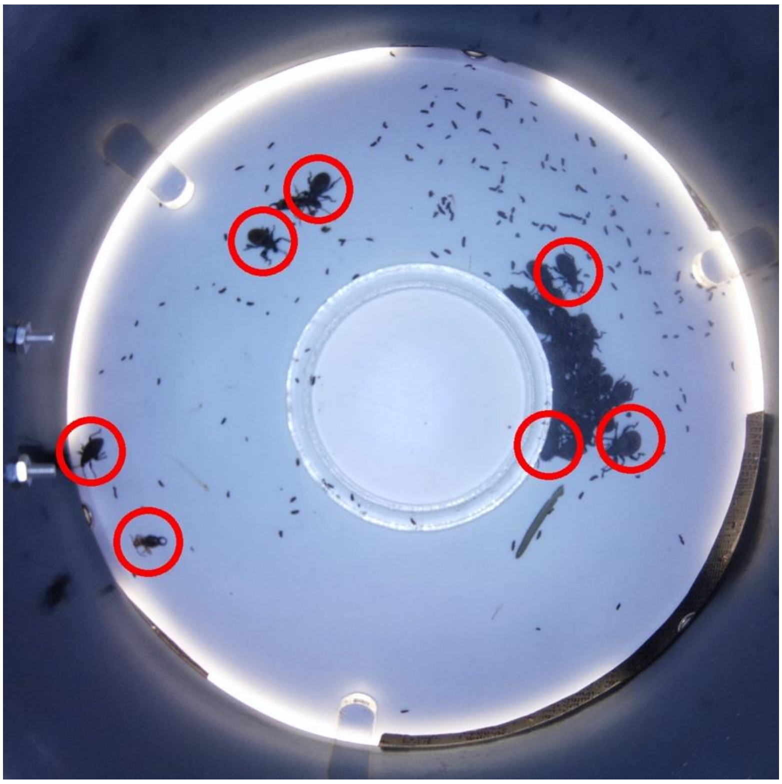

Figure 3 An image captured from the ‘smart’ trap illustrating vine weevil thigmotactic behaviour (black mass on right hand side of the image) during daylight hours. Red circles illustrate individuals that have moved since the preceding image was captured.

3.2.3. Training an Image Classification Model

Although Raspberry Pi Zero 2W microcontrollers are relatively powerful computing units, they do not contain a graphical processing unit (GPU) so are not capable of training and executing a machine learning model locally. A newly developed machine learning approach designed for low-powered computing units called TensorFlow Lite (Google, California, USA), in combination with the Colaboratory cloud service (Google), was used in this project to address this issue. To train a machine learning model that classifies an insect entering the monitoring tool into pre-defined categories (*i.e.*, either a vine weevil or an earwig). Captured ROI images were manually sorted by species into their corresponding folder. These folders were then imported into TensorFlow Lite Model Maker to create a small, trained image classification model able to run locally on a Raspberry Pi Zero 2W with minimal user input.

3.2.4. Reporting

An image was taken every ten minutes when the monitoring tool was operating under testing conditions and the ROIs extracted from these images were input into the trained model for classification. This model was able to classify ROI images as containing either a vine weevil or earwig as well as providing classification confidence. Each hour the accumulated classification for that hour, lux, temperature and humidity were logged as individual data points. At 12:00 each day these data points were plotted as bar charts and emailed to the user, along with a 5 x 5 grid montage of ROI classifications. Additionally, the full image taken each 10 minutes was uploaded to a website so that the user could have a complete view of the monitor in near real time. Each uploaded image overwrites the last to prevent the web server becoming overloaded. The image also has text showing the current environmental conditions should the user want this information.

3.3. Testing

3.3.1. Laboratory Conditions

Basic monitoring tool functionality was beta tested under laboratory conditions. A known population of 20 adult vine weevils were released into a 47.5 cm^3 white mesh cage (BugDorm-4S4545) containing a single ‘smart’ vine weevil monitoring tool along with a sprig of yew and a moist cotton wool pad. The mesh cage and its contents were housed within a controlled environment room (20 °C; 60 % relative humidity; 16:8 photoperiod) (Fitotron) for two days to establish whether the Raspberry Pi Zero 2W and associated camera / LED light ring captured usable images and test the environmental monitoring sensors. Once beta testing was complete, the ‘smart’ vine weevil monitoring tool was deployed in a 47.5 cm^3 white mesh cage under the environmental conditions previously described for ten days to collect training images for the image classification model.

3.3.2. Semi-Field Conditions

'Smart' monitoring tool performance was tested against an equivalent commercially available monitoring tool in a semi-field environment simulating a susceptible crop. This experiment aimed to determine whether the 'smart' monitoring modifications had a negative impact on its performance compared to an unmodified monitoring tool. To create a semi-field environment, five potted strawberry plants (cv. Elstanta) were placed in a 'tent' cage (145 × 145 × 152 cm) (Insectopia, Austrey, UK) situated within a glasshouse fitted with an environment management system (20 °C; 60 % relative humidity; 18:6 photoperiod). Two un-baited monitoring tools (one commercially available and one modified to be 'smart') were placed in a tent cage with five potted strawberry plants to provide both a food source and a range of alternative refuges (*e.g.*, under pots, around rims, within compost). A known population of 40 adult vine weevils (approximately 19 weevils m^2) were released into the centre of the experiment cage at 18:00. The number of vine weevil adults within each trap was enumerated between 07:00 and 09:00 each day for four days. Due to the shortage of Raspberry Pi Zero 2W units available for purchase, only a single fully functional 'smart' monitoring tool was constructed during this project. It was, therefore, only possible to set up a single experimental cage to test 'smart' monitoring tool efficacy. The tent cage to which the monitoring tools were allocated was re-randomised each day to exclude the effect of tent cage position and/or simulated crop. Monitoring tool position was also altered between days to minimise the impact of directional bias on monitoring choice. Adult vine weevil populations were changed between each replicate.

3.3.3. Statistical Analysis

Statistical analysis was carried out using R (V 4.1.3) (R Core Team, 2022). Monitoring tool performance (*i.e.*, the number of insects within a monitoring tool) was analysed using an exact binomial test against the null hypothesis that number of insects seeking refuge had a 50:50 distribution. Prior to carrying out statistical analyses, replicated results from each of the four days were pooled. Insects not recorded in the monitoring tools were excluded from statistical analysis (Fezza *et al.*, 2022). No statistical analyses were carried out on the data collected during laboratory testing as the primary purpose of these tests were operational functionality and collect training images.

4. Results

4.1. Image Classification

4.1.1. Training Image Collection

It was initially anticipated that a range of ground-dwelling invertebrates would be used to train the image classification model deployed onto the Raspberry Pi 2W. However, due to timing of this project coinciding with winter it was not possible to collect large enough numbers of non-target organisms to achieve this objective. A population of earwigs was discovered in an experimental polytunnel that served as a relevant non-target organism for model training. During training image collection, a total of 1499 individual images were collected: 1300 images containing at least one adult vine weevil and 199 images containing at least one earwig. From these images it was possible to parse out 5977 potential ROI, however manual screening for image quality reduced this number to 199 vine weevil ROI and 199 earwig ROI suitable training images.

4.1.2. Image Classification Accuracy

The laboratory earwig population used to collect training images during this project unfortunately perished prior to use for testing image classification model accuracy and could not be replaced before testing due to low temperatures. Image classification model confidence (*i.e.*, how certain the model was on its identification) was 85 ± 10 % during laboratory testing and did not incorrectly identify any adult vine weevils as earwigs (Fig. 4). Approximately 16 ± 2 % of images were categorised as 'unsure' during laboratory testing, indicating that these images were unable to be classified as either adult vine weevils or earwigs.

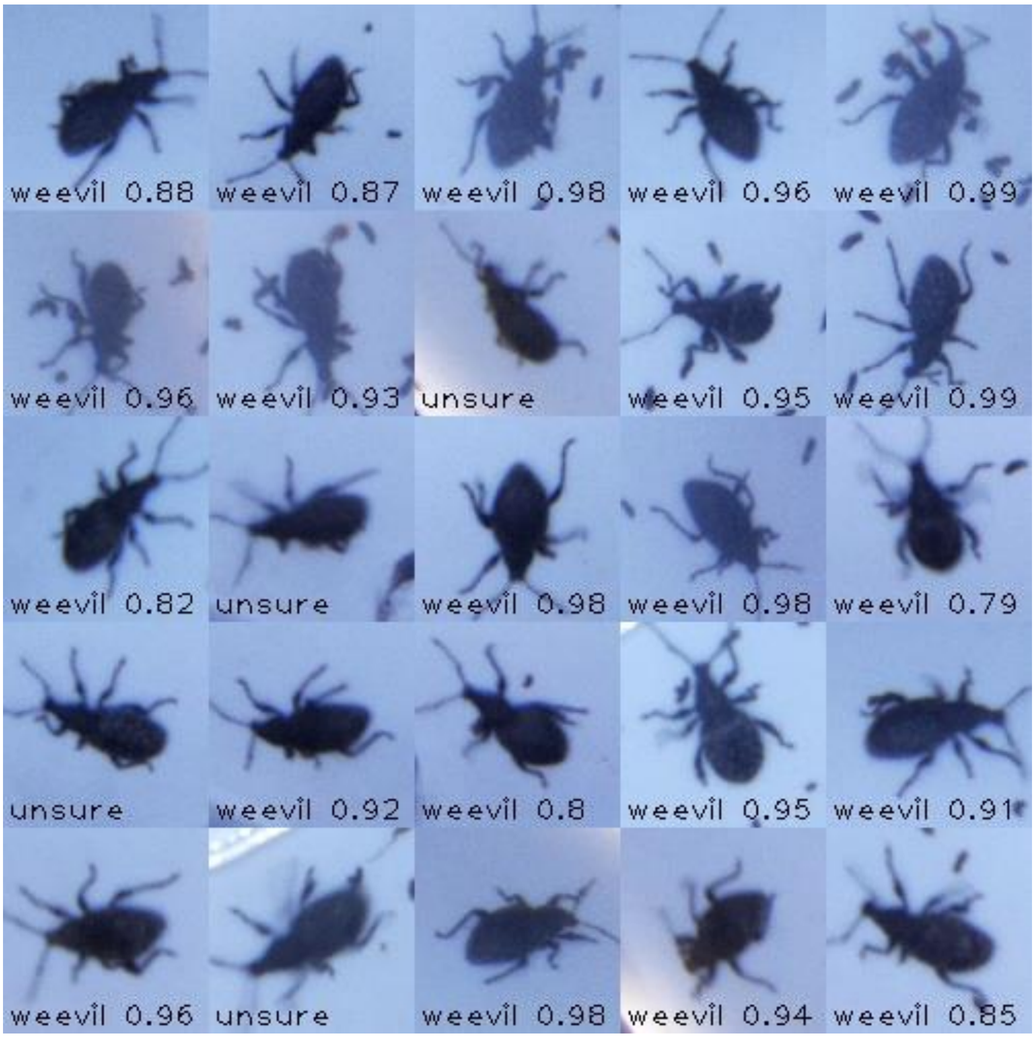

Figure 4 Representative montage illustrating 25 images captured from within the ‘smart’ monitoring tool along with their classification (weevil = vine weevil) and the model confidence in this classification. Confidence is presented as a proportion between 0 and 1 that can be converted to a percentage by multiplying by 100.

4.2. Monitoring Tool Performance Under Semi-Field Conditions

In a binary choice experiment presenting adult vine weevil with an unmodified monitoring tool and a ‘smart’ monitoring tool under semi-field conditions there was no significant difference in the number of individuals seeking refuge in each monitoring tool when assessed over four days (binomial exact test: no. successes = 30, no. trials = 65, p = 0.6201) (Fig. 5). Monitoring tools contained a combined 40.6 % of the released vine weevil population during testing under semi-field conditions, with 18.7 % in the unmodified monitoring tool and 21.9 % in the ‘smart’ monitoring tool. Image classification model performance under semi-field conditions was comparable to that under laboratory conditions.

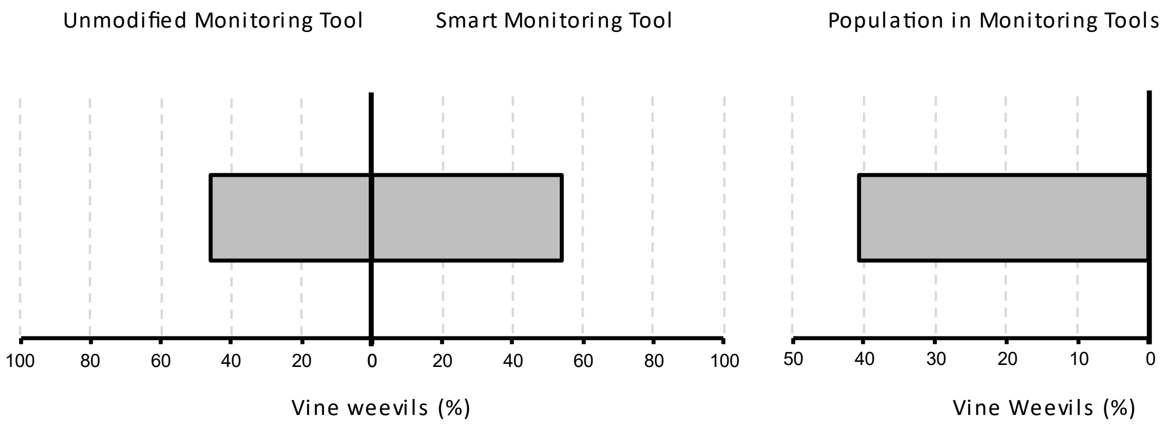

Figure 5 Percentage of vine weevil adults recorded in the unmodified and 'smart' monitoring tools when released as groups of 40 into a tent cage containing five strawberry plants (n = 4).

5. Discussion

This 3.75-month project set out to develop a prototype monitoring tool that could automatically identify adult vine weevil entering into it, providing a platform for further research and development to improve IPM for this economically important pest. Results presented here indicate that pre-trained machine learning models can reliably identify adult vine weevil in laboratory and semi-field environments as well as demonstrating that retrofitting existing monitoring tools with low-cost electronic components enhances functionality without negatively impacting insect-monitoring tool interactions. While 'smart' monitoring tools exist for a range of Lepidopteran pests, this is the first report of such technologies being specifically developed for vine weevil.

5.1. 'Smart' Monitoring Tools

Early detection of vine weevil within crops is essential for successful management. Conventional vine weevil monitoring methods (*e.g.*, visual plant assessments for leaf notching or dislodging adults during night-time assessments) are notoriously unreliable and impractical (Pope and Roberts, 2022). 'Smart' tools could provide a reliable, cost-effective approach to vine weevil monitoring and better inform management decisions to align with an IPM framework. Most efforts to develop automated monitoring systems have focused on Lepidopteran pests as they are often morphologically distinct from one another due to their wing colouration and patterns, which makes them relatively easy to classify using machine learning approaches (Cardim Ferreira Lima *et al.*, 2020). Although vine weevil is not overly colourful, it was able to be successfully identified using a machine learning model within this project as it does have some key morphological features (*e.g.*, extended snout and elbowed antennae). With a classification accuracy of 85 % the machine learning model developed during this project is comparable to other systems (Kang, Cho and Lee, 2014; Thenmozhi and Srinivasulu Reddy, 2019). Many of these systems, however, also benefit from deployment alongside species-specific pheromone lures that enhance monitoring tool catch and reduce incidences of non-target organisms entering (Cardim Ferreira Lima *et al.*, 2020). Despite significant attention in recent years (Roberts *et al.*, 2019; van Tol, Elberse and Bruck, 2020), no effective semiochemical lure has been identified for adult vine weevil. The value of any vine weevil monitoring tool is, therefore, limited as previous work has identified only moderate efficacy in un-baited monitoring tools (Roberts *et al.*, 2020).

5.2. Project Limitations and Future Development Opportunities

While the prototype 'smart' monitoring tool developed during this project was able to accurately identify adult vine weevil, it was tested under simple conditions with no non-target organisms present in the experimental arena. This is largely due to the project running through the UK winter months (December to March), so there was a lack of non-target organisms available within the wider environment to provide a broader range of training images for the machine learning model. It is, therefore, possible that the 'smart' monitoring tool could mistakenly identify certain non-target organisms as adult vine weevil. There are several important carabid beetle species (*e.g.*, *Pterostichus melanarius*, *Harpalus rufipes* and *Calathus fuscipes*) as well as weevil pests (*e.g.*, *Anthonomus rubi*) commonly found in the same soft-fruit and ornamental crops as vine weevil, which can have a similar appearance to adult vine weevil (Solomon, 2000). It would be possible to augment the training image repository for the machine learning model with standardised images representing a wider species range by using online databases such as iNaturalist. While this would undoubtedly enhance machine learning model performance, it relies on extensive knowledge of which non-target organisms are present in the relevant soft-fruit and ornamental crops. Deploying several 'smart' monitoring tools without machine learning models and only camera functionality in different crops would enable researchers to develop a database of non-target organisms that enter the 'smart' monitoring tool. This information could better inform the training of machine learning models to enhance their performance and reliability under field conditions.

In its current configuration, the 'smart' monitoring tool is unable to provide an accurate count for the number of individual insects within the tool at any given time (except that at least one individual is present). This is largely due to adult vine weevils exhibiting thigmotactic behaviour, which results in a large mass of individuals that cannot be distinguished from one another (Roberts *et al.*, 2020). Having an accurate count for the number of individuals within a monitoring tool is crucial information required to determine whether a pest population has exceeded the economic injury or action thresholds that guide decisions within IPM frameworks (Dara, 2019). However, such thresholds do not yet exist for vine weevil and their determination would rely on development of better monitoring systems. Future research could exploit the 'smart' monitoring tool developed during this project to contribute to wider knowledge on vine weevil population dynamics and establishment of thresholds. If such thresholds can be established for adult vine weevil then the 'smart' monitoring tool would be required to count the number of individuals present. It may be possible to derive this information by dividing the area of monitoring tool base by the mean area of an adult vine weevil, though this is a crude approach and would not differentiate between target and non-target organisms. A more appropriate approach would utilise the activity levels already calculated by the 'smart' monitoring tool and environmental data to develop a predictive model for the number of individuals per square meter. Such predictive models have been developed for other pest species (Cardim Ferreira Lima *et al.*, 2020). For the prototype 'smart' monitoring tool to be deployed in-field it would need to be converted to run on battery power and transfer data via a cellular network. Further design iterations should focus on making the 'smart' monitoring tool field ready.

5.3. Conclusion

Current vine weevil monitoring approaches are variable and do not accurately predict pest presence or density. This project has successfully demonstrated that a camera-based monitoring tool with integrated machine learning model for image classification can identify adult vine weevils in the laboratory and under semi-field conditions. Further development is required for this prototype 'smart' monitoring tool to be suitable for deployment in commercial nurseries, particularly with respect to machine learning model optimisation as it is currently too simplistic. Wider efforts to identify an effective semiochemical lure would further enhance monitoring tool efficacy and facilitate adoption of 'smart' monitoring tools once commercially available.

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