Final report

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Using artificial intelligence to develop automated monitoring systems for the banana and fruit spotting bugs

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Public summary

Banana Spotting Bugs (BSB) and Fruit Spotting Bugs (FSB) are among the most economically damaging native pests in Australian horticulture, affecting a broad range of crops including macadamia, avocado, custard apple, lychee, passionfruit and papaya. In heavy infestations, fruit-spotting bug damage can result in the loss of more than 90% of green fruit. In macadamia, FSB damage has been identified as a major source of factory rejects, while the current macadamia industry prioritisation also identifies fruit-spotting bug and banana-spotting bug as high-priority pests. Despite the scale of this impact, growers are relying on on-site field scouting and manual inspections of sticky traps as the primary early detection methods.

To address this challenge, the project aimed to develop an automated, Artificial Intelligence (AI) driven monitoring system capable of detecting BSB and FSB. By leveraging advanced AI and specially designed hardware, the project sought to create *smart-traps* that could automatically identify and quantify pest populations. This would enable growers to implement more precise, timely, and sustainable pest management strategies while reducing reliance on manual monitoring methods.

Project Approach

Stage 1 of the project delivered a first-of-kind technology for AI-assisted spotting-bug monitoring in Australia. The project developed what is understood to be Australia's first specialised, benchmarked AI detection model for BSB and FSB. The model was trained using farm and laboratory imagery and exceeded the project's original 80% accuracy target, achieving a 93.8% balanced detection score under controlled test conditions. This is an important step forward for Australian horticulture, creating a dedicated AI capability for BSB and FSB detection.

Stage 2 of the project focused on transforming the AI model's capabilities into a practical, field-ready solution by developing a physical smart-trap prototype. A smart-trap prototype was engineered and deployed on a commercial avocado farm in the Mt Garnet area of North Queensland for a 10-week field trial. The deployment demonstrated that the system could be installed by a non-technical user, operate in all-weather farm conditions, capture imagery and send updates for remote automated monitoring. Further multi-season validation is recommended to confirm live pest capture and detection performance across different farms, lure placements, climates and seasonal conditions. Stage 2 has established a practical foundation for automated early detection of BSB and FSB on farms.

Industry Impact and Benefits

The resulting AI-based monitoring system could provide substantial benefits to the Australian horticulture industry:

- **A first-of-kind AI capability**: The validated detection model gives Australian horticulture, for the first time, a benchmarked AI tool specifically trained to recognise its two most damaging spotting-bug pests. This capability did not exist before this project.
- **A practical platform for future adoption**: The smart-trap prototype provides researchers, growers, and industry with a working foundation to improve future remote monitoring, test different lure and trap placements, and explore practical pathways toward wider use on farms.
- **Technological Advancement:** The project demonstrates how AI and smart-farming technologies can be explored as promising options for automated early detection of FSB and BSB, modernising pest monitoring and improving industry productivity.

Technical summary

Stage 1

Stage 1 of BY23000 focused on building and validating the Artificial Intelligence (AI) capability that underpins the smart-trap system. The objective was to develop a specialised AI model to identify spotting bugs in images with at least 80% accuracy.

A purpose-built dataset of 1,777 images was compiled, drawing on imagery supplied by Macquarie University and additional photographs collected during targeted farm visits. Every image was manually labelled by the project team to give the AI training process reliable reference points. To make the dataset more reliable, the images were standardised in size and orientation, and additional variations were generated through techniques such as flipping, rotation and grayscale conversion [1].

The AI model was trained on a high-performance computing platform using a modern object-detection architecture [2], consistent with approaches used in similar pest monitoring research [3, 4]. Training progress was monitored using validation metrics and loss trends to diagnose model performance during development and identify possible weaknesses in detection behaviour [5-7].

The final model achieved 93.8% balanced detection score under controlled test conditions, exceeding the project's 80% target and proved fast enough to produce results in real time.

These outcomes confirmed the project's underlying hypothesis: that a well-designed AI system can act as the foundation for an accurate, automated detection system for BSB and FSB.

Stage 2

Stage 2 of BY23000 delivered a self-contained, solar-powered, cellular-connected smart trap built around a single-board computer (SBC) running a managed device operating system. The trap was paired with a high-resolution camera that captures imagery of an OCP-supplied lure and sticky board [8] at a pre-set interval. Captures are written to an on-device queue and then forwarded to an online ingestion service via secure HTTPS uploads.

Power was supplied by a 100 Wh lithium iron phosphate battery, charged from a 12–18 V solar panel via a solar charge controller. Two independent step-down converters split the load: one feeding the SBC via a fused power line, and the other feeding the accessory rail (sensor electronics and cooling fan) through a separate fuse. Multiple fuses and safety circuits were used to minimise any risk of electronics burnout or fire.

On-device telemetry included processor and memory utilisation, cellular signal strength, ambient temperature and humidity, air pressure, ambient light, and three independent measurement channels covering battery, SBC power-rail and accessory-rail voltage and current. A real-time clock kept capture timestamps accurate during cellular outages, and a controlled cooling fan with a hardware cut-off managed internal temperature.

The outer structure was fabricated in heavy-duty metal for the prototype build. The complete kit comprises:

- Camera and processing unit with cellular communication capability
- Solar panel for autonomous power generation
- Battery storage
- Mounting gear for attachment to standard star pickets
- Detachable component design (to be shippable in a single box to a farm)
- Installation instructions

OCP lure-mounting kits (commercially purchased) and compatible lure samples (obtained through liaison with support from the Queensland Department of Primary Industries) were included with the unit to support the field trial [8, 9].

On the cloud side, a web admin dashboard exposed two ingestion endpoints (one for image upload and one for device health), de-duplicated incoming records, and queued uploaded images for downstream AI inference. The Stage 1 spotting-bug computer-vision models were applied server-side. The field trial provided real-world background imagery for ongoing model refinement. The web dashboard was available throughout the trial for remote monitoring.

The smart trap was deployed on a commercial avocado farm at Mt Garnet (Tablelands region, North Queensland – approx. 160 km from Cairns) for 10 weeks from February to April 2026. Installation and remote operation were validated end-to-end. Lure performance and final BSB detection accuracy under field conditions remain inconclusive. The technical work for the trap, its software stack and its cloud backend is complete and validated. Further validation across multiple seasons with varied lure placements is recommended.

Keywords

banana spotting bugs; fruit spotting bugs; BSB; FSB; artificial intelligence; machine learning; computer vision; object detection; smart trap; pest monitoring; pest detection; integrated pest management; precision agriculture; avocado; macadamia; Amblypelta lutescens lutescens; Amblypelta nitida;

Introduction

Banana Spotting Bugs (BSB, *Amblypelta lutescens lutescens*) and Fruit Spotting Bugs (FSB, *Amblypelta nitida*) are major pests affecting a broad range of horticultural crops across Australia, including macadamia, avocado, custard apple, lychee, passionfruit, and papaya [10, 11]. These insects cause substantial economic losses across Australian horticulture. In heavy infestations, fruit-spotting bug damage can result in the loss of more than 90% of green fruit [11]. In macadamia, FSB damage has been identified as a major source of factory rejects, while the current macadamia industry prioritisation also identifies fruit-spotting bug and banana-spotting bug as high-priority pests [12]. The scale and persistence of this issue highlight the urgent need for a more effective, sustainable, and technologically advanced pest management solution.

This project addressed the challenges posed by FSB and BSB by developing and deploying an AI-assisted smart trap system. The system is intended to provide real-time monitoring and counting of pest populations, providing timely, data-driven insights to support more targeted and efficient pest control strategies [3, 4].

To ensure the effective implementation of this solution, a two-stage approach was designed. Stage 1 focused on building and validating a specialist AI model capable of identifying banana spotting bugs at ≥ 80% accuracy. Stage 2 translated that validated AI capability into a deployable, solar-powered smart-trap prototype and trialled it on a commercial avocado farm in North Queensland. It is a strategic step toward modernising pest detection and management in Australian horticulture.

Alongside improving pest detection, the project explored how this technology could be adopted in a real farm, while generating new knowledge with the field research undertaken. The work also aims to reduce reliance on chemical pesticides and supports more environmentally sustainable farming practices. These outcomes fit with the priorities set out in the relevant industry and fund Strategic Investment Plans, which back advanced, integrated pest management solutions [13].

Methodology

The project followed a two-stage methodology. Stage 1 focused on building and validating the underlying AI detection model under controlled laboratory conditions. Stage 2 translated that validated AI capability into a deployable smart-trap prototype and evaluated it through a real-world field trial. Project reach was national, with the field trial conducted in the Cairns region of North Queensland. Target audiences include avocado and macadamia growers, the industry partners who support them, and AI and AgTech researchers.

Stage 1 – AI Model Development

Objective

The hypothesis underpinning Stage 1 was that a well-crafted AI system could lay the foundation for an efficient and accurate smart detection system to address the pressing issue of fruit and banana spotting bugs threatening horticultural commodities.

Validation Method

The primary objective of Stage 1 of the project was to build a specialist spotting-bug AI detection model, that's capable of reaching an accuracy level of beyond 80% within the given timeline. Consistent with similar pest-detection studies [14], model performance was assessed using F1 score as a balanced measure of precision and recall.

Research Design

A targeted review of the published literature was undertaken during the project, together with consultations with research partners, which identified no prior scientific research literature or a commercially available AI detection model for either FSB or BSB identification.

Our controlled methodology for model research centred on refining and validating an AI-based pest detection model under consistent conditions. We followed a structured workflow that involved carefully curated datasets, systematic model training, and iterative performance evaluations [15]. By leveraging the latest advancements in object detection and closely monitoring key metrics (precision, recall, and mean average precision), we assessed the model's reliability using standard object-detection evaluation measures reported in similar work [5-7]. Controlled image augmentation was used to increase training-data variation and support model generalisation, while training and validation settings were kept consistent across project experiments [1].

After multiple validation experiments, we established that the following AI training architecture yielded optimal results.

Parameter	Value
Model Architecture	YOLO11n (optimised version with 2.58 million parameters and 6.3 GFLOPs)
Training Duration	200 epochs with early stopping (patience=20)
Batch Configuration	32 images per batch, optimised for NVIDIA A100 GPU
Training Hardware	NVIDIA A100-SXM4-40GB GPU
Image Processing	640×640 pixel input size with automatic mixed precision
Optimisation Strategy	AdamW optimiser with cache dataset loading

Table 1: AI Model Training Specifications

The controlled methodology incorporated periodic checkpointing and monitoring of training and validation outputs, including precision, recall, mAP and F1 [6, 7].

Dataset Sources

The Stage 1 datasets consisted of:

- 1,777 images collected through farm visits and collaboration with Macquarie University.
- All images were manually labelled by our team to ensure accuracy.
- An additional 3,464 images from an open-source dataset of similar-looking bugs were collected as negative examples. These were not incorporated into the model training as they were not required to reach the target metrics. This step should be reassessed in future model improvement work.

See Appendix A for further details on data processing and the augmentation pipeline.

Stage 2 – Prototype Development and Field Trial

Objectives

The primary objectives of Stage 2 were as follows:

- Deploy the smart trap prototype in a commercial farming environment to validate real-world performance.
- Assess the trap's ease of installation and usability from a farmer's perspective, gathering practical feedback to inform future design iterations. This is important because ease of use is an important factor in smart-farming adoption [16].
- Conduct a 10-week (including a 10-week observation period) field trial during the avocado season (February–April 2026) to collect data under conditions of expected pest activity.
- Evaluate the effectiveness of the smart-trap when used with a commercially available BSB lure and sticky-board system for BSB detection under live field conditions. Testing for independent FSB detection was out of scope because a commercial FSB lure was not yet synthesised.
- Collect photographic and sensor telemetry data remotely via the trap's cellular communication system for AI analysis and model refinement.
- Identify practical issues relating to device performance, trap placement, and lure effectiveness to guide future hardware and deployment improvements.

Validation Method

- Validation was conducted by developing and deploying the smart trap prototype in a commercial farming environment, with end-to-end performance assessed via remote telemetry and cross-verified against on-site visit data.
- Validation criteria covered installation usability, remote data transmission integrity, power system resilience, lure/sticky-board bug activity, and AI detection of spotting-bugs in returned imagery.

Research Design

The purpose-built smart trap was designed and built to support our objectives. The unit was prepared for in-field deployment to evaluate its performance under real-world agricultural conditions. The field trial methodology encompassed prototype deployment, installation assessment, observational monitoring, and remote data collection over a 10-week period.

The smart trap unit was shipped as a complete, self-contained kit in a single box, designed for ease of deployment by the end user. The kit comprised the following components:

- Camera and processing unit with cellular communication capability
- Solar panel for autonomous power generation
- Battery storage
- Mounting gear for attachment to star pickets
- Installation instructions

In addition to the smart trap hardware, sample BSB lure mounting kits [8] were included.

Field Trial Site and Installation

The prototype was shipped to a Project Reference Group (PRG) participant, who coordinated with a local farmer and installed the trap on an avocado farm near Mt Garnet, Tablelands region, North Queensland. The trial was conducted over a 10-week period between January and April 2026, coinciding with the North Queensland avocado season and the expected BSB activity period [11, 17]. The physical installation location was selected based on previously observed hotspot areas with high spotting-bug infestation activity, with visible damage to the fruits.

The trap was mounted on standard star pickets, which are readily available from most hardware stores in Australia. Boards were positioned so that only a single sticky side faced the camera, leaving the reverse side non-sticky. The lure was positioned forward, oriented towards the camera, to attract BSB towards the front face of the sticky board. A gap of approximately one metre was maintained between the camera unit and the lure.

Observational Monitoring

Observations were conducted primarily by the Elegant Media (EM) team via remote monitoring of the lure and sticky boards through the trap's camera system. In addition:

- Visits were conducted by a PRG group participant to the farm site every 1 to 2 weeks to replace the sticky boards, thereby maintaining the trap's capture effectiveness. This servicing interval is consistent with available BSB trap guidance, which recommends replacing sticky surfaces fortnightly or sooner if they are dirty or saturated [8, 9].
- OCP lures were replaced approximately every three to four weeks, which was within the manufacturer's recommended replacement interval [9].
- The Elegant Media team conducted a field visit to make additional adjustments to the trap configuration and to perform on-site data verification.
- During the trial period, the surrounding avocado trees bore fruit, and the farmer left several trees unpicked in the vicinity of the trap to assist in attracting pest activity for the duration of the trial.

Photos of Installation and Trap

Fig 1.1 – Installation of Lure and Board

Fig 1.2 – Installation of camara housing (enclosed camara, electronics, battery), and solar panel mounted on top. Custom fabricated metal setup.

Fig 1.3 – Installed lure and board (left), and the AI camera system (right). Approx 1m apart. Overhead branches cleared to improve solar access.

 Fig 1.4 – Modified OCP setup, with brackets to swap sticky boards and lure. (closeup)	 Fig 1.5 – Close up of the camera enclosure.

For photo attributions, refer to Appendix A.

Data Collection Instruments

The datasets collected during this stage were generated directly from the deployed smart trap and its onboard sensor array. Following successful trap placement and activation, all data collection was conducted remotely via the trap's cellular communication link.

The primary data sources comprised:

- Photographic imagery: High-resolution photographs of the lure and sticky board were captured at regular intervals by the trap's integrated camera for subsequent AI analysis and manual review.
- Manual trap observations: Manual trap observations were conducted every 1 to 2 weeks to inspect the lure, board, and camera setup for anomalies and were later compared with the electronically recorded data.
- Environmental and system telemetry: The trap's onboard sensors collected a comprehensive suite of operational and environmental data, including:
  - CPU usage and memory usage
  - Cellular connection status and signal strength
  - Trap temperature and internal electronics temperature
  - Trap humidity and air pressure
  - Ambient light levels
  - Battery health and voltage measurements

– Power usage measurements (overall, sensor electronics, and main board, cooling fan measurements)

All collected data was transmitted to a cloud-based dashboard for remote monitoring of device health.

The field testing/data collection was conducted from 16/02/20026 through 26/04/2026 inclusive.

Results and discussion

Key Achievements

Stage 1 – Achievements

Achievement	Outcome
A first specialised AI model for Australian spotting bugs	A targeted literature review undertaken during the project identified no prior peer-reviewed AI detection model for FSB and/or BSB. This finding was further strengthened by consultations with industry experts and research partners. To the best of our knowledge, this project has produced the first specialised, benchmarked AI detector of its kind for FSB and BSB detection.
Hypothesis Validation	The AI model demonstrated superior accuracy in detecting and quantifying spotting bugs, confirming our initial hypothesis that a well-crafted AI system can effectively address this agricultural challenge.
Objective Surpassed	The model exceeded the 80% Stage 1 target, achieving a project-measured 93.8% F1 score under controlled test conditions. F1 score is calculated from precision and recall and is commonly used to balance false positives and false negatives [6, 19, 20].
Production Readiness	The model's fast inference speed (3.1ms per image) and high accuracy made it likely suitable for real-time field deployment.

Stage 2 - Achievements

Key achievements on Stage 2 include:

- End-to-end deployment of a self-contained, remotely monitored smart trap in a real-world agricultural setting.
- Confirmation that the installation process is accessible to non-technical end users, requiring no specialised electrical knowledge.
- Successful remote data collection capability validated over the full 10-week observation period, with photographic and telemetry data transmitted to a centralised cloud dashboard.
- Collection of valuable on-farm and stakeholder feedback on practical usability, hardware design, and deployment considerations.
- Identification of critical areas for improvement in power management, lure positioning, and trap placement strategy.
- Production of a complete, documented bill of materials, electronic component diagram, wiring guide, on-device firmware, cloud back-end, API specification and user documentation to assist in exploring future paths toward commercialisation.

The Stage 2 outcomes mark a substantial step forward in automating the early detection of FSB and BSB. The project has brought advanced computer vision, real-time telemetry, autonomous solar power and secure remote monitoring together in a single, field-ready unit that can be installed by a non-technical user and monitored remotely on a commercial Australian farm.

This represents a meaningful step toward modernisation of a spotting-bug monitoring approach that has relied on manual scouting in the past. Of the several technical directions that could be pursued toward automating FSB and BSB early detection, the smart-trap approach realised here has emerged as a highly promising one - with a working prototype already deployed and tested in the field, and a clear development trajectory ahead toward real-time, AI-assisted pest surveillance for Australian horticulture.

Results

Stage 1 Results

Research and experiments achieved high performance, surpassing our initial 80% accuracy benchmark. The results demonstrated strong detection capabilities, with a balanced detection score exceeding 93% in controlled testing.

Our AI model achieved the following performance metrics:

Metric	Value	Explanation
Precision	94.6%	When the model identifies a bug, it is correct 94.6% of the time.
Recall	93.1%	The model successfully identifies 93.1% of bugs present in images.
F1 Score	93.8%	Taking both missed bugs and false alarms into account, the model achieved a 93.8% balanced detection score [19, 20].
mAP@0.50	96.2%	Mean Average Precision with 50% overlap threshold
mAP@0.50-0.95	81.0%	COCO-standard evaluation metric measuring precision across multiple overlap thresholds.
Inference Speed	3.1ms	The model's fast inference speed (3.1ms per image) and high controlled test accuracy make it suitable for real-time deployment, subject to field trials.

Table 2: AI Model Performance Metrics

The model's performance indicated robustness in identifying the target pest species across various conditions and image types. The final model training has successfully validated our hypothesis and exceeded the established objective. The achieved 93.8% balanced detection score (F1 Score) provides a strong foundation for progressing automated spotting-bug detection toward field validation, consistent with wider evidence that camera-equipped traps and AI models can support automated pest monitoring [3, 15].

Stage 2 Results

The Stage 2 work and the trial yielded the following key results:

1. **Prototype design development**

   The smart-trap hardware is built from off-the-shelf components to maximise speed-to-market and reliability. All physical housing, fabrication, and design of the supporting placement of electronics and arrangements were done in-house at Elegant Media, with the goal of ease of use for the final product. Over 50 physical component prototypes were trialled to fabricate and ship the final unit.

2. **Prototype deployment**

   The smart trap was shipped as a complete, self-contained kit in a single box, designed for ease of deployment by the end user. The kit comprised the camera and processing unit (with cellular communication), the solar panel, the battery, the mounting gear and the printed installation instructions. OCP lure mounting kits and lure samples were supplied alongside.

3. **Installation and Usability Evaluation**

   The installation process was assessed positively in the field. The setup procedure, comprising connecting the battery's positive wire and activating a single switch, required no electrical or technical expertise, as simplification is important for smart-farm technology adoption [16].

4. **Real Farm Data Collection**

   Remote data collection and observation were conducted following trap activation. The trap's camera captured photographs of the lure and sticky board at regular intervals for AI analysis, and the onboard sensor array transmitted expected environmental and system telemetry data to a cloud dashboard. Consistent with smart-agriculture IoT systems that combine sensing, monitoring and networked data transfer, the prototype transmitted trap imagery and operational telemetry to a cloud dashboard [21]. Data reported included CPU and memory usage, cellular signal strength, trap and electronics temperatures, humidity, air pressure, ambient light, battery health and voltage, power consumption, and cooling fan metrics.

Additionally, AI analysis identified one false positive (refer to Table 3 below) in week 4 of the trial.

Bug Activity Dataset Summary

The following is a summary of the collected data during the observation period.

Measurement of the lure and the board's effectiveness for spotting-bug attraction was out of scope for this project. While the trap's electronic and engineering performance showed nominal conditions, no BSB were captured with the sticky board during the observation period. BSB activity and capture rates may vary with seasonality, spatial distribution and host/canopy context [17, 18]. This result should be treated as inconclusive for lure-assisted end-to-end pest-detection performance.

Week	Date Range	AI Smart Camera Health Metrics	AI Smart Camera Identified BSB Count on Trap	Manually Observed BSB Count on Trap	AI Smart Camera Identified False Positives on Trap	Manually Observed False Positives Count on Trap
1	16/02/26 – 22/02/26	Nominal	0	0	0	0
2	23/02/26 – 01/03/26	Nominal	0	0	0	0
3	02/03/26 – 08/03/26	Nominal	0	0	0	0
4	09/03/26 – 15/03/26	Nominal	0	0	1	1
5	16/03/26 – 22/03/26	Nominal	0	0	0	0
6	23/03/26 – 29/03/26	Nominal	0	0	0	0
7	30/03/26 – 05/04/26	Nominal	0	0	0	0
8	06/04/26 – 12/04/26	Nominal	0	0	0	0
9	13/04/26 – 19/04/26	Nominal	0	0	0	0
10	20/04/26 – 26/04/26	Nominal	0	0	0	0

Table 3: Observed bug activity on lure and sticky pad

Discussion Points

Stage 1

The observed +10.7% precision improvement after full-dataset training is consistent with computer-vision evidence that larger training datasets can improve model performance [22]. Using standard metric interpretations, the observed high recall and high precision indicate that the model detected most labelled bugs while minimising false alarms [6, 20]. This balance is a critical requirement for practical deployment. These results provide strong evidence that our approach was technically feasible and ready for progression to Stage 2, where practical deployment considerations were addressed.

Stage 2

The field trial provided critical insights into both the strengths and limitations of the current prototype.

1. **Lure and Sticky Board Effectiveness Observation**

   The effectiveness of the lure and sticky-board system in capturing BSB was the primary operational challenge encountered during the trial. Despite the trial being conducted during the avocado season, no BSB were captured on the sticky boards over the monitoring window. The sticky-boards were observed to lose their adhesive effectiveness rapidly, generally within a few days under real-world field conditions, necessitating frequent replacement.

   It should be noted that, as a commercial farm, the trial farm was subject to a fortnightly spray programme to reduce pest damage, which may have contributed to the absence of observable bug activity in the vicinity of the trap [23]. The only activity detected was one false positive. This was physically the only bug (of any kind) found on the sticky-boards. While BSB and FSB remain the primary focus, further screening of non-target pests potentially improves smart-trap performance.

   The smart-trap and its AI camera, electronics, and remote-communication subsystems all operated as designed. The absence of captures should therefore be treated as inconclusive. Plausible contributing factors include seasonal activity, lure performance, trap placement, pesticide pressure, climate, weather conditions and sticky-board performance [17, 18].

   As a consequence, end-to-end validation of the smart trap's pest-detection performance under genuine field-trial conditions remains inconclusive. Further field trials spanning multiple seasons, lure placements, and multiple trial sites are recommended as future research.

2. **Trap Placement Optimisation Observation**

   Despite external spraying, observations during the field visits revealed that fruit located within the tree canopy exhibited spotting damage consistent with BSB activity. The farmer's feedback indicated that spray applications are directed to the exterior of the canopy, potentially leaving fruit within the interior susceptible to pest damage. The farmer recommended that future iterations of the trap be positioned within the canopy, ideally mounted from or closer to the tree trunk, where greater bug activity is expected. Such placement may also reduce direct exposure of sticky boards to sunlight and heat, factors that may contribute to adhesive degradation [24].

3. **Solar and Power Supply Monitoring**

   The solar panel, mounted atop the trap at approximately two metres in height, was found to be susceptible to shading from the surrounding tree canopy. Additionally, extended periods of overcast weather, characteristic of the region, resulted in insufficient solar charging and intermittent power loss to the trap. This identified the need for design improvements to the power system, including consideration of a larger solar panel, a detached panel installation at the end of tree rows (requiring approximately 20–25 metres of low-voltage wiring), optimisation of electronics to reduce power consumption, and the potential use of a higher-capacity battery. The prototype's battery size was kept at 100 Wh to remain within the small lithium-ion battery threshold used by many air-freight and postal/courier services to reduce dangerous-goods shipping restrictions [25]. Batteries above 100 Wh generally fall outside the simplified lithium-battery provisions and may need to be shipped as regulated dangerous goods with additional packaging and regulatory requirements, thereby increasing overall unit cost. [26, 27].

4. **Device Installation and Usability Feedback**

   Feedback on the installation process was sought from the farmer to assess the ease of setup from an end-user perspective. The overall feedback was positive. Set up required only connecting the battery's positive wire and activating a power switch, which was viewed favourably as it does not require any electrical or technical knowledge. Once activated, the trap could be monitored entirely remotely. Therefore, a similar setup can be encouraged in future projects. This design direction aligns with research on smart-farming technology adoption, which shows that ease of use is an important factor [16].

In addition, the following suggestions for future improvements were noted:

1. The total weight of the assembled prototype is excessive, primarily due to the heavy-duty metal fabrication used in the current prototype.
2. A mounting template could be provided to simplify attaching the trap to star pickets.
3. The lure mounting system would benefit from a clipboard or bracket mechanism to facilitate quick and easy swapping of sticky boards. While the OCP kits are supplied with replaceable sticky paper [8], farmers reported that applying this paper is time-consuming. Replacing the entire corrugated (corflute) sticky pad was found to be faster and more convenient.

Outputs

A summary of the final outputs generated by each Stage is listed below.

Output	Description	Detail
Stage 1		
Spotting bug detection AI model	AI model that identifies and counts spotting bugs with controlled-test detection performance above the 80% target. The model achieved a 93.8% balanced detection score.	The source code and algorithms used to generate the model have been submitted to Hort Innovation as part of milestones MS107 and MS113.
Stage 2		
Smart trap prototype	Self-contained, solar-powered, cellular-connected smart trap built around a single-board computer (SBC), with a high-resolution agricultural camera, a LiFePO4 battery and on-device telemetry.	Bill of materials, electronic component diagram, API specification, source code delivered to Hort Innovation.
Smart trap prototype field deployment	Deployment and 10-week field trial (with a 10 week observation window) on a commercial avocado farm in North Queensland.	The prototype was deployed on a farm in the Mt Garnet area, Tablelands Region, North Queensland, in collaboration with Australian Produce Partners. Data collection and findings are documented in this report. Insights gathered are informing the next phase of hardware and deployment improvements.
Trap firmware / on-device application	Application running on the trap under a managed device operating system, covering capture, queue, uploader, telemetry and hardware controllers.	Firmware source code delivered to Hort Innovation.
Cloud-based monitoring dashboard	Centralised dashboard receiving photographic and sensor telemetry data from the deployed trap for remote analysis.	Dashboard operational throughout the trial. Access is currently limited to the project team. The URL is retained in the project record, although the live service may not remain available after the project closure period. Source code delivered to Hort Innovation.

Output	Description	Detail
Farmer installation and usability feedback	Qualitative feedback from the farmer and field partners on the installation process and usability of the trap system. Intended audience: project team and hardware designers.	Feedback was gathered during the trial and through on-site visits. Key findings relate to unit weight, mounting ease, and lure board replacement. Recommendations have been incorporated into the improvement roadmap for future, and shared with Macquarie University as well as the Project Reference Group.

Table 4: Outputs summary

Recommendations

Banana and fruit spotting bugs cause some of the biggest economic damage seen in Australian horticulture, with reported crop losses of up to 90% in green fruit production and significant annual losses in macadamia. Conventional pest monitoring is labour-intensive and slow to respond, and growers have few practical tools for early, accurate detection.

Using AI for pest monitoring offers a major opportunity to advance the field. The Stage 1 work in BY23000 showed that an AI model can identify the target pest species with high accuracy, and Stage 2 showed that the supporting hardware and cloud back-end can be built and deployed in the field. The remaining challenge is to turn the validated technology into a tool that consistently captures and detects BSB under real farm conditions.

Extended Field Trial Recommendations

The most important recommendation from this project is an extended field-validation programme, given the urgency for a solution and potential benefits to Australian horticulture. The 10-week Stage 2 trial returned no BSB captures, and the underlying cause cannot be confidently attributed. The result could reflect seasonal pest activity, the host farm's fortnightly spray programme, the rapid loss of adhesive on the OCP boards, the trap's placement on the outside of the canopy, or other unknown factors [17, 18, 23, 24]. Until these external factors are tested, the smart-trap's end-to-end pest-detection performance remains inconclusive. Repeat trials are essential before any wider rollout to industry.

Future trials should consider;

1. **Subsequent Multi-season Trials**

   Notwithstanding the engineering completeness of Stage 2, the overall results of the BSB capture trial are inconclusive. We recommend an extended field-validation programme that focuses specifically on, extended multi-season trials and lure batches to reduce reliance on seasonal factors.

2. **New Lure Comparison Trials (Macquarie University)**

   Once the new potential BSB lure formulation under development at Macquarie University is available for trials, a follow-up field trial is recommended. Both the current OCP lure and the proposed new lure could be trialled simultaneously to reduce cycle time.

3. **Trial Site Selection**

   Future field trials should consider deploying the trap on farms where the spraying programme can be adjusted or paused in the immediate vicinity of the trap, to provide a clearer assessment of lure effectiveness and BSB capture rates independent of pesticide suppression.

4. **Trap Placement Strategy**

   Future deployments should investigate positioning the trap within the tree canopy, ideally mounted from the tree trunk, where greater BSB activity has been observed. This approach may also extend the effective life of sticky boards by reducing their exposure to direct sunlight and heat.

5. **Weather Considerations on Farm Sites**

   Different areas in Queensland can have varying climate and weather conditions. For example, the Mt Garnet area is at a high altitude and would experience different conditions than a low-altitude area. The trap electronics already have on-board sensors capable of accurately monitoring these climate conditions as they change.

Trap Hardware Improvement Recommendations

The following improvements are recommended for future iterations of trap hardware.

1. **Power System Improvements**

   The solar charging capacity should be increased to accommodate extended overcast periods typical of tropical

North Queensland.

Options to evaluate include:

a. Installing a larger solar panel;
b. Detaching the solar panel from the trap and locating it at the end of tree rows with approximately 20–25 metres of low-voltage buried wiring; and
c. Redesigning the electronics to minimise power consumption and conserve battery capacity.
d. The feasibility of a higher-capacity lithium battery should also be assessed, noting that batteries exceeding 100 Wh introduce additional regulations.

2. **Trap Weight Reduction**

   The heavy-duty metal fabrication of the current prototype should be reviewed with a view to reducing the overall weight of the unit, thereby improving portability and ease of installation in the field.

3. **Mounting and Installation Aids**

   A mounting template should be developed and included with future kits to simplify attachment to star pickets. A clipboard or bracket system should be incorporated into the lure mounting assembly to enable rapid swapping of sticky boards.

AI Model Improvement Recommendations

The current AI model performs well under lab conditions for spotting bug detection. Further improvement steps would be:

1. **Incorporate Negative Dataset**

   Integrate the images of other bugs that were collected but not used in the interim and final models. This can help the model better distinguish between target bugs and other insects, likely reducing false positives in in-field applications. However, at this stage we recommend deferring this work until false positives under farm conditions are verified. With no BSB captures from the Stage 2 trial yet, the model has not been tested under the conditions where false positives would matter most, and re-training without that real-world feedback would be premature. The recommended sequence is to complete the next field trial first, capture genuine in-field imagery and any false-positive events, and then re-train the model using both the negative dataset and the new field-collected data.

2. **Data to Model Feedback Loop**

   Although the current dataset proved sufficient for establishing proof of concept, additional data reflecting real-world on-farm conditions should be collected in Stage 2 to ensure robust performance in diverse scenarios. This can contribute to improved model detection in challenging conditions such as low light.

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- **Mary Burton**
  Formerly RD&E Coordinator, Avocados Australia
- **Dr. Soo Jean Park**
  Research Group Leader, Macquarie University
- **All Project Reference Group Participants**

Intellectual property

Below is a summary of the IP for MS190. Full details are listed in the IP Register attached to the milestone submission.

Pre-existing IP:

1. Open-source software licences, libraries, and source code used towards the final software
2. Elegant Media's pre-existing software, architecture, and source code are supplied as a foundation for software development
3. Foundation Model Weights for Computer Vision

IP Created:

1. Computer Model for Spotting Bug Identification
2. Source Code for Banana and Fruit Spotting Bug Identification Model Generation
3. Labelled and Segmented Dataset for Banana Spotting Bug Identification
4. Labelled and Segmented Dataset for Fruit Spotting Bug Identification
5. Evaluation Results from the Banana and Fruit Spotting Bug Model
6. Smart Agricultural Pest Trap – Electronic Component Diagram
7. Smart Agricultural Pest Trap – API Specifications
8. Web application, including infrastructure and backend
9. Smart trap/camera unit fabrication, including 3D models, component placement, metal housing, mounting system specs, battery risk safety evaluation, internal arrangement of components and sensors - including waterproofing, ventilation and component health monitoring.
10. Trap firmware / on-device application source code (Firmware application incl. capture, queue, uploader, telemetry, hardware controllers)

Appendices

Appendix A

Dataset Sources

Stage 1

Our datasets consist of:

- 1,777 images collected through farm visits and collaboration with Macquarie University.
- All images were manually labelled by our team to ensure accuracy.
- An additional 3,464 images from an open-source dataset of similar-looking bugs have been collected as negative examples, but was not incorporated into the model training as it was not required to reach the target metrics.

Data Preprocessing

Each image underwent several preprocessing steps:

- Auto-orientation to ensure consistent image positioning
- Resizing to 1024×1024 pixels with edge reflection to maintain important visual information
- All bug classes were consolidated into a single category called "spotting-bug"

Data Augmentation

To expand our training dataset and improve model robustness, we performed several augmentation techniques:

- Horizontal and vertical flipping to teach the model that bug orientation doesn't matter
- Rotation (15% of images) to simulate bugs viewed from different angles
- Grayscale conversion (15% of images) to reduce dependency on colour

These augmentation techniques expanded our original dataset from 1,777 images to 4,213 images (3,657 for training, 375 images for validation, and 181 images for testing).

Data Usage

- The curated dataset was split into training, validation, and testing sets, ensuring broad coverage of different scenarios. The final training utilised the entire refined dataset for maximum model performance.
- Although sufficient data were gathered to achieve our Stage 1 objectives, further collection efforts may be required in the future to fine-tune under real-world conditions.

Appendix B

Photo credits

Photo	Title	Taken By	Date Taken
Figure 1.1	Installation of Trap	Shane Perera, Elegant Media Level 1, Building 3 195 Wellington Rd Clayton VIC 3168 P: 1300 470 580 E: shane@elegantmedia.com.au	17 February 2026
Figure 1.2	Installation of AI/Camera system and Solar Panel Package		
Figure 1.3	Installed Lure and Board, and the AI Camera System		
Figure 1.4	Modified Trap Setup		
Figure 1.5	Camera Enclosure		