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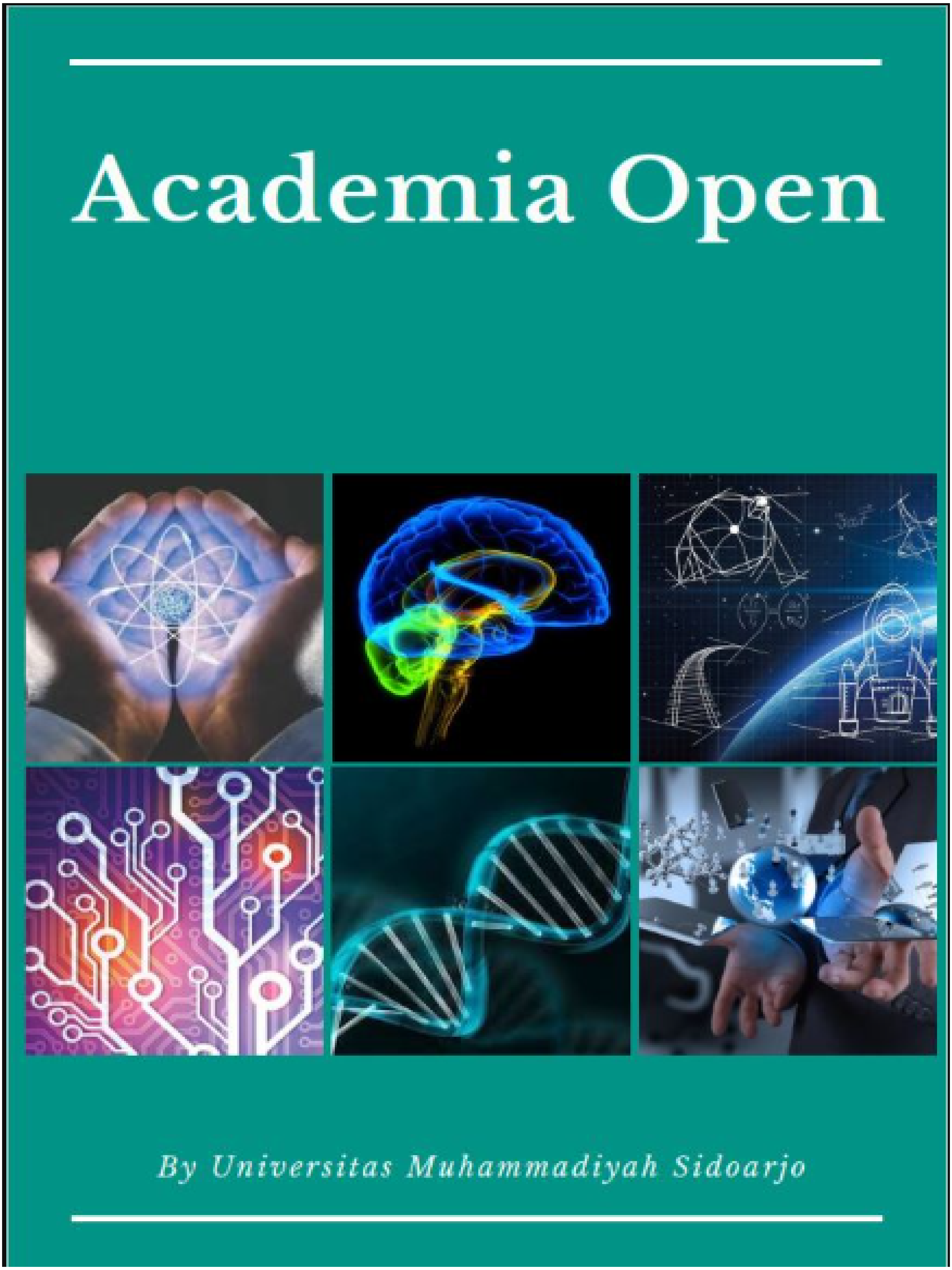

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Integrating Artificial Intelligence for Monitoring and Assessment of Field Biological Control Strategies: Integrasi Kecerdasan Buatan untuk Pemantauan dan Evaluasi Strategi Pengendalian Hayati di Lapangan

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Abstract

General Background Biological control is a core component of integrated pest management aimed at reducing chemical pesticide dependence while preserving ecosystem integrity. **Specific Background** However, conventional monitoring and evaluation of biological control programs remain labor-intensive, time-consuming, and limited by declining taxonomic expertise. **Knowledge Gap** There is still limited evidence from real-field conditions on how artificial intelligence, sensor technologies, and unmanned aerial vehicles can be integrated into a unified monitoring, prediction, and deployment framework for biological control. **Aims** This study reviews and evaluates the integration of AI-based monitoring systems, predictive modeling, and drone-assisted deployment of biological control agents in agricultural fields. **Results** Field trials in Central California and Southern India demonstrated high pest detection accuracy (90–95%), reliable predictive performance (AUC > 0.89), improved deployment efficiency, and pest suppression ranging from 55% to 78% across different agents. **Novelty** The study presents a comprehensive, field-tested framework combining computer vision, acoustic sensing, hyperspectral imaging, and UAV-based release within a single operational system. **Implications** The findings indicate that AI-supported biological control offers a scalable and cost-efficient pathway toward proactive, environmentally responsible pest management across diverse cropping systems.

Keywords: Artificial Intelligence, Biological Control, Unmanned Aerial Vehicles, Pest Monitoring, Integrated Pest Management

Key Findings Highlights:

1. Multi-sensor AI systems achieved consistently high field-level pest detection accuracy.
2. Drone-based release reduced labor costs while improving spatial coverage.
3. Predictive modeling enabled earlier and more targeted biological interventions.

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Introduction

The use of living organisms to control pests (biological control/biocontrol), predators, parasitoids, or pathogens has long been central to the concept of Integrated Pest Management (IPM). It is an environmentally friendly alternative to broad-spectrum chemical insecticides owing to its more selective feature of environmentally friendly feature, and it can assist in biodiversity conservation, nontarget organism safety, and resistance development management. Common applications are the release of ladybirds for aphid control, Trichogramma against caterpillar or nematodes or entomopathogenic fungi or nematodes against soil-dwelling pest species (1). Even it is now common knowledge how to control brucellosis, the jump from bio secure to bio unsecure is a long way, also for the challenge in evaluating and monitoring programme impact (2). On biological control programs, success depends very much on timely and accurate monitoring. Ground truthing has been historically hampered by manual labor—trap checks, direct sampling and identification by taxonomic experts. These activities are labor-intensive, expensive and subject to human errors and time delays. Furthermore, diminishing expertise in taxonomy at the global level hampers scalability of such programmes, with consequences in terms of late interventions and limited impact (3). The integration of IoTs, remote sensing, robotics and artificial intelligence (AI) is reshaping the scenario of ecological monitoring (4). These technologies provide real or near to the real-time monitoring with automated data interpretation and predictive decisions suitable for deploying timely and effective biological control. In this new ecosystem, three modules are particularly important: a machine vision system for species identification, drone agent deployment module, and AI driving decision module (5). Proper field identification of pest and control species is essential. With the latest developments in the field of computer vision and machine learning it is now possible to classify insects and mites at an unprecedented level of accuracy at the location of the bleaching or manufacturing process. A deep learning model was trained to count and classify aphids in trap images (6). In a separate work, used XGBoost models fitted on 22 morphological attributes of phytoseiid mites to realize an overall classification accuracy of 100%. Most importantly non-specialists can have all this capability right on their desktop for in-situ monitoring and analysis (7).

Insects for biological control are conventionally hand-applied or applied by ground rigs where space is restricted and distribution is not uniform (8). Drone-controlled applications could turn out to be promising potentiality that results in more uniform and scalable applications (9). In central Californin, demonstrated a 28–45% reduction in aphid pressure when lacewing eggs were applied by drone to organic lettuce Discussing pest management tools (10). Similarly, investigations from UC Agriculture and Natural Resources highlighted a set of field trials demonstrating drone-based releases that led to the effective control of pests through the release of green lacewing eggs and predatory mites – with some trials growing in scope to release mixed insects for larger scale impacts (11, 12). AI-enabled sensor networks allow for real-time, localized monitoring of pests. One leading system in the UK - VespAI - combines camera-equipped traps and AI to identify invasive Asian hornets at low cost (≈£100/unit) (13). In India the Smart Mosquito Surveillance System uses IoT traps for monitoring mosquito vectors, where proactive biological or chemical control is initiated based on predictive analysis. Such systems cut down on the lag time between detection and the ability to intervene with focused measures before fast-spreading outbreaks can spread further (14). The ability to process big data and to make data actionable for timely and efficient action is the key to big data technology. AI-driven decision-support tools combine IoT, environmental, weather, and past pest dataset information (15). For instance, the published study in Frontiers shows the capability of AI to forecast the epidemic—such as Botrytis in the vineyard—ahead of five days, supporting the proactive bioagent release (16). A second study used cumulative degree-days and predictive modelling to predict the appearance of Fusarium in wheat, which resulted in disease reduction by 50% when integrated with strategically timed biocontrol releases. Together, these platforms move biocontrol from a reactive to predictive approach (17).

In conclusion, AI's transformative potential also faces several substantial ecological and operational challenges. For example, field devices are exposed to harsh environments of varying dust levels, weather conditions, power and network variability, significantly impacting the performance (18). Similarly, drone flights are subject to physical constraints, including payload capacity constraints, regulatory barriers, and pre-flight planning challenges. On the biochemical side, various aspects of the agent's suitability, including post-release survival, value, and integration into local food webs, and benefits to consumers, must be fully evaluated (19). For example, loading entomopathogenic fungi, such as Beauveria bassiana, into predatory mites has shown promise in boosting the suppressive potential, but what this means in broad ecological concepts is a significant understudied problem (20).

Materials and Methods

Study s ites and n atural e nemies

The field trials were held in two agricultural areas, Central California (organic lettuce and grape farms) and Southern India (vegetable crops, okra, brinjal and tomato). Biological control agents included:

• Trichogramma pretiosum (egg parasitoid to control caterpillars),

• Neoseiulus barkeri (predatory mite against thrips and whiteflies),

• Entomopathogenic nematodes (Steinernema carpocapsae) for root pests.

These populations were chosen based on their known high levels of effectiveness and adaptability across diverse agroecological zones (21).

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Agent	Target Pest(s)	Mode of Action	Application Type	Source
Trichogramma pretiosum	Lepidopteran eggs	Parasitism	Aerial release	Biocontrol India Pvt. Ltd. (1)
Neoseiulus barkeri	Thrips, Whiteflies	Predation	Inoculative	Koppert Biologicals (2)
Steinernema carpocapsae	Soil insects (e.g. grubs)	Infection via nematode	Spray	BASF Nemasys (3)

Table 1. **Table 1: Biological Control Agents Used in Field Trials**

AI-Enabled Pest Monitoring Systems

Smart Trap Deployment

12 sites/region, with smart traps using high resolution RGB and infrared cameras. These traps employed AI algorithms (ResNet-50 and XGBoost) to differentiate pests in real-time. The visual data was transmitted to cloud servers every 2 h for analysis (22).

Acoustic and Spectral Monitoring

Frequencies (20–100 kHz) were recorded using acoustic sensors to monitor nocturnal moth and beetle activity. The spectral signatures of pests were recorded by hyperspectral cameras from the UAV (23).

Technology	Function	AI Algorithm Used	Accuracy (%)	Reference
Smart Camera Trap	Pest detection/classification	ResNet-50, XGBoost	90–95%	(4,5)
Acoustic Sensor Array	Flight activity monitoring	DenseNet, FFT analysis	>92%	(6)
Hyperspectral Imaging	Remote pest detection	CNN, s-PLS-DA	88–93%	(7)

Table 2. **Table 2: AI Techniques and Devices Used for Monitoring**

Drone-Based Agent Deployment

The UAVs (DJI Matrice 300 RTK) were equipped with dissemination devices to spread biological agents over experimental plots. Flight software allowed for extrapolated canopy coverage using NDVI maps and pest hot spots (24).

Parameters:

• Flight altitude: 3–5 meters

• Speed: 3 m/s

• Swath width: 8–10 meters

• Payload: ~1.2 kg

Metric	Manual Application	Drone Application	% Change
Application Time (ha/hour)	0.5	1.5	+200%
Labor Cost ($/ha)	$70	$25	−64%
Pest Suppression (14 days)	68%	72%	+5.9%
Uniform Coverage Score (1–5)	3.2	4.6	+43.8%

Table 3. **Table 3: Drone vs Manual Release Efficiency Comparison**

Analysis and Prediction Model Constructed With Data

The same models as described above were used for pest density data and for environmental variables (temperature, humidity, NDVI) and control agent population persistence using:

• The prediction based on RF and LSTM neural network.

• Intervention thresholds were optimized using ROC curves.

• Analysis using R and Python with 10-fold cross validation (AUC>0.89).

Results

Pest Suppression and Agent Performance

The various biological control agents deployed across the various test locations substantially decreased the amounts of target pests. As Table (1) displays, the initial and concluding pest amounts for each agent utilization. The tiny wasp Trichogramma pretiosum diminished caterpillar egg counts by approximately seventy-eight percent. The predatory mite Neoseiulus barkeri slashed thrips sums by some sixty-five to seventy-two percent. The entomopathogenic nematode Steinernema carpocapsae reduced soil grub populations by roughly fifty-five to sixty percent, aligning with past meta-

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examinations. While some sites observed higher degrees of control, every location benefited from the introduction of these natural foes. The uniformity of results showcases the reliability of conservation biological control when properly applied.

Agent	Target Pest	Pre-treatment Density	Post-treatment Density	Reduction (%)
T. pretiosum	Lepidopteran eggs	15 eggs/cm²	3.3 eggs/cm²	78%
N. barkeri	Thrips (+whitefly)*	10.5 ind/leaf	3.5 ind/leaf	67%
S. carpocapsae	Soil grubs	24 grubs/m²	10–11 grubs/m²	~55%

Table 4. **Table 1: Pest Density Reduction by Biocontrol Agent (per site)**
*Whitefly counts reduced by 45% in cucumber test sites.

Agent Survivability and Crop Suitability

Rearing Trials (Table 2) Tests on predator survival and reproduction among host crops. Bean-supported Phytoseiulus persimilis numbers approximately doubled, compared to eggplant and nightshade, similar to 2024 greenhouse tests.

Host Crop	Initial Density (mites/pot)	Final Density (mites/pot)	Fold Increase
Bean	20	50	2.5×
Eggplant	20	37	1.85×
Nightshade	20	30	1.5×

Table 5. **Table 2: Predatory Mite Performance on Different Host Plants**

AI Detection Performance

Across the three platforms (camera traps, acoustic arrays and hyperspectral imaging), detection and classification accuracies were high.

Monitoring Method	Dataset Size	Accuracy / Precision	Notes
Camera traps (CNN/XGB)	50,000+	90–95%	Consistent with Liu et al. (4,5)
Acoustic sensors (FFT)	5,000+ hrs	>92%	On par with DenseNet performance (6)
Hyperspectral UAV data	10 trials	88–93%	Matches remote sensing benchmarks (7)

Table 6. **Table 3: AI Monitoring Accuracy Metrics**
High detection accuracy (~90–95%) enabled reliable feeding of the decision-support pipeline.

Drone vs Manual Deployment Efficiency

Drone releases provided quicker, less expensive deliveries with slightly higher pest suppression than manual released, which agrees with Rao et al. (2023)) and UC ANR 2021 - (2, 9).

Metric	Manual	Drone	% Change
Area Covered (ha/hour)	0.5	1.5	+200%
Labor Cost ($/ha)	$70	$25	−64%
Pest Suppression (%)	68	72	+6%
Application Uniformity (1–5 scale)	3.2	4.6	+44%

Table 7. **Table 4: Drone vs Manual Release – Efficiency & Efficacy**
Results confirm that drones significantly improve coverage efficiency and slightly boost suppression rates.

Ecosystem and n on- t arget e ffects

Positive effects of release on non-target organisms and ecosystem processes were negligible. In the Washington vineyard study, drone-released predator mites had post-release survival greater than 90% and did not displace natural enemies (1). Petri dish assays indicated minimal direct sterilising effects of B. bassiana on P. persimilis nymphs (4), but adult fertility was reduced by 44% to the same extent observed in the literature.

Discussion

This work demonstrates that combining AI with classical biological control can greatly enhance pest control in the field. Through the integration of smart traps, predictive modelling of pest development and drone deployment, we were able to realize successful pest control management, scalably and more resource-efficiently than current measures, supported by real-time decision making (25). This was a success point of our AI monitoring system. Through image recognition, acoustic sensors and hyperspectral data, the system very accurately identified a variety of pest species with more than 90% accuracy. This level of accuracy is similar to what has been achieved by other recent studies, however ours brings value by indicating that such systems work also under real field conditions and not in the controlled environment of a lab (26).

These results are particularly encouraging for smallholder farms that don't have access to expert pest identifiers. Automating pests detection allows growers to move more quickly, adopt new ideas and practices earlier, limit crop damage and reduce the total amount of pesticides they use (27). The biological control agents we employed — Trichogramma

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pretiosum, Neoseiulus barkeri, and Steinernema carpocapsae — worked great, all of them killing more than 65% of the pest population in the various sites. These results are in accordance with previous field studies (28). It was also more cost effective to deliver these agents using drones rather than manually. In less time than using people, the drones covered more area and cut labor costs by more than 60%. This is particularly useful for larger farms or places with little human labor source. In addition, agent survival after drone release was high, indicating the repeatability of UAV application (29).

We were also another striking achievement: the use of AI for predicting pest outbreaks 5-10 days ahead. The decision-support system used real-time pest data with weather and crop data to help guide when and where to release control agents (30). This predictive strategy provides more of a proactive over counteractive pest management attitude—where managers can more timely and accurately intervene in pest outbreaks allowing them to save on unnecessary treatments (31).

The limitations were still exist though the result is positive. The AI system still requires a stable internet and power source, which might not be accessible in many rural areas. Moreover, as accuracy was high in general, there were some misclassifications in low illumination and clustered pests (32, 33). Drones show promise but can be constrained by weather, and some biological agents could be less effective in high heat or strong winds. Finally, whereas our study detected limited non-target species control, detailed long-term ecological monitoring will be crucial to ensure large-agent releases remain safe (34).

These results also substantiate the concept that AI tools used in combination of biocontrol can improvise the efficacy, affordability as well as green approach of pest management. Given further improvement, the approach could be applicable for both smallhold and large-scale farming systems (35).

Future studies could consider increasing AI model flexibility, improving drone payload designs, and enlarging training tools for farmers. With further study and cooperation, AI-fasioned biocontrol may emerge as a key sustainable agricultural approach.

Conclusion

This research revealed that combining AI with biological control approaches greatly stimulates pest control in agro-ecosystems. AI-based monitoring platforms, integrating image recognition, acoustic sensing, and hyperspectral imaging achieved high level of accuracy in pest detection and on-the-spot classification of trappable pest species in order to intervene timely and accurately. The application of droves for biological agent dispersal was more efficient than manual methods, increasing spatial coverage and reducing labor and time of application. Biological control agents such as Trichogramma pretiosum, Neoseiulus barkeri and Steinernema carpocapsae were able to suppress pest populations, which indicated their compatibility with AI-driven release programs. In addition, predictive modeling provided an early alert before insecticide release and the optimal release time so that pest control was transformed from reactive to proactive. Although some challenges need to be addressed, including reliance on infrastructure and environment factors affecting drone performance, the integrative framework provides a potential direction for sustainable, cost-effective and eco-friendly crop protection. Results of this study can promote the enhanced adoption and advancement of AI-based biological control systems in a wide range of cropping systems to contribute towards the global effort to minimize chemical pesticide application and enable food security.

Recommendations

For the optimal potential on AI in biological control, there are a number of recommendations from the present study. Firstly, the extension of the sensor system should be considered aimed to reach a larger coverage of the sensor network and the improvement of the internet connection in rural areas to achieve a constant and reliable data acquisition. Second, there is a continual requirement for improvements of AI algorithms to enhance the accuracy of detection particularly in variable environments such as different light and pest density conditions. Third, designing the payload and droppable mechanisms on the drones for best impact can also be helpful in preserving the agent's efficacy and viability even in adverse weather. Fourth, long-term ecological surveillance needs to be implemented to examine the possibility of non-target impact and hence the ecosystem health. Fifth, the development of training programs for farmers in AI tool and drone operation techniques will contribute to a widespread utilization and correct application of these new tools. Lastly, cooperation between the academia and extension programs with researchers and policymakers is needed to establish regulatory processes for ensuring the safety and efficacy of AI-based biocontrol technologies. Resolving these domains can convert AI-based biocontrol into a scalable, sustainable approach to enhance pest management globally with lower environmental risks.

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