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ARTIFICIAL INTELLIGENCE IN PEST DETECTION AND CONTROL: INNOVATIVE SOLUTIONS FOR AGRICULTURAL PESTS

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ABSTRACT & KEYWORDS

Crop pests threaten yield, quality and food security. Conventional visual inspections, manual trapping and routine chemical control can be slow, labor-intensive and environmentally burdensome. This qualitative review examines AI applications in pest identification, monitoring, forecasting and control, including machine learning, deep learning, computer vision, IoT sensors, automated traps, UAV imagery and predictive analytics. These tools can turn images and environmental observations into more frequent monitoring and decision support. Their value depends on representative labelled data, field validation, biological interpretation and integration with Integrated Pest Management (IPM). High investment, limited infrastructure, data gaps and specialist skills remain barriers. AI is therefore a decision-support layer—not an automatic replacement for field verification or expert judgement.

KEYWORDS Artificial Intelligence • agricultural pests • pest detection • machine learning • precision agriculture

1 INTRODUCTION

Agricultural pests damage plant tissues, reduce photosynthetic capacity and affect crop quality across cereals, vegetables, fruits and industrial crops. Climate change, globalization and intensified production can alter pest development, reproduction, migration and geographical distribution.

Traditional visual inspections, trapping and chemical or biological measures remain important, but large fields, uneven pest populations and similar damage symptoms make early identification difficult. Excessive pesticide use can contaminate soil and water, harm non-target organisms and contribute to resistance.

Integrated Pest Management (IPM) combines prevention, monitoring, biological knowledge and targeted intervention. AI can strengthen the information base for these decisions.



Illustrative pest image with detection frame

2 MATERIALS AND METHODS

Qualitative, descriptive and analytical assessment of scientific literature and relevant case studies. The paper compares technological capabilities, potential agricultural applications, environmental implications and implementation barriers. No original pest sampling, field experiments, image-dataset construction, AI model training or pesticide trials are reported. The manuscript also notes that a final systematic review should specify databases, search dates and publication-selection criteria.

SIX ANALYTICAL DIMENSIONS

01 Automated identification
ML and deep-learning classification of pest species.

02 Image-based monitoring
Cameras, automated traps and UAV observations.

03 Intelligent sensors
IoT measurements of environmental conditions.

04 Predictive modelling
Weather, crop phenology and historical pest records.

05 Precision control / IPM
Decision support for targeted, threshold-based action.

06 Technological access
Costs, infrastructure, datasets, skills and validation.

EVALUATION CRITERIA

Detection reliability | Monitoring efficiency | Predictive usefulness | Environmental relevance | Implementation feasibility

AI-TO-IPM DECISION PATHWAY

01 CAPTURE — Images, traps, UAV, sensors, weather

› **02 PROCESS** — Image analysis, feature extraction

› **03 ANALYSE** — ML / DL, detection, risk estimation

› **04 VERIFY** — Field check, pest ID, threshold assessment

› **05 ACT** — IPM choice, targeted intervention if justified

INTERPRETATION RULE • DETECTION IS NOT AN AUTOMATIC TREATMENT SIGNAL

- **Pest presence ≠ economic damage.** Detecting an insect does not by itself show that crop protection is required.
- **Trap counts need context.** Captures depend on trap design, attractants, weather, placement, maintenance and pest behaviour.
- **Crop stress is not pest-specific.** UAV imagery can flag anomalies caused by drought, nutrient deficiency, disease or pests; field verification is essential.
- **IPM sets the decision.** Pest identity, abundance, crop stage, economic thresholds, beneficial organisms and regulations must guide intervention.

3 RESULTS & DISCUSSION | AI TECHNOLOGY LANDSCAPE

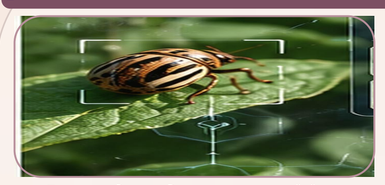


Image-based pest recognition



Camera-enabled smart traps



UAV and remote sensing

Machine learning / deep learning
Classifies selected pest categories from labelled data; image models learn visual patterns and can support automated recognition.

Computer vision
Detects, localizes and counts insects in photographs; performance can fall under shadows, blur, occlusion and complex backgrounds.

Intelligent traps + IoT
Cameras, sensors and connectivity can increase observation frequency and transmit insect images and environmental measurements.

Predictive analytics
Combines temperature, humidity, precipitation, crop phenology and historical observations to estimate infestation risk.

Precision pest control
Spatial pest information can prioritize field checks and support targeted interventions within an IPM framework.

UAV / remote sensing
Aerial imagery maps vegetation anomalies and affected zones; it identifies stress patterns, not necessarily a specific pest.

COMPARATIVE OVERVIEW | CAPABILITY AND LIMITATION

Technology	Main capability	Key limitation / condition
Machine learning	Pest classification from labelled data	Needs representative, correctly annotated datasets
Deep learning / CV	Image detection, localization and counting	Sensitive to lighting, overlap, blur and similar species
Smart traps / IoT	Repeated observations and environmental data	Trap bias, calibration, connectivity and maintenance
UAV / remote sensing	Spatial mapping of crop-stress anomalies	Stress has multiple possible causes; verify in field
Predictive models	Early-warning estimates from climate + pest records	Uncertainty and limited transferability across regions
AI decision support	Combines evidence for precision IPM decisions	Requires expert interpretation and threshold logic

POTENTIAL BENEFITS & IMPLEMENTATION CHALLENGES

POTENTIAL BENEFITS

More frequent and scalable pest observations.
Earlier identification and risk-based monitoring.
Spatial prioritization of field inspections.
More targeted interventions within IPM.
Potential reduction of unnecessary pesticide use and non-target impacts.

CHALLENGES / LIMITS

High initial investment and operating costs.
Limited rural connectivity and digital infrastructure.
Need for diverse, labelled and reliable datasets.
Field variability can reduce model generalization.
Specialized expertise, maintenance and farmer training.

4 CONCLUSIONS

AI can complement traditional crop protection through automated identification, frequent monitoring and predictive risk assessment.

Machine learning, computer vision, intelligent traps, IoT and UAV imagery can improve the information available for field decisions.

Environmental benefits are conditional: reductions in unnecessary treatments must be demonstrated, not assumed from technology adoption.

AI should support IPM and expert judgement; detection alone does not justify pesticide application.

CORE CONDITIONS FOR RESPONSIBLE USE

VALIDATED DATA | FIELD VERIFICATION | IPM INTEGRATION

5 FUTURE RESEARCH DIRECTIONS

Develop robust, multi-species recognition models for varied crops, pest stages and field conditions.

Build diverse, open and correctly labelled image datasets with entomological validation.

Test systems under real conditions using precision, recall, F1-score, false-positive rate and detection speed.

Measure economic and environmental outcomes: pesticide use, crop losses, costs and effects on non-target organisms.

MODEL EVALUATION INDICATORS

PRECISION | RECALL | F1-SCORE | FALSE POSITIVES | DETECTION SPEED

STUDY SCOPE • Conceptual qualitative synthesis of literature and case studies; no original pest sampling, dataset construction, model training or field trials were conducted. Images are illustrative.