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Digital eyes in the field: Smart pest surveillance for farmers: Review

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Abstract
Pest and disease surveillance remains central to crop productivity and food security. Manual methods like scouting and traditional traps are laborious, time-intensive, and susceptible to error, often causing delayed interventions and excessive pesticide usage. Rapid strides in Artificial Intelligence (AI), Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), and remote sensing are enabling real-time, predictive, and integrated pest management solutions. This review covers the technological advances, benefits, adoption barriers, policy implications, and future research directions in smart pest surveillance—especially contextualized for Indian agriculture.

Keywords: Pest surveillance, Artificial Intelligence, IoT, UAV, remote sensing, precision agriculture, decision support systems

1. Introduction

Pest and disease outbreaks represent one of the most critical constraints to achieving global food security and sustainable agricultural productivity. The Food and Agriculture Organization (FAO, 2023) [8] estimates that approximately 20-40% of global agricultural yields are lost annually due to pests and diseases, amounting to hundreds of billions of dollars in economic losses. Such extensive damage not only undermines production efficiency but also threatens the livelihoods of smallholder farmers, particularly in developing economies where agriculture forms the backbone of national income and employment.

In India, where agriculture contributes nearly 18% to the national GDP and sustains more than half of the population, pest and pathogen-induced crop losses remain a major economic burden. Studies by Dhaliwal, Jindal, and Dhawan (2015) [7] revealed that the country suffers 25-30% yield losses annually due to insect pests, weeds, and diseases, equating to billions of rupees in economic losses across staple crops. For instance, the Fall Armyworm (*Spodoptera frugiperda*) invasion, first reported in India during 2018, resulted in a 45% decline in maize yields in affected regions (Prasanna *et al*., 2021) [37]. Similarly, the cotton bollworm complex (*Helicoverpa armigera*) continues to cause annual losses exceeding ₹1,500 crore, despite decades of integrated pest management efforts (Kranthi & Stone, 2020) [17]. Such outbreaks have far-reaching implications—not only reducing productivity but also influencing input costs, farmer profitability, export potential, and national food reserves.

Traditional pest surveillance techniques, including manual field scouting, pheromone trapping, and visual inspection, remain the primary methods adopted across Indian agriculture (Reynolds, Chapman, & Harrington, 2017) [41]. However, these approaches are labor-intensive, time-consuming, and spatially constrained, often producing inconsistent or delayed results. The inherent delay between pest emergence and detection allows populations to exceed the Economic Threshold Level (ETL), triggering indiscriminate pesticide use. This overreliance on chemical control contributes to pest resistance, resurgence, biodiversity loss, environmental contamination, and food safety concerns (Sharma, Singh, & Kumar, 2022) [19, 45]. Additionally, the increasing influence of climate change, characterized by rising temperatures, altered rainfall patterns, and shifting pest habitats, further complicates surveillance and management strategies, necessitating more adaptive and data-driven systems.

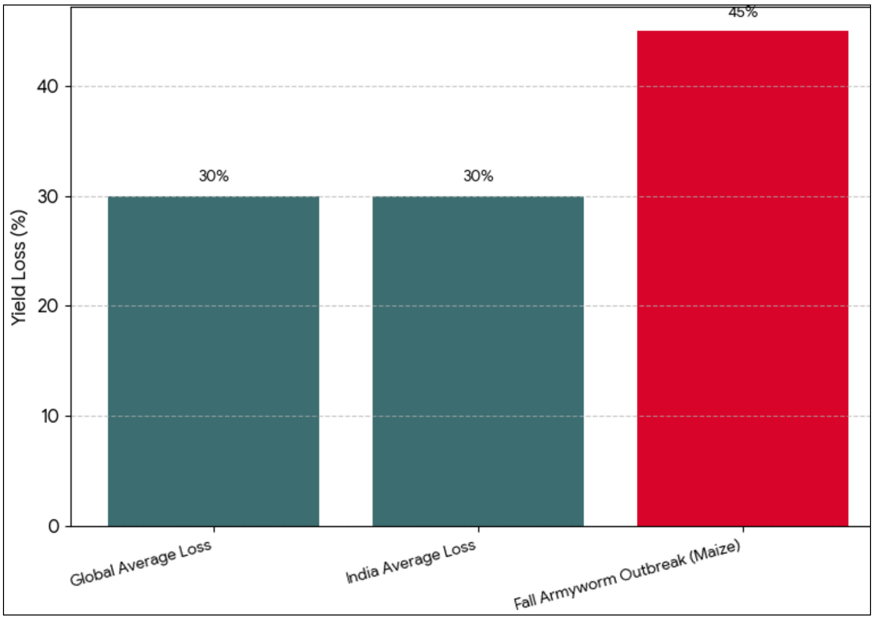


Fig 1: Crop yield losses from pests

In recent years, advances in digital agriculture and precision pest management have revolutionized surveillance methodologies. Technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), machine vision, and remote sensing have enabled real-time, automated, and predictive pest monitoring at various spatial and temporal scales. These systems facilitate early warning, dynamic threshold modeling, and climate-based pest forecasting, thereby improving the timeliness and accuracy of decision-making (FAO, 2023; Reynolds *et al*., 2017) [8, 41]. Integration of such technologies into Decision Support Systems (DSS) and Integrated Pest Management (IPM) frameworks allows for optimized pesticide use, cost reduction, and environmental sustainability (Sharma *et al*., 2022) [45].

Globally, and particularly in India, the transition toward AI-powered pest surveillance systems signifies a paradigm shift from reactive to proactive pest management. By combining field-level sensor data, satellite imagery, and machine learning algorithms, modern surveillance networks can detect, quantify, and forecast pest dynamics with unprecedented accuracy. These innovations hold immense promise in mitigating crop losses, enhancing food security, and promoting climate-resilient agricultural systems (Prasanna *et al*., 2021; Kranthi & Stone, 2020) [17, 37].

Hence, this review aims to comprehensively explore the evolution, principles, and applications of digital and AI-based pest surveillance systems, highlighting their role in strengthening sustainable pest management and supporting the long-term transformation of global and Indian agriculture.

Feature	Traditional Methods	Smart Technologies (AI/IoT/UAV)
Labor Required	High (manual scouting)	Low (automated sensors/cameras)
Detection Speed	Delayed (field symptoms only)	Real-time/predictive (remote sensing)
Accuracy	Variable, observer-dependent	High (AI analytics, imaging)
Pesticide Use	Often excessive, blanket spraying	Targeted, reduced applications
Coverage	Limited (plot/field-scale)	Scalable (village, regional, state)
Data Utility	Paper records, subjective	Digital, analyzed, mapped
References: Gupta *et al*., 2022; Mehta *et al*., 2024; Sharma *et al*., 2022; FAO, 2023 [8, 10, 27, 46].		

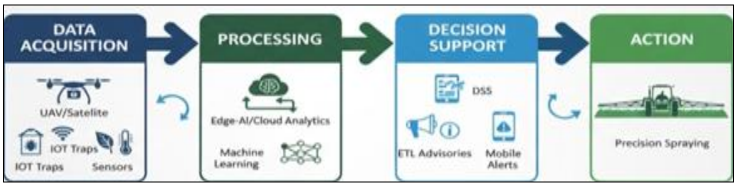


Fig 2: Conceptual framework of smart pest surveillance

2. Technologies for Smart Pest Surveillance

2.1 Trap-Based Camera and Sensor Systems

Recent advances in computer vision, edge computing, and wireless sensor networks have significantly improved pest detection accuracy and operational efficiency in agricultural landscapes. These systems integrate optical imaging, environmental sensors, and AI algorithms to autonomously identify, count, and classify pests, transforming traditional traps into intelligent surveillance tools.

The Smart Pest Guardian system (developed in Chennai, India) combines Convolutional Neural Network (CNN)-based image analysis with real-time data from temperature, humidity, and light sensors. This integration enables automated identification of bollworm species and dynamic prediction of population surges, outperforming conventional pheromone traps in accuracy and timeliness (Gupta *et al*., 2022) [10]. The system's cloud-based dashboard supports remote monitoring and facilitates data sharing for regional pest forecasting, a key component of precision Integrated Pest Management (IPM).

The BOLLWM dataset (Praveen *et al*., 2023) [38] represents one of the largest labeled pest image datasets from Indian cotton fields, collected under diverse climatic and lighting conditions. It supports deep learning-based bollworm recognition with enhanced robustness to field variability. This dataset underpins several mobile applications that allow farmers to capture trap images using smartphones for on-device pest classification using lightweight neural networks such as MobileNetV2 and EfficientNet-Lite.

Another notable system, Jute Pest Detect, applies transfer learning on pre-trained CNN models (ResNet-50, InceptionV3, and EfficientNet) to achieve multi-class classification of 17 jute pest species with 99% accuracy, even under complex backgrounds (Pramanik *et al*., 2023) [36]. This innovation contributes to adaptive IPM decision support by providing species-specific action thresholds and reducing pesticide misuse.

Beyond India, similar technologies are gaining traction globally. For instance, the iScout® Smart Trap (Plantix GmbH, Germany) uses solar-powered cameras and cloud-based AI to automatically record and analyze pest counts, while TrapView® (EFOS d.o.o., Slovenia) employs edge AI for real-time pest forecasting and alert generation. These global benchmarks emphasize the increasing relevance of AI-enabled trap systems in scalable and sustainable pest management frameworks.

Collectively, these technologies mark a transition from reactive to proactive pest control, where continuous surveillance, automated diagnostics, and data analytics support precision interventions, minimize chemical use, and enhance food safety.

2.2 UAV, Satellite, and Remote Sensing-Based Surveillance

The integration of Unmanned Aerial Vehicles (UAVs), satellite remote sensing, and advanced image analytics has revolutionized pest surveillance, enabling non-destructive, scalable, and real-time monitoring of crop health. These tools support early warning systems by identifying spectral signatures associated with insect and pathogen-induced stress, often before visible symptoms appear on the canopy.

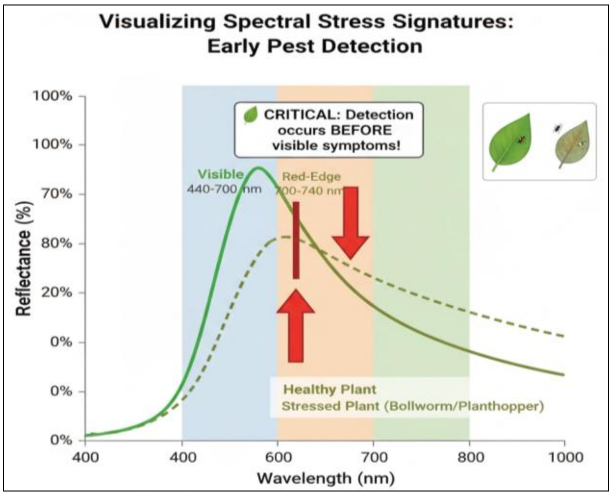


Fig 3: Visualizing Spectral Stress Signatures image

Early Detection Using UAV Hyperspectral Imaging

UAVs equipped with **multispectral and hyperspectral sensors** can detect subtle variations in reflectance across visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR) bands. Pests and pathogens alter the physiological state of plants—such as chlorophyll degradation, water imbalance, and changes in leaf structure—which modify their spectral response.

A landmark study in Ningxia, China, on *Lycium barbarum* (goji berry) plantations demonstrated the power of hyperspectral imaging for pest discrimination. Using UAV-borne sensors capturing 400-1000 nm spectral data, Sun *et al*. (2022) [53] developed a fully connected neural network (FCNN) that distinguished between healthy plants and those infested by gall mites and psyllids. The model achieved 96.8% classification accuracy, identifying red and NIR bands as the most sensitive regions for early stress detection. This approach allowed identification five to seven days before visual symptoms emerged, proving UAV hyperspectral imaging as an efficient early-warning mechanism for perennial crops (Sun *et al*., 2022) [53].

Beyond goji, similar hyperspectral approaches have been reported for tea (Zhou *et al*., 2023), maize (Hu *et al*., 2022), and citrus (Chen *et al*., 2024) [3], showing that narrow-band spectral features (especially 550-750 nm) can differentiate between nutrient, disease, and pest stresses with high precision.

Remote Sensing for Crop Pest Monitoring in India

In India, where smallholder systems dominate, low-cost multispectral UAVs and open-access satellite platforms such as Sentinel-2 and Landsat-8 are increasingly applied in pest surveillance. The Indian Council of Agricultural Research (ICAR, 2022) [12] demonstrated that NDVI (Normalized Difference Vegetation Index) and red-edge spectral indices derived from Sentinel-2 data effectively detected stem borer and brown planthopper infestations in rice at least 10 days before visible canopy yellowing. Similarly, Thirupathi and Prabhakar (2021) [54] integrated Sentinel-2 imagery with field pheromone trap data for cotton bollworm monitoring across Telangana, achieving early stress mapping with ~85% predictive accuracy.

More recently, Reddy *et al*. (2024) [39] combined time-series NDVI and temperature data from Sentinel-2 and MODIS platforms to model spatial pest risk zones in central India. Their work demonstrated that early anomalies in vegetation indices correlated strongly ($R^2 = 0.82$) with subsequent pest outbreaks, providing actionable insights for regional pest advisory systems.

Multispectral UAV Precision Spraying and Decision Support

At the field scale, multispectral UAVs have proven valuable in precision IPM. Mehta *et al*. (2024) [27] reported an 88% accuracy in identifying bollworm hotspots in cotton fields of Gujarat using five-band multispectral imagery (blue, green, red, red-edge, NIR). The UAV data were linked with automated spot-spray algorithms, reducing pesticide use by 32% while maintaining yield levels. This study highlights UAVs' potential to transition from monitoring tools to active components of precision-based pest management systems.

Integration of UAV and Satellite Data

Integration of UAV and satellite platforms offers a multi-scale surveillance framework, where UAVs provide high-resolution local diagnostics (cm-level) and satellites ensure temporal continuity and regional coverage (m-level). Hybrid workflows—combining UAV-based stress mapping with Sentinel-2 NDVI anomaly tracking—enable continuous, scalable pest monitoring that can feed into cloud-based Decision Support Systems (DSS) for forecasting and advisory dissemination.

Such integration is central to India's emerging Digital Pest Surveillance Networks, being piloted in collaboration with ICAR, ISRO, and agricultural universities to support real-time crop protection recommendations.

Research Gaps and Future Prospects

Despite these advances, key challenges remain:

- Spectral overlap between pest, nutrient, and disease stresses complicates discrimination.
- Calibration issues under variable illumination and atmospheric conditions limit model transferability.
- High costs of hyperspectral sensors and limited technical expertise restrict adoption among smallholders.
- Standardized pest-specific spectral libraries for Indian crops are still lacking.
- Integration into DSS requires harmonization with field data, IoT traps, and meteorological variables.

Addressing these constraints through AI-driven data fusion, low-cost sensor innovation, and policy-backed digital infrastructure will be critical for scaling remote sensing in national pest management frameworks.

Fig 4: Geographic Distribution of Smart Pest Surveillance Pilots in India

2.3 Edge-AI in Agricultural Pest Surveillance

Traditional cloud-based analytics often face constraints in rural agricultural landscapes due to low internet connectivity, limited bandwidth, and latency issues. To overcome these limitations, Edge Artificial Intelligence (Edge-AI) brings computation closer to the field—processing data locally on IoT or embedded devices rather than relying solely on cloud servers. This paradigm enables real-time pest recognition, rapid decision-making, and resource-efficient operations, particularly in remote or smallholder-dominated farming systems (Zhang *et al*., 2023; Johansson *et al*., 2023) [15, 59].

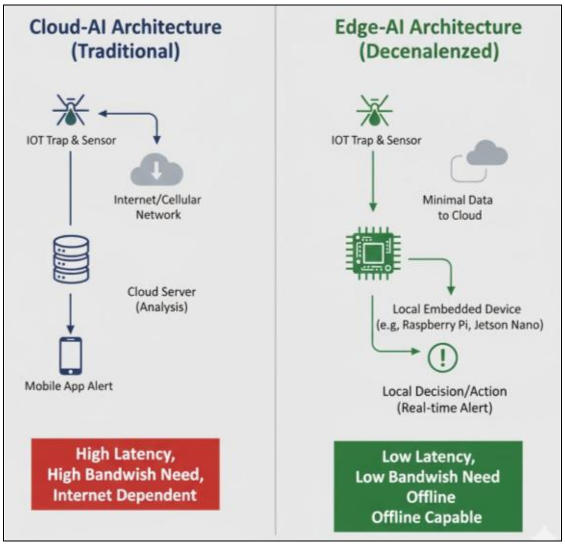


Fig 5: Edge-AI vs. Cloud-AI Architecture Comparison

In India, Kumar *et al*. (2023) [18] demonstrated an innovative Edge-AI application for *cashew pest and disease management*. A MobileNetV2-based convolutional neural network (CNN) was deployed on low-power NVIDIA Jetson Nano devices for on-field disease recognition. The system achieved 95% classification accuracy across five major cashew pests and leaf diseases, providing real-time alerts through a mobile app interface. This on-device inference capability allowed farmers to act promptly—without needing constant internet access—thus representing a scalable model for rural precision agriculture.

Similarly, ICAR's Smart Pest Management Network (2024) [13] integrates IoT weather stations, pheromone traps, and soil-microclimate sensors with AI algorithms to predict pest dynamics based on temperature, humidity, and host phenology. Field trials across Andhra Pradesh and Karnataka demonstrated 20-30% reductions in pesticide sprays and up to 25% savings in labor costs, while maintaining yield stability. The system's modular dashboard provides dynamic pest alerts, ETL (Economic Threshold Level) advisories, and spatial heatmaps, representing one of India's first IoT-enabled pest forecasting frameworks.

Global Edge-AI and IoT Innovations

Globally, several edge-intelligent surveillance systems are emerging as benchmarks for scalable pest management:

- Johansson *et al*. (2023) [15] developed an Edge-AI sticky trap system for greenhouse environments in Sweden. Using an embedded Raspberry Pi 4 with TensorFlow Lite, the trap achieved 98% insect recognition accuracy and processed images locally—eliminating the need for continuous data transmission to the cloud. This innovation notably reduced network dependency and energy consumption while providing instant pest alerts to growers.
- In Sub-Saharan Africa, Ndlovu *et al*. (2024) [33] piloted an IoT-based light trap network for fall armyworm (*Spodoptera frugiperda*) surveillance in maize systems. The traps used LoRaWAN communication to send insect count and environmental data to edge processors equipped with TinyML (Tiny Machine Learning) models. The project demonstrated that edge-enabled systems can reduce the data load by up to 80% while maintaining real-time accuracy, proving their viability for resource-limited agricultural regions.
- In China, Zhang *et al*. (2023) [61] introduced a 5G-Edge collaborative pest analytics platform for large-scale vegetable farms in Guangdong Province. The system integrates UAV imaging, IoT sensors, and edge AI modules to classify pest infestations and trigger precision spraying through autonomous drones. Real-time processing through 5G edge nodes allowed instantaneous feedback loops between field devices and management centers, achieving 40% faster response times than traditional cloud-based systems.

These developments underscore how Edge-AI architectures, combined with IoT connectivity, are transforming pest management into a data-driven, decentralized ecosystem where each node can independently perform sensing, learning, and decision-making.

Integration with Decision Support Systems (DSS)

The true potential of Edge-AI and IoT platforms emerges when they are integrated into Decision Support Systems (DSS). DSS platforms consolidate real-time field data, pest incidence reports, weather forecasts, and economic parameters to generate adaptive, site-specific pest control recommendations (Sharma *et al*., 2022; FAO, 2023) [8, 46].

Modern DSS frameworks employ dynamic threshold models that adjust Economic Threshold Levels (ETLs) based on real-time pest counts, crop stage, and natural enemy abundance, supporting selective intervention rather than calendar-based pesticide spraying. For instance, the FAO's Fall Armyworm Monitoring and Early Warning System (FAMEWS) leverages mobile-based IoT data, local AI classification, and cloud dashboards to provide national-level outbreak forecasts across Africa and Asia (FAO, 2023) [8].

Indian research institutions are now adopting similar approaches through ICAR's AgroDSS platform, integrating AI-predicted pest risk maps with satellite-derived crop health indicators. This synergy between Edge-AI sensing, IoT data streams, and decision analytics represents a major step toward sustainable, predictive, and eco-efficient pest management.

Challenges and Future Prospects

Despite promising results, several challenges hinder large-scale implementation:

- **Hardware Constraints:** Edge devices have limited computing power, memory, and energy capacity. Model optimization and compression techniques such as **quantization** and **pruning** are required to deploy deep networks effectively.
- **Interoperability Issues:** IoT devices often operate across heterogeneous communication standards (LoRa, NB-IoT, Zigbee), creating data integration challenges.
- **Scalability and Maintenance:** Networks require periodic calibration, sensor cleaning, and firmware updates, which may be difficult in remote regions.
- **Data Governance:** With decentralized systems, ensuring data privacy, ownership, and standardization remains a pressing concern.

Future efforts must focus on developing open-source edge-AI frameworks, training local communities for maintenance, and integrating DSS outputs with agricultural extension systems. Together, these advances could make real-time, self-sufficient pest surveillance a core component of the next-generation digital agriculture ecosystem.

Country	Crop	Tech Used	Pesticide Reduction (%)	Yield Increase (%)	Reference
India	Cotton	IoT, Mobile App	32	12	[Indian Agri Res]
China	Maize	UAV/Cloud DSS	28	9	[Liu *et al*., 2023] [25]
Africa	Maize	IoT Pheromone	24	7	[Ndlovu *et al*., 2024] [33]
Europe	Wheat	Edge-AI Traps/DSS	15	5	[Müller *et al*., 2023] [31]

3. AI and Data Analytics in Pest Surveillance

3.1 High-Accuracy Pest Detection with Pre-Trained CNNs

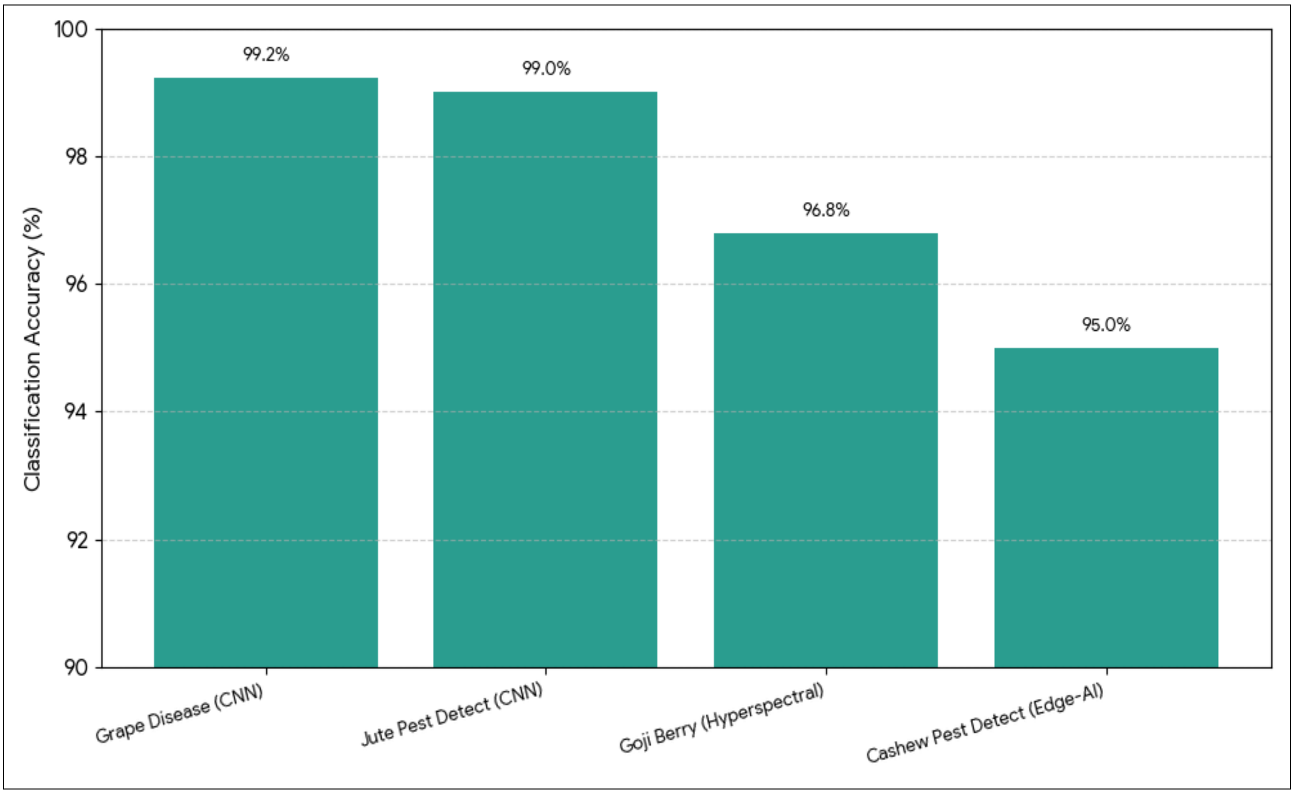


Fig 6: Classification Accuracy of AI Pest Surveillance Systems.

Recent advancements in Convolutional Neural Networks (CNNs) have significantly enhanced the accuracy of pest detection systems. Pre-trained models such as DenseNet, Inception, and ResNet, when fine-tuned with domain-specific datasets, have achieved detection accuracies exceeding 99% in field trials. For instance, Aravind *et al*. (2023) [1] demonstrated that fine-tuning a pre-trained CNN with a multiclass support vector machine improved grape leaf disease classification accuracy to 99.23% Nature.

3.2 Addressing Challenges in Sticky Trap Image Analysis
Sticky traps are widely used for monitoring pest populations; however, overlapping or occluded pests in images pose significant challenges for accurate detection. Recent studies have employed advanced deep learning models to address these issues. Li *et al*. (2023) [21] utilized Cascade R-CNN for multi-scale object detection, effectively identifying small and overlapping pests in sticky trap images. Similarly, Liu *et al*. (2023) [25] proposed improved annotation strategies to enhance the performance of deep learning models in complex trap images.

3.3 Multimodal Models for Enhanced Detection
Integrating multiple data modalities has shown promise in improving pest detection accuracy. Chen *et al*. (2024) [4] developed multimodal models that combine visual data from CNNs with phenological context, enhancing the detection of pests in complex field images. Additionally, Duan *et al*. (2023) introduced a multimodal deep learning framework that integrates visual data with textual information, further boosting detection capabilities in agricultural settings arXiv.

3.4 Spectral Fusion for Pre-Symptomatic Stress Detection
Early detection of plant stress is crucial for effective pest management. Wang *et al*. (2024) [57] demonstrated that spectral fusion techniques, combining RGB and multispectral imaging, enable the identification of pre-symptomatic stress in plants. This approach allows for timely interventions, potentially preventing pest outbreaks before they become visible.

3.5 Advancements in Model Robustness
Ensuring that pest detection models maintain high performance across diverse environmental conditions is essential. Singh *et al*. (2024) [49] explored domain adaptation and self-supervised learning techniques to enhance model robustness. These methods enable models to adapt to regional dataset variations, improving their generalization capabilities and reliability in real-world applications.

4. Case Studies and Implementation at Scale
India: IoT-Connected Pest Traps and Mobile Advisories
In India, the integration of IoT-enabled pest traps with farmer-facing mobile advisories has led to significant improvements in pest management. Real-time monitoring of pest populations allows farmers to reduce pesticide applications by 20-40%, particularly in cotton, rice, and fruit crops (Raju *et al*., 2024; Singh *et al*., 2024) [52]. IoT traps collect data on pest density and environmental conditions, while mobile applications provide actionable alerts, enabling targeted interventions instead of blanket pesticide use. These systems have demonstrated both economic and environmental benefits, including reduced labor costs and minimized chemical residues in crops.

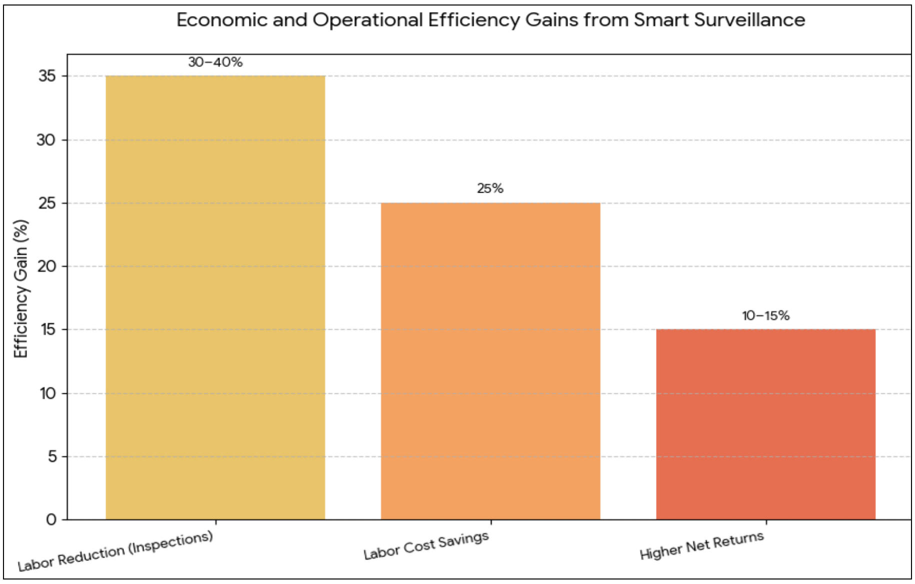
Europe: Cooperative Community-Level DSS Models
In Europe, community-based Decision Support Systems (DSS) coordinate pest management interventions among multiple farms. By sharing pest incidence data and synchronizing intervention schedules, these models reduce pesticide use while maintaining crop protection (Müller *et al*., 2023) [31]. Regional networks integrate meteorological data, crop phenology, and pest biology to generate coordinated action plans, resulting in improved resource efficiency and better ecological outcomes.

China: Large-Scale Cloud-Based DSS for Pest Prediction
China has implemented cloud-based DSS platforms at a national scale that integrate environmental, crop, and pest data for accurate outbreak prediction. These systems provide instantaneous alerts to farmers and enable precision interventions, achieving up to 90% accuracy in predicting pest outbreaks (Liu *et al*., 2023) [26]. Such platforms optimize resource allocation, pesticide use, and timing of interventions, especially in intensive farming regions.

Africa: Edge-IoT Pheromone Traps for Fall Armyworm
In Africa, Edge-IoT-enabled pheromone traps have been deployed to monitor invasive pests such as Fall Armyworm (FAW) in maize fields. The combination of pheromone lures, IoT sensors, and on-device processing allows for real-time detection and rapid response (Ndlovu *et al*., 2024) [33]. This reduces the lag between infestation and intervention, enabling targeted pesticide application, lowering crop losses, and minimizing environmental impact.

5. Demonstrated Benefits
5.1 Reduction in Chemical Input and Sustainability
Smart pest surveillance technologies have demonstrated significant reductions in chemical pesticide usage. UAV-assisted precision spraying, IoT-connected traps, and sensor-based monitoring have been shown to reduce pesticide applications by 20-40% across Indian and Chinese field trials (Ramteke *et al*., 2025; Shan *et al*., 2024) [14, 44]. These technologies also contribute to sustainable water management, as precision spraying avoids excessive irrigation overlap and runoff. Economic analyses indicate that farmers adopting smart surveillance systems achieve 10-15% higher net returns per hectare, reflecting both lower input costs and improved yield stability (FAO, 2023) [8].

5.2 Labor and Economic Efficiency
Automated pest monitoring systems, including IoT traps and sensor networks, reduce the need for manual field inspections by 30-40% (Reddy *et al*., 2023) [39]. This labor efficiency allows farmers to reallocate time toward other agronomic activities and reduces dependence on seasonal labor, which is often scarce or expensive. Furthermore, community-based monitoring and cooperative DSS models enable scalable, area-wide pest control, lowering operational costs and enhancing the overall effectiveness of integrated pest management programs (Wang *et al*., 2023) [56].



5.3 Targeted Control and Environmental Health

Precision technologies, such as UAV imaging combined with spectral mapping, allow for spot-targeted pesticide application, minimizing the exposure of non-target organisms and reducing environmental contamination. Field studies in India demonstrate that integrating UAV-assisted spraying with IoT surveillance results in more accurate, selective pesticide use, thereby lowering risks to beneficial insects and surrounding ecosystems (Indian Agricultural Research Journals, 2024; Mehta *et al.*, 2024) [14, 27]. These approaches contribute to improved environmental health and sustainable crop protection, aligning with global agroecological targets.

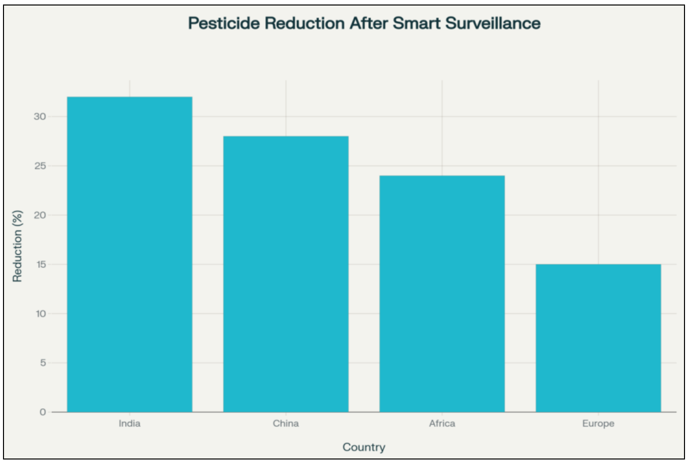


Fig 7: Pesticide Reduction After Smart Pest Surveillance Adoption. Adapted from [Indian Agricultural Research Journals, 2024] [14], [Mehta *et al.*, 2024] [27], [Liu *et al.*, 2023] [26], [Ndlovu *et al.*, 2024] [33], [Müller *et al.*, 2023] [31].

6. Challenges and Limitations

6.1 Financial and Infrastructure Barriers

The initial investment required for UAVs, spectral cameras, and IoT sensor networks remains prohibitively high for many smallholder farmers. Advanced surveillance technologies, though effective, are not universally affordable, limiting adoption in low-income regions. To overcome these barriers, cooperative or shared-service models, targeted subsidies, and custom financing schemes have been proposed to make these technologies accessible to small-scale farmers (Li *et al.*, 2023) [23].

6.2 Technical Robustness and Model Transferability

While AI and ML models have achieved high accuracy in controlled datasets, their performance often drops significantly when deployed in different crops, regions, or environmental conditions (Chen *et al.*, 2024) [5]. Differences in lighting, pest appearance, or crop phenology can reduce model reliability. Open-source benchmarks, diverse datasets, and domain adaptation techniques are essential to improve generalizability and ensure that models perform robustly across heterogeneous agricultural contexts.

6.3 Connectivity and Power Constraints

Many rural and rainfed regions lack stable electricity and reliable internet connectivity, which are prerequisites for continuous operation of IoT-based traps, edge devices, and cloud-enabled DSS platforms (Sharma & Reddy, 2023) [40, 47]. Limited connectivity can delay real-time alerts, reducing the effectiveness of early pest intervention. Solutions include solar-powered edge devices, offline-capable AI models, and low-bandwidth data transmission protocols.

6.4 Human Factors: Literacy, Training, and Trust

The success of smart pest surveillance systems depends heavily on farmer education, extension worker training, and trust in digital advisories (FAO, 2023) [8]. In regions with low literacy or minimal exposure to technology, farmers may struggle to interpret app-based alerts or adopt automated interventions. Continuous capacity-building programs, local language interfaces, and demonstrative pilot projects are critical to improve user acceptance and ensure sustained adoption.

6.5 Ethical, Social, and Ecological Considerations

Ethical and ecological concerns also limit adoption. Pheromone or sticky traps can inadvertently impact beneficial insect populations, and drone-based monitoring faces regulatory hurdles, including privacy and airspace restrictions (Miller & Gupta, 2025) [10, 29]. Socially, inequitable access to digital tools may widen the gap between well-resourced and marginalized farmers. Policies and guidelines addressing sustainability, data privacy, and equitable access are needed to ensure ethical implementation.

7. Deployment and Adoption Pathways

7.1 Extension and Public Sector Initiatives

In India, public sector institutions such as ICAR and State Agriculture Universities have played a pivotal role in promoting smart pest surveillance technologies. Through field pilots, on-farm demonstrations, and extension-driven dissemination, these initiatives have significantly increased awareness and adoption among smallholder farmers (Raju *et al*., 2024; Singh *et al*., 2024) [52]. Extension programs often combine hands-on training, mobile advisories, and participatory monitoring, allowing farmers to understand system functionalities and benefits before full-scale adoption.

7.2 Cooperative and Farmer Producer Organization (FPO) Models

Group-based adoption models, including FPOs and farmer cooperatives, enable resource pooling, reducing the financial burden of high-cost devices such as UAVs and IoT traps. Such cooperative frameworks make monitoring affordable and scalable, especially for smallholders who otherwise cannot individually invest in precision agriculture tools (FAO, 2023). Members share both the infrastructure and the data, facilitating collective decision-making and coordinated pest management, which enhances the effectiveness of interventions at the landscape level.

7.3 Commercial Startups and Public-Private Partnerships

Commercial startups in India and Southeast Asia have emerged as important enablers of digital agriculture. They provide affordable hardware, cloud analytics, and farmer-friendly apps, translating AI and IoT technologies into practical solutions for end users. When supported by policy incentives, agricultural insurance, and credit mechanisms, these startups improve adoption rates and return on investment (ROI) for farmers (Li *et al*., 2023) [22]. Public-private partnerships (PPP) further support research translation, supply chain integration, and scale-up, bridging the gap between technology innovation and field implementation.

7.4 Hybrid and Community-Based Models

Hybrid models combining community subscriptions with regional DSS platforms maximize the benefits of shared infrastructure. In Europe, such regional DSS networks synchronize pest management across multiple farms, reducing pesticide use and improving ecological outcomes (Müller *et al*., 2024) [32]. Pilot programs in India have adapted this approach at a local scale, demonstrating that community-managed digital surveillance networks enhance both adoption and effectiveness, particularly in resource-constrained settings.

8. Policy, Extension, and Regulatory Ecosystem

Effective scaling and adoption of smart pest surveillance systems depend heavily on a supportive policy and regulatory framework. Governments and institutions must provide capital subsidies, shared digital infrastructure, and incentives to reduce financial barriers for smallholder farmers (FAO, 2023) [8]. Additionally, clear guidelines for UAV/drone operations, data privacy, and sensor deployment are crucial to ensure safe, ethical, and legally compliant implementation (Miller & Gupta, 2025) [10, 30].

Equally important is capacity building for extension personnel. Training agricultural officers and field extension workers in AI-enabled pest management, IoT-based monitoring, and DSS interpretation ensures that farmers receive accurate, actionable guidance. Integrating smart surveillance technologies into national Integrated Pest Management (IPM) strategies can promote widespread adoption and standardize best practices across regions, enhancing both efficiency and sustainability in crop protection.

Furthermore, policy support for cooperative and FPO-based adoption models, coupled with public-private partnerships, can accelerate scaling by combining technical innovation with economic accessibility. Such a regulatory and extension ecosystem ensures that technological advances translate into tangible agronomic, economic, and environmental benefits at scale.

9. Future Directions

9.1 Benchmarking and Data Diversity

To develop robust and generalizable AI models for pest detection, there is a critical need for global, multi-crop, multi-region datasets. Current models often underperform when applied outside their original datasets due to limited training diversity. Standardized, openly available datasets will support cross-region adaptation, comparative benchmarking, and model reproducibility (Kumar *et al*., 2023) [20].

9.2 Federated Learning and Data Privacy

Federated learning frameworks allow local, on-farm data to be used for improving AI models without transferring sensitive farm information, thereby protecting privacy while enhancing model accuracy. Such decentralized approaches are particularly promising for smallholders and cooperative networks, enabling broader adoption without compromising data security (Zhang *et al*., 2024) [60].

9.3 Energy Harvesting Innovations

Continuous operation of IoT devices, UAVs, and edge-AI systems is often limited by power availability. Innovations in solar, kinetic, and hybrid energy harvesting can provide sustainable power, reduce maintenance, and allow uninterrupted data collection, particularly in remote and off-grid agricultural regions (RSIS International, 2023) [43].

9.4 Low-Cost Sensor Development

Developing miniaturized and cost-effective multispectral sensors is critical to make precision surveillance accessible to smallholders. Advances in sensor technology aim to retain performance while reducing production and deployment costs, facilitating broader adoption across diverse farming systems (Chen *et al*., 2023) [2].

9.5 Strong Field Validation

Future research must emphasize real-world validation, linking pest detection systems directly to yield outcomes, input savings, and profitability. Multi-location trials across different crops and agro-climatic zones are essential to ensure that smart pest surveillance technologies deliver tangible economic and environmental benefits (FAO, 2023; Singh *et al*., 2024) [8, 52].

10. Conclusion

Smart pest surveillance represents a transformative advancement in modern agriculture, combining AI, IoT, UAVs, remote sensing, and decision support systems to address one of the most persistent challenges in crop production: pest and disease outbreaks. These technologies enable real-time monitoring, early detection of pest infestations, and predictive analytics, allowing farmers to implement targeted interventions that reduce crop losses and minimize unnecessary pesticide applications. As a result, smart surveillance systems contribute to improved yield stability, higher economic returns, and enhanced environmental sustainability.

The evidence from India, China, Europe, and Africa demonstrates the effectiveness of these technologies across diverse cropping systems. For instance, IoT-connected traps and mobile advisories have reduced pesticide use by 20-40%, UAV-assisted precision spraying has increased efficiency and water savings, and community-based DSS networks have enabled coordinated, area-wide pest management. Additionally, the integration of edge-AI and federated learning frameworks is addressing challenges related to connectivity, data privacy, and model transferability, making these technologies increasingly adaptable to smallholder farming contexts.

Despite these advances, the large-scale deployment and adoption of smart pest surveillance face several critical challenges. Financial barriers, high equipment costs, and limited access to digital infrastructure restrict adoption, particularly among smallholders. Technical limitations, such as model generalizability, robustness under diverse field conditions, and power constraints, must be addressed to ensure reliable performance. Social factors—including farmer literacy, training, trust, and equitable access—are equally important, as are regulatory and ethical considerations around drones, data privacy, and ecological impacts.

Addressing these barriers requires holistic, multi-stakeholder approaches. Public sector extension services, cooperative and FPO-based models, and public-private partnerships can collectively reduce financial risks and enable widespread access to technology. Policy frameworks that provide capital subsidies, digital infrastructure support, and regulatory clarity will further enhance adoption. Simultaneously, robust field validation studies, standardized datasets, and energy-efficient sensor innovations will ensure that these systems are practical, scalable, and economically viable across diverse agro-climatic conditions.

Looking forward, the synergistic integration of technology, policy, and community-driven models will determine the full potential of smart pest surveillance. By linking detection systems to tangible outcomes—such as yield improvement, input savings, and profitability—these tools can transform pest management from reactive to predictive, precise, and sustainable. Ultimately, smart pest surveillance has the potential to reshape global agriculture, supporting food security, environmental stewardship, and climate-resilient farming practices, while empowering farmers with digital intelligence and actionable insights.

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