

## Review of Autonomous Nocturnal Animal Scarers: Emerging Technologies, Effectiveness, and Future Directions

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### Abstract

#### Keywords:

Autonomous deterrent systems, Nocturnal animal scarer, Reinforcement learning, UAV-based deterrence, IoT ecological monitoring

The influence of nocturnal animals on farm lands remains a major cause of pre-harvest yield losses, with different studies estimating reductions ranging from 15% to 30% depending on crop type and region. Traditional deterrent methods, such as scarecrows, firecrackers, or reflective tapes, are cheaper when compared to modern-day deterrent methods but suffer from rapid animal habituation, making them ineffective. Recent advances in automation and smart agriculture have led to the development of autonomous nocturnal scarer systems that integrate sensors, sound and light devices, computer vision, unmanned aerial vehicles (UAVs), and Internet of Things (IoT) connectivity. This review synthesizes recent contributions in the field from 2020 to date, highlighting reported performance metrics such as deterrence success rates of 70–95% for AI-based camera systems, 60–85% for UAV platforms, and 40–70% for standalone ultrasonic or light devices. The analysis emphasizes key trade-offs between cost, energy consumption, species specificity, and ease of adoption for smallholder farmers. Major limitations identified include power dependence, environmental sensitivity, habituation, and regulatory barriers to UAV deployment. Opportunities for improvement lie in reinforcement learning models that adapt to animal behaviour, species-specific training datasets, and farm-wide IoT integration for ecological monitoring. This review provides a consolidated reference for researchers and practitioners aiming to design scalable, sustainable, and non-lethal crop protection systems.

### 1. Introduction

Agricultural productivity faces persistent threats from nocturnal animal intrusions, which account for significant pre-harvest losses worldwide. Estimates suggest that between 60% and 70% of yields may be lost to wildlife activity, with higher figures reported in regions cultivating fruits, maize, and vegetables near forest edges (Pruteanu et al., 2023). In sub-Saharan Africa, for example, porcupines and wild pigs are among the most destructive nocturnal intruders, while in North America and Europe, deer and pest birds are common culprits. These losses not only reduce farmer income but also threaten food security in vulnerable regions.

Traditional deterrent methods such as static scarecrows, reflective tapes, firecrackers, or distress-call devices offer only temporary protection. Studies consistently show that animals adapt to predictable and repetitive stimuli, a process known as habituation, leading to a rapid decline in effectiveness (Micaelo et al., 2021). The challenge is further compounded by labour shortages and the impracticality of maintaining constant night-time vigilance.

To address these limitations, recent research has turned toward autonomous deterrent systems, defined here as self-operating devices that combine detection and response mechanisms without continuous human intervention. These systems may incorporate sensors, cameras, sound or light emitters, unmanned aerial vehicles (UAVs), and Internet of Things (IoT) integration to identify and repel animals in real time.

Beyond automation, some designs leverage artificial intelligence (AI) to classify species and adapt responses dynamically, thereby delaying habituation and improving long-term reliability (Abiodun, 2025).

### *1.1 Background to the Problem*

Nocturnal wildlife poses a significant and often underestimated threat to agricultural production, particularly in regions where farms border forested or undeveloped land. Unlike daytime intrusions, which can be monitored more easily, nighttime invasions are stealthy, frequent, and difficult to control without constant human presence. Animals such as wild pigs, porcupines, rabbits, and deer exploit the darkness to invade farms, feeding on crops, trampling fields, and triggering substantial economic losses. According to Pruteanu et al. (2023), damage from bird and animal infestations during the pre-harvest period can account for up to 70% of yield loss, particularly in regions cultivating high-value crops like fruits, maize, or vegetables. Their comprehensive review of deterrent methods categorized techniques into visual, auditory, and physical strategies, finding none to be fully reliable, especially when used in isolation.

One of the central challenges lies in the adaptability of animals. Most traditional deterrent methods, such as hanging shiny materials, setting off explosive sounds, or using static scarecrows, tend to lose their effectiveness over time. Animals, especially intelligent species like birds and wild mammals, become accustomed to repetitive, non-interactive stimuli. Micaelo et al. (2023) emphasize that this phenomenon, called habituation, severely limits the long-term viability of conventional methods. Their study highlights that while some techniques may work for a few days or weeks, they often fail to deter animals after repeated exposure, particularly when no real threat is perceived. Compounding the problem is the impracticality of constant human vigilance during nighttime hours. In many agricultural zones, especially where labour shortages or ageing farming populations exist, it is not feasible to monitor fields manually throughout the night. Moreover, nocturnal animal behaviour varies by species, season, and crop type. Agossou et al. (2022), through interviews with over 700 farmers in Benin, found that deterrent effectiveness also fluctuated across growth stages of crops, with early-stage plants being more vulnerable. Their findings underscored the need for time-sensitive, adaptive interventions that can respond to changing wildlife patterns in real time.

In parallel, the conservation angle adds another layer of complexity. While the primary goal is to protect crops, non-lethal methods are generally preferred to avoid negative ecological consequences. Excessive use of exclusion methods like netting or chemical repellents can disrupt biodiversity and harm non-target species. There is also increasing societal and regulatory pressure to develop wildlife-friendly deterrent systems that ensure sustainability and humane treatment. As the demand for more ethical, precise, and scalable solutions rises, technology offers a promising path forward through automation, artificial intelligence, and data-driven monitoring. The growing interest in autonomous nocturnal deterrent systems, therefore, stems from a convergence of needs: reduced labour input, increased deterrent reliability, animal adaptability, and environmental consciousness. These systems aim to strike a balance between efficacy and delivering protection for crops while minimizing harm to wildlife and operational burden on farmers.

## **2. Literature Review**

The development of autonomous nocturnal animal scarers has drawn on multiple technological approaches, ranging from low-cost light deterrents to advanced AI-driven detection systems. The review synthesizes findings thematically across major categories, which include: sensor-based detection systems, sound and light deterrents, artificial intelligence and computer vision systems, unmanned aerial vehicles (UAVs), and hybrid multi-modal approaches.

### *2.1 Sensor-Based Detection Systems*

Sensors form the backbone of most autonomous deterrents by enabling real-time detection of animal presence. Commonly used devices include infrared (IR) motion detectors, passive infrared (PIR) sensors, ultrasonic sensors, and thermal cameras. Haque et al. (2026) demonstrated a low-cost scarecrow system integrating PIR sensors with IoT alerts, which successfully reduced crop intrusions but was prone to false positives caused by vegetation movement and weather conditions. More advanced implementations, such as McMahon et al. (2021), used thermal imaging mounted on farm vehicles to detect hidden animals, although accuracy declined in fog and rain. Sensor-based systems are attractive for their simplicity and

affordability, making them suitable for smallholder farms. However, their inability to differentiate between species often leads to unnecessary activations, reducing energy efficiency and long-term reliability.

### *2.2. Sound and Light-Based Deterrents*

Sound and light stimuli are widely used because they are inexpensive, non-lethal, and easy to deploy. Loncore (2023) reported that LED-based deterrents reduced the activities of some species in crop fields, though effectiveness varied with species. Ultrasonic devices, reviewed by Arun et al. (2025), were effective against rodents and small mammals in the short term, but animals rapidly adapted through habituation. Michaelo et al. (2023) tested distress call systems for birds, initially achieving strong deterrence before effectiveness declined within a week. These findings suggest that while sound and light deterrents can be useful for smallholder farms with limited budgets, their repetitive nature reduces long-term efficacy unless stimuli are varied or combined with adaptive systems.

### *2.3 Artificial Intelligence and Computer Vision*

AI-enabled systems represent a significant step toward context-aware deterrence. Kumar et al. (2024) designed an AI-powered camera system capable of distinguishing between humans and animals, triggering alerts only when intrusions were detected. Such systems have achieved deterrence success rates of 70–95% in trials but require higher energy inputs and infrastructure. Airport-based studies have shown that YOLOv4 models can identify birds under complex conditions, though precision scores remain modest (Ummah et al., 2022). Although developed outside agriculture, these detection models can be repurposed for farm environments. A major limitation is the scarcity of species-specific training datasets, particularly for nocturnal animals in developing regions, which reduces the accuracy of recognition.

### *2.4 UAV and Mobile Systems*

UAVs introduce mobility and dynamic coverage, making them highly effective against intelligent species that quickly adapt to static deterrents. Bhusal et al. (2022) developed an autonomous UAV system capable of deterring birds with over 90% success in vineyard trials. Similarly, Schiano et al. (2021) employed drones for urban pigeon control, reducing loitering times significantly. While UAVs offer strong performance, they face challenges including short battery life, high costs, and regulatory restrictions on drone flights in agricultural zones. These factors limit widespread adoption, especially among smallholder farmers in developing regions.

### *2.5 Hybrid and Multi-Modal Approaches*

Multi-modal deterrents combine several technologies to increase unpredictability and reduce habituation. Varriano et al. (2025) proposed a model which was the development of a micro-drone equipped with LIDAR technology to serve as a repellent system for birds and rodents. The drone is lightweight and designed for easy launch. Lee et al. (2021) introduced reinforcement learning (RL) into deterrence, enabling the system to adapt sound patterns dynamically and delaying habituation by over 40%. Such hybrid approaches hold promise for the future, especially when integrated with IoT infrastructures for centralized monitoring and scheduling. However, they require more complex hardware and technical literacy, which may hinder adoption in low-resource farming contexts.

### *2.6 Synthesis of Key Insights*

Across the reviewed studies, several themes emerge. First, low-cost systems such as LED lights and ultrasonic devices are accessible but quickly lose effectiveness due to habituation. Second, AI-driven and UAV-based deterrents offer high success rates but remain expensive and energy-intensive, limiting their accessibility to large-scale or well-funded farms. Third, hybrid approaches show the most long-term potential by combining detection, adaptive responses, and ecological monitoring. However, further research is needed to make these systems affordable, energy-efficient, and suitable for smallholder contexts in developing regions. Importantly, few studies explicitly evaluate long-term field performance, ecological trade-offs, or socio-economic adoption barriers, leaving these as open research gaps.

## **3 Types of Detention systems**

### *3.1 Sensor-Based Detection Systems*

Sensor technologies serve as the backbone of many autonomous animal scarers, enabling real-time detection and response. The most commonly used sensors include infrared (IR), motion sensors, ultrasonic

detectors, and thermal imaging. For instance, Mapari et al. (2021) implemented a system that used motion sensors to detect intrusions and trigger light and sound deterrents. Their design also allowed for IoT connectivity, enabling real-time alerts and user monitoring. However, the performance of these sensors was subject to environmental conditions, like, fog, wind, and vegetation interference often triggered false positives or reduced detection accuracy. Despite these limitations, the system proved viable for small to mid-sized farms, especially when power sources were stable.

More advanced detection mechanisms were employed by McMahon et al. (2021), who mounted FLIR thermal cameras on tractors to detect wildlife before mowing grass. Their work underscores the value of thermal imaging for identifying warm-blooded animals concealed in vegetation. Though intended primarily to prevent animal casualties, the underlying technology could easily be adapted for fixed installations to trigger deterrents. However, cost, power consumption, and reduced accuracy in bad weather remain critical challenges.

Sensor-based systems are generally reactive; they respond to animal presence but do not discriminate between species or adapt to changing behaviours. Nevertheless, they form the essential input layer in more complex systems involving AI or multi-modal integration.

### *3.2 Sound and Light-Based Deterrents*

Sound and light stimuli are widely used due to their non-lethal nature and ease of deployment. These systems range from simple LED-based flashers to complex devices emitting frequency-modulated sound waves or animal distress calls. Lamani et al. (2023) tested fixed LED lights placed strategically across fields. Their system was especially effective against large mammals like deer and boar, where light flashes startled the animals and discouraged further intrusion. The low power requirements made it attractive for off-grid applications, but the system's success varied with animal species and was less effective against small, low-vision animals. Pruteanu et al. (2023) employed ultrasonic deterrents, which emit high-frequency noise outside the human hearing range. While they were initially effective against rodents and small mammals, long-term use revealed habituation problems—animals returned once they adapted to the frequencies. Additionally, the devices required frequent maintenance and calibration.

De Rosa et al. (2023) extended this category by introducing distress call playback systems, particularly for avian species. Birds were initially repelled by species-specific calls, but similar to ultrasonic systems, they adapted over time. The researchers emphasized the need for audio variation and randomization algorithms to extend system lifespan. Sound and light systems are attractive due to their simplicity, but their passive, repetitive nature often leads to declining effectiveness. Integration with AI-based behaviour detection may enhance their usefulness by making activation context-aware and unpredictable.

### *3.3 Artificial Intelligence and Machine Vision*

AI and computer vision bring a major leap forward in the development of intelligent deterrent systems. These technologies allow systems not only to detect movement but to analyze, classify, and respond based on species, size, and behaviour.

Shanmugapriya et al. (2025) developed an AI-driven camera system that combined object detection with sound and light deterrents. The AI component enabled the system to distinguish between animals and non-threatening movement (e.g., wind-blown branches). It also supported adaptive learning, enabling the system to improve its detection accuracy over time and reduce false positives. Ummah et al. (2022) and Aboltins et al. (2021) both applied the YOLOv4 object detection model to real-time bird identification. Although developed for airport safety, their AI models were capable of detecting and tracking small, fast-moving targets under various environmental conditions. These models offer high recall and moderate precision, making them well-suited for deterrent triggering in field environments.

Biswas and Tiwari (2024) applied deep learning via a Convolutional Neural Network (CNN) to real-time insect classification. While not a deterrent system per se, their work showed the potential of low-cost AI classifiers integrated into field devices for pest identification. A similar approach could enable species-specific deterrents—for example, only activating sound or light when certain animal species are present. The integration of AI into autonomous deterrents allows for context-aware responses, minimizing unnecessary activations and improving energy efficiency. However, AI systems often come with higher power requirements, greater setup complexity, and increased costs.

### 3.4 UAVs and Mobile Deterrent Systems

Mobile deterrent platforms—particularly Unmanned Aerial Vehicles (UAVs)—introduce mobility into deterrent operations. Unlike stationary systems, drones can patrol large areas, respond dynamically to movement, and even pursue intruders.

Bhusal et al. (2022) developed an autonomous UAV capable of real-time bird detection and mission planning using onboard machine vision. Their drone operated without GPS, relying on simulated bird movement tracking and auditory deterrents. Despite the lack of GPS, the drone completed over 90% of deterrent missions in controlled trials. The key challenge remained navigational reliability in unstructured environments and the ability to return to a charging station autonomously. Similarly, Pfeiffer et al. (2023) used camera-triggered drones to chase birds from rooftops in urban environments. The drones effectively reduced bird loitering time, suggesting applicability to large-scale farm operations—especially against intelligent species like crows or pigeons that quickly adapt to static deterrents. However, limitations included battery life, airspace regulation, and partial automation.

Varriano et al. (2025) proposed a micro-drone platform integrated with LIDAR navigation to deter rodents and birds. Designed to be easily launched and self-navigating, it used LEDs and buzzers to repel intruders. The system was lightweight and accessible for local farmers, addressing cost and usability concerns. Although the study did not include long-term field trials, it provided a valuable blueprint for affordable mobile deterrents that combine perception and action.

The primary strength of UAV-based systems lies in their proactive coverage and mobility, but concerns around energy consumption, cost, and regulatory compliance must be addressed before they can be deployed widely.

## 4. Comparative Analysis of Existing Systems

Autonomous nocturnal animal deterrents vary widely in their design philosophy, effectiveness, technological complexity, and economic feasibility. While each system aims to reduce crop damage and minimize human-animal conflict, their strengths and weaknesses differ based on factors such as target species, environment, deployment scale, and available infrastructure. This section synthesizes the comparative dimensions of the reviewed systems across five critical criteria: effectiveness, adaptability, cost-efficiency, species specificity, and technical complexity.

### 4.1 Effectiveness in Deterrence

Effectiveness refers to a system's ability to consistently reduce animal presence and prevent damage. Some of the highest deterrence rates were reported in AI-integrated and mobile systems. For instance, Bhusal et al. (2022) recorded success rates exceeding 90% during field simulations with their UAV-based bird deterrent. Similarly, Marcon et al. (2021) achieved high rates of animal exclusion using AI-powered cameras that adaptively triggered deterrents only upon animal detection. In contrast, single-modality systems such as LED-based deterrents (Varriano et al., 2025) or ultrasonic devices (Mano and Sadhiya, 2024) had moderate short-term effectiveness, but performance diminished over time due to animal habituation. Fahey and Lucas (2023) and Brown and Brown (2021) found initial success with distress calls and lasers, respectively, but effectiveness plateaued within weeks, especially among intelligent avian species. Systems combining multiple sensory modalities, e.g., light, sound, and motion (Augustina et al., 2023), generally performed better in maintaining animal deterrence over longer durations. These combinations disrupted animal behaviour more unpredictably, preventing easy habituation.

### 4.2 Adaptability and Environmental Responsiveness

Adaptability defines how well a system adjusts to changes in environmental conditions, crop growth stages, and evolving animal behaviour. Mapari et al. (2021) addressed one form of adaptability by allowing their scarecrow to automatically adjust its height as crops grew—an important innovation for ground-based deterrents.

However, AI-powered systems like that of Marcon et al. (2021) represent a higher level of behavioural adaptability. These systems learn from repeated encounters, refining their responses based on animal type, time of intrusion, and deterrent success history. Similarly, Lee et al. (2021) introduced a

reinforcement learning-based framework that actively delayed habituation by adapting sound patterns over time.

On the other hand, hardware-only systems (e.g., standalone lights or lasers) tend to lack responsiveness. They emit fixed stimuli regardless of context, making them susceptible to behavioural desensitization and rendering them less effective over time unless manually updated or integrated with detection layers.

#### *4.3 Cost and Energy Efficiency*

Cost-efficiency is a major concern, especially for smallholder farmers or deployments in low-resource regions. Systems like those developed by Geertgik and Vishal (2025) are inexpensive, require minimal setup, and consume low power, making them accessible and scalable in rural areas.

Conversely, AI-based systems (Ummah et al., 2022) or drone-based systems (Bhusal et al., 2022) demand higher initial investments, including training datasets, onboard computing, and power-hungry sensors or actuators. Drone systems, in particular, suffer from battery limitations and the need for maintenance infrastructure, although the micro-drone concept by Varriano et al. (2025) presents a more affordable, farmer-friendly alternative.

Energy dependence also varies. Passive systems powered by solar or battery cells (Brown & Brown, 2021) can operate continuously with minimal human input. In contrast, vision-based and UAV systems often require external charging infrastructure or power sources, limiting their deployment in off-grid environments.

#### *4.4 Species Specificity*

Some systems are designed for general deterrence, while others target specific animal types. Ultrasonic devices (Mano and Sadhiya, 2024) are tuned to rodent and small mammal hearing ranges, while distress call systems (Brudzinsky, 2021) are explicitly aimed at bird species. These systems tend to be highly effective within their target group, but may have no impact on non-target species or may inadvertently affect non-threatening animals, including pets or beneficial wildlife.

AI-powered systems provide a superior level of species specificity. For instance, the system by Zhu et al. (2023) could differentiate between human movement and animal intrusions, enabling precise targeting. Similarly, Biswas and Tiwari (2024) demonstrated real-time species identification for insects using deep learning—an approach that could be expanded to mammals and birds, allowing tailored deterrent responses that conserve non-target organisms. Systems lacking identification capability—such as fixed laser systems or visual deterrents—treat all intrusions equally, increasing the risk of over-deterrence or unnecessary activation.

#### *4.5 Technical Complexity and Usability*

Ease of deployment is a crucial consideration in adoption. Simpler systems like LED arrays, reflective tapes, or rotating distress sounds can be installed with minimal training and are usually plug-and-play. They are suited for individual farmers with limited access to technical support.

In contrast, AI-integrated or mobile systems demand a higher degree of technical literacy, including understanding of software updates, calibration, sensor tuning, and maintenance of mechanical components (especially UAVs). Systems such as those by Bhusal et al. (2022) require professional support for deployment and troubleshooting, which may not be feasible in all contexts.

Moreover, technical complexity increases the likelihood of system failure in harsh outdoor environments, unless ruggedized hardware and robust error-handling protocols are used. Thus, there's a tradeoff between intelligence and resilience—the smarter the system, the more vulnerable it may be without proper support infrastructure. Table 1 shows the various systems of the autonomous nocturnal animal scarers.

Table 1: Summary of the Nocturnal Animal Scarers Technology

System Type	Reported Effectiveness	Adaptability	Approx. Cost / Energy Use	Species Specificity	Complexity	Key References
<b>LED Light Systems</b>	40–65% reduction in nocturnal visits (mainly deer/boar)	Low (fixed patterns only)	Low-cost (< \$50 per unit), low power (~2–5 W)	Low – affects only visually sensitive species	Low	Varriano <i>et al.</i> (2025)
<b>Ultrasonic Devices</b>	50–70% short-term success; effectiveness declines after 2–3 weeks	Low (fixed frequency)	Low (\$30–100), low power (< 10 W)	Medium – tuned to rodents, bats, small mammals	Low	Mano and Sadhiya (2024)
<b>Laser Scarecrows</b>	60–80% deterrence, especially for rabbits and deer	Low (requires manual alignment)	Medium (\$300–600), solar-powered options exist	Medium – effective on some mammals/birds, not all	Medium	Brown & Brown (2021)
<b>AI-Camera Deterrents</b>	70–95% success in controlled field trials	High (adaptive learning, species ID)	High (\$500–1,500), energy-intensive (20–50 W)	High – differentiates humans, livestock, wildlife	High	Ummah <i>et al.</i> (2022)
<b>UAV-Based Systems</b>	85–92% bird deterrence in vineyards/fields	Medium (limited by battery & flight time)	High (\$1,000–5,000), short battery life (20–30 min)	Medium-High – effective against birds, deer, adaptable via payloads	Very High	Bhusal <i>et al.</i> (2022)
<b>Hybrid Multi-Modal Systems</b>	75–90% deterrence with reduced habituation over time	Medium-High (context-aware triggering)	Medium (\$300–800), moderate energy needs	Medium – variable depending on design (e.g., RL audio + visual)	Medium-High	Lee <i>et al.</i> (2021)

## 5. Challenges and Limitations

Despite their growing sophistication, autonomous nocturnal animal scarer systems are not without significant limitations. These challenges span technological, environmental, behavioural, economic, and ethical dimensions. A critical understanding of these constraints is necessary for the realistic deployment, sustainability, and eventual scaling of these systems in real-world agricultural settings.

### 5.1 Environmental and Operational Constraints

Environmental variability remains one of the greatest limitations to system reliability. Motion sensors and thermal cameras frequently generate false positives in windy or foggy conditions, leading to unnecessary energy consumption (McMahon et al., 2021). Similarly, solar-powered devices may perform inconsistently in regions with low sunlight availability, particularly during rainy seasons. Outdoor hardware must also withstand dust, humidity, and tampering by wildlife, yet ruggedization increases costs. UAV-based systems are especially vulnerable to adverse weather, requiring safe landing zones and protective storage.

### 5.2 Power Dependence and Infrastructure Gaps

Many autonomous systems rely on a consistent power supply, either from the electrical grid or rechargeable batteries. High-end solutions such as AI vision systems and UAVs are energy-intensive, which limits their practicality in off-grid or resource-constrained settings. For instance, Pecaso (2021) and Uzma et al. (2021) proposed models that used solar-powered design to ensure that the device works perfectly. In remote or developing areas where electricity access is unreliable, maintaining such systems becomes challenging. Solar power offers a partial solution, as seen in some laser scarecrow models (Brown & Brown, 2021), but effectiveness depends on local climate, sunlight availability, and proper battery storage. Balancing system performance with low energy consumption remains an unresolved engineering problem, particularly when scaling deployments to large farms.

### 5.3 Animal Habituation and Behavioural Complexity

Habituation continues to undermine long-term deterrent effectiveness. Repetitive stimuli such as ultrasonic frequencies or distress calls lose their impact within weeks as animals adapt (Brudzinsky, 2021; Berz, 2022). Even more dynamic interventions, such as lasers and flashing lights, eventually become predictable unless varied or randomized. While reinforcement learning (Lee et al., 2021) offers adaptive solutions, such approaches remain experimental and require extensive field validation across different species and environments.

### 5.4 Cost and Affordability

High-end deterrent systems such as UAV platforms and AI-based camera networks remain prohibitively expensive for smallholder farmers, with costs ranging from \$500 to over \$5,000 per unit. Even when external funding or subsidies offset initial expenses, ongoing maintenance and technical support pose barriers to sustained use. Low-cost alternatives (e.g., LEDs, ultrasonic devices) are more accessible but provide limited long-term effectiveness. This cost-effectiveness trade-off is a recurring barrier, particularly in developing regions where farms operate on thin margins.

### 5.5 Socio-Economic and Cultural Barriers

Beyond costs, socio-economic factors play a critical role in adoption. Many farmers lack the technical literacy to operate, calibrate, or maintain AI-driven or UAV-based systems. In some rural communities, cultural perceptions also influence adoption; for example, persistent flashing lights or distress calls may be viewed as intrusive or incompatible with local farming practices. Additionally, cooperative use of shared deterrent systems across multiple farms requires trust and coordination, which may not always exist.

### 5.6 Regulatory and Policy Restrictions

Regulatory frameworks, particularly for UAVs, present a growing challenge. In many countries, agricultural drone operations require licensing, restricted flight zones, and compliance with aviation safety laws (Bhusal et al., 2022). These restrictions limit the use of mobile deterrents even where they have proven effective. Similarly, sound-based devices may be subject to noise regulations in rural communities, while laser-based systems face safety concerns for human operators and non-target species. Without supportive policy environments, deployment of advanced deterrent technologies remains constrained.

### 5.7 Ethical and Ecological Considerations

Finally, ecological impacts must be carefully assessed. Some deterrents risk harming non-target species, such as pollinators or domestic animals, if not properly calibrated. Bright lights may disrupt nocturnal insect populations, while distress-call systems can alter the behaviour of non-pest birds critical to ecosystem balance (Agossou et al., 2022). Ensuring that deterrents are non-lethal, species-specific, and ecologically responsible is essential for long-term sustainability.

## 6. Opportunities for Improvement and Future Work

The limitations identified in current autonomous deterrent systems point to fertile ground for innovation. As agriculture increasingly turns to automation and data-driven decision-making, future animal scarers must evolve beyond static, single-mode systems to become intelligent, resilient, and ecosystem-aware. This section explores technological opportunities and research directions that can shape the next generation of deterrent solutions.

### 6.1 Adaptive Learning and Reinforcement Models

A key frontier is the integration of reinforcement learning (RL) to counter habituation. Unlike static deterrents, RL algorithms can adapt stimulus patterns over time based on animal behaviour feedback. For instance, Q-learning and Deep Q-Networks (DQN) could be applied to vary sound or light sequences, while Actor–Critic models offer potential for balancing deterrence effectiveness against energy efficiency. Early pilot studies, such as Lee et al. (2021), have shown that adaptive audio systems delay habituation by up to 40%, but broader field validation across species and environments is lacking.

### 6.2 Species-Specific Training Datasets

AI-powered detection systems are constrained by the absence of annotated datasets for nocturnal animals in agricultural contexts, particularly in developing regions. Most current datasets are biased toward urban environments (e.g., bird detection at airports). Building region-specific datasets of nocturnal intruders—such as porcupines, civets, wild pigs, or fruit bats—would enable models like YOLOv8 or EfficientDet to achieve higher precision and recall in real-world farm settings. Ummah et al. (2022) demonstrated the feasibility of dataset-driven improvements in bird detection, though their work was limited to aviation contexts. Collaborative data-sharing platforms involving universities, agricultural research institutes, and farmer cooperatives could accelerate this effort.

### 6.3 IoT-Enabled Ecological Monitoring

The next generation of deterrent systems should be embedded within broader ecological monitoring frameworks. IoT-based networks of cameras, motion sensors, and sound detectors can provide real-time intrusion logs, enabling predictive analytics of animal behaviour. Drone-based surveys could complement ground sensors by mapping nocturnal animal movement patterns across landscapes. Similar IoT integrations have been piloted in precision agriculture systems for crop and soil monitoring (Agossou et al., 2022), and adapting these approaches to wildlife–agriculture conflict holds considerable promise. Cloud dashboards and mobile applications would allow farmers to track intrusion frequency, deterrent effectiveness, and device status remotely.

### 6.4 Cost Reduction and Scalability

For widespread adoption, especially among smallholder farmers in sub-Saharan Africa and South Asia, systems must be affordable, low-maintenance, and easy to operate. Opportunities lie in modular, open-source designs that combine locally available hardware (e.g., solar panels, low-power microcontrollers) with adaptable software platforms. Bhusal et al. (2022) highlighted cost as a major barrier in UAV deterrent adoption, while Mapari et al. (2021) showed that low-cost sensor-based systems are more accessible though less effective. Cooperative ownership models, where farmer groups share deterrent infrastructure, may also enhance affordability and scalability. Partnerships with governments and NGOs could further support subsidized access and training.

### 6.5 Regulatory and Policy Innovation

UAV-based deterrents will remain constrained without supportive regulatory frameworks. In many regions, drone use requires licensing and compliance with flight restrictions, limiting their applicability for nocturnal crop protection (Bhusal et al., 2022). Similarly, ethical guidelines are needed to ensure non-lethal

operation, prevent disturbance to non-target species, and maintain ecological balance. Shannon et al. (2016) also stress the need to evaluate unintended ecological impacts of auditory deterrents, such as altered bird migration patterns. Addressing these policy and ethical dimensions will be critical for sustainable deployment.

## Conclusion

The growing challenge of nocturnal animal intrusion in agricultural fields, particularly from rodents, birds, and wild mammals, demands innovative solutions that go beyond traditional deterrence. As farmers continue to suffer significant yield losses due to wildlife activity, the transition from manual and static systems to autonomous, intelligent deterrents is not only logical but necessary for long-term sustainability and productivity.

This review has examined a diverse array of technological interventions ranging from motion-triggered lights and ultrasonic devices to AI-integrated surveillance systems and autonomous drones. Each represents a step forward in automating animal detection and repulsion. Systems like those by Mapari et al. (2021) and Brown and Brown (2021) demonstrate practical, cost-conscious designs that are already deployable, while high-end implementations, just as Bhusal et al. (2022) point toward a future in which deterrent systems are not just reactive but adaptive, predictive, and learning-capable. However, widespread adoption of these systems is still constrained by several factors. Environmental sensitivity, power dependency, animal habituation, and high technical and financial barriers must be addressed to ensure these systems perform consistently in real-world agricultural environments. Equally important are the ethical and ecological implications of deploying deterrent technologies at scale. As Agossou et al. (2022) highlighted, certain methods can threaten biodiversity or unintentionally impact non-target species, emphasizing the importance of non-lethal and species-specific designs.

Looking forward, the most promising path lies in multi-modal, modular systems that combine sensor data, machine learning, behavioral modelling, and low-cost hardware. The integration of deterrent platforms into IoT-connected smart farm ecosystems will enable greater control, monitoring, and resource efficiency. Moreover, by incorporating reinforcement learning and real-time adaptability, future systems can outpace animal habituation and deliver longer-lasting protection. To maximize global impact, researchers and engineers must focus not only on technical performance but also on affordability, simplicity, and contextual appropriateness. Community-driven designs, open-source frameworks, and partnerships with local stakeholders can help bring these advanced technologies into mainstream agriculture, even in regions with limited infrastructure.

In summary, autonomous nocturnal animal scarers hold transformative potential. With continued research, ethical engineering, and practical deployment strategies, they can become a cornerstone of sustainable, intelligent crop protection, safeguarding food production in an increasingly uncertain and ecologically complex world.

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