A Survey on Farm Protection Systems

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Abstract—**Wild animal intrusion poses a significant and persistent threat to agricultural productivity, particularly in rural and forest- adjacent areas. This paper presents a detailed comparative survey of different research studies that propose smart protection systems to deter animal intrusions using modern technologies such as the Internet of Things (IoT), Wireless Sensor Networks (WSN), Artificial Intelligence (AI), image processing, and geofencing. The reviewed systems encompass a variety of detection mechanisms—including PIR, ultrasonic sensors, computer vision, RFID tagging, and circuit-based triggers—and deploy deterrents ranging from sound and light to real-time alerts and virtual fencing. Each system is evaluated for its technical design, effectiveness, scalability, power efficiency, cost, and ethical considerations. Although many demonstrate innovation in theory, gaps remain in environmental robustness, large-scale deployment, and experimental validation. The paper concludes by identifying opportunities for hybrid, energy- aware solutions that balance technological sophistication with practical feasibility for farmers. This work aims to inform future research and policy in precision agriculture and wildlife management.**

Keywords—Wild animal intrusion, IoT, machine learning, crop protection, artificial intelligence, wireless sensor networks, virtual fencing, farm security, GSM, RFID.

I. INTRODUCTION

As someone who has closely followed the intersection of agriculture and emerging technologies, it is noticed that a growing urgency in solving the issue of wildlife intrusion into farmlands. With rapid urbanization and the continued degradation of natural habitats, animals are increasingly entering human spaces in search of food. This has led to significant crop damage, financial distress for farmers, and rising human-animal conflict.

Traditionally, farmers have relied on physical fencing, scarecrows, or manual patrolling—methods that are not only labor-intensive but often ineffective across large and remote agricultural landscapes. Fortunately, the digital transformation in agriculture is opening new avenues. Technologies like IoT, computer vision, and machine learning are enabling proactive and non-invasive approaches to this problem. However, while innovation is abundant, the path to practical implementation remains bumpy. Many proposed systems look promising on paper but struggle to meet the challenges posed by rugged outdoor environments, power constraints, and the need for continuous, real-time operation.

In this paper, a closer look at various studies that tackle this challenge from different technological angles. The goal is not only to understand the individual contributions of each but also to reflect on the broader patterns—what works, what doesn't, and what might guide future solutions.

II. METHODOLOGY FOR LITERATURE SELECTION

To ensure a focused and credible review, a structured search across major academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, PubMed, and Google Scholar is done. Targeted keywords like "wild animal intrusion detection," "smart farm protection," and "IoT in agriculture" are used to filter relevant studies, employing Boolean operators to refine the results.

The selection focused on peer-reviewed works published between 2015 and 2024 that presented technology-driven solutions for farm protection. Studies based purely on traditional or non-technical methods were excluded to keep the emphasis on innovation. Each chosen paper was evaluated for its technological framework, implementation strategy, and reported outcomes.

In the end, some different papers were selected, offering a balanced mix of sensor-based, AI-driven, and IoT-enabled systems. These works were assessed not only for their conceptual value but also for their practical viability in real-world agricultural environments.

III. COMPARATIVE ANALYSIS AND TECHNICAL EVALUATION

As some selected research papers reviewed, it became increasingly clear that while each system targets the same underlying problem—protecting crops from wild animal intrusions—they diverge significantly in how they approach detection, deterrence, communication, and practical deployment. In this section, it is aimed to offer not just a technical comparison, but also a synthesis of my personal reflections on the effectiveness, feasibility, and future potential of each methodology.

Sensor-Based Detection and Deterrence Systems

A number of papers focused on sensor-driven systems, which tend to be relatively easy to implement and cost-effective. For instance, RFID tags injected into animals for identification—a clever way to track movement and initiate deterrent responses such as sound and fog. Conceptually, it's impressive, particularly for its tiered response (intimation, irritation, repellent). However, the ethical implications of injecting tags into wild animals raise serious concerns [1]. As a researcher, it is believed that any practical system must account for wildlife regulations and ethical deployment practices, something this paper unfortunately overlooks.

When an animal touches the wire, a circuit completes and triggers alarms and lights [2]. It is appreciated the simplicity and non-lethality of this design—it feels rooted in real-world usability. But concern lies in the lack of experimental validation. Without real test data, it's hard to know how it would perform across varying weather conditions or on larger farms.

Wireless Sensor Networks (WSN) [3] and this system stood out to me for its attention to energy optimization. By focusing on low-power communication protocols and smart sensor deployment, the authors created a system that feels scalable—at least in theory. The downside, however, is the issue of false detections. It is found that without fine-tuned classification algorithms, motion sensors alone can't reliably distinguish between real threats and harmless movement (e.g., wind-blown branches or farm animals).

Theme using PIR and ultrasonic sensors, coupled with IoT for alerting [4]. Its strength lies in its practical automation and the use of a light-dependent camera system for added monitoring. While it is appreciated the clarity of the system architecture, it couldn't be helped but noticed the lack of scalability discussion. A few well-placed sensors might work for a small farm, but what about large, open agricultural plots?

Geofencing and GPS-Driven Monitoring

Geofencing through GPS and LTE communication is nothing but shifting from traditional sensors which is a more modern route [5]. Particularly impressed with its mobile app integration—it's a nod to the kind of real-time responsiveness farmers increasingly expect. One feature really liked was how the geofencing logic distinguished between animal intrusions and human (farmer) activity, which helps reduce false alarms.

That said, the implementation felt a bit too centralized. The system uses a single GPS unit at the centre of the farm and extrapolates boundaries—an approach that might not work reliably for irregular terrain or very large fields. Also, while the authors mention a promising notification delay of only 1.57 seconds, there's minimal exploration of how the system performs under poor connectivity or power loss, both of which are common in rural settings.

Similar goals can be attempted with IR sensors and GSM-based virtual fencing [8]. However, it is found that the execution rather underwhelming. While it's accessible in terms of hardware and low-cost design, the lack of range, insufficient power planning, and minimal field testing reduce its viability. The addition of a mild shock as a deterrent is ethically debatable and likely to face regulatory challenges.

AI and Vision-Based Detection Systems

The most technically ambitious systems lie in the domain of computer vision and artificial intelligence. CNN-based model detects and classifies animals from camera feeds [6]. What admired most here is the multi-functionality—apart from animal detection, the system even monitors water levels, which is a practical feature for any farmer. However, the implementation lacks key technical disclosures, such as training data, model performance metrics, and hardware limitations. Without these, it's difficult to gauge how well the system performs under varying light and weather conditions, or how scalable it is.

Traditional computer vision methods like SIFT and frame differencing techniques [7] are a bit dated, it is found that the application compelling—especially for regions with limited computational resources. The results were promising for common animals like goats and cows, but again, there's no mention of detection performance in low light or during heavy rains, which could compromise accuracy.

A data-driven machine learning approach, comparing models such as Random Forest, SVM, and Logistic Regression for animal classification [9]. The strength here lies in the comparative evaluation—Random Forest achieving 95.65% accuracy is notable. What resonated was the authors' focus on preprocessing (e.g., Canny edge detection), which clearly improved classification outcomes. However, the system remains a lab prototype. For it to become a viable farm solution, we need real-world validation with unpredictable variables like animal movement, camera vibrations, and occlusion.

YOLO and MobileNet SSD for real-time animal detection [10]. Though conceptually strong, still confused by the inconsistent methodology (mentioning one model in the abstract and another in the body). The absence of detection metrics, energy usage stats, or real deployment scenarios limits its practical value. It is believed that the authors had the right idea, but the presentation needs polish and deeper technical depth.

Final Thoughts

Across all papers, it is noticed a common gap—field validation. Regardless of the technology stack, many solutions lack rigorous, real-world testing in diverse environments. Sensors behave differently in rain, fog, or heat. Cameras lose precision in low light. Power constraints remain the Achilles' heel of most systems. Key takeaway is that the future of smart farm protection lies not just in novel ideas, but in systems that are rugged, adaptive, and field-tested. Integration of hybrid models—combining sensors with AI and IoT—is the most promising.

IV. STRENGTHS AND WEAKNESSES

In analyzing each of the reviewed systems, it became clear to me that while all shared the common goal of mitigating wild animal intrusions into farmland, their methods varied not only in technical design but also in practical readiness. Table 1 distills reflections on each paper into a structured comparison— summarizing their core strengths, notable limitations, and my personal takeaways based on implementation depth, real-world feasibility, and innovation relevance.

Table I

Comparative Analysis and Author's Perspective

References	**Strengths**	**Weaknesses**	**Author's Perspective**
S. Santhiya *et. al,* 2018 [1]	Introduces a layered, multi-response system (intimation,irritation, repellent); low-cost; non-lethal	Raises ethical questions with RFID tagging in wild animals; no real testing data; power concerns unaddressed	Conceptually innovative, but lacks field sensitivity. The solution needs a redesign that respects animal welfare and includes performance trials. Without these, its potential stays theoretical.
A. V. Deshpande, 2016 [2]	Simple, low-cost fencing alternative using circuit-based detection; non- lethal deterrents; good for local farmers	No field validation; lacks performance metrics; vague technical design	The paper has practical charm but feels more like an academic proposal than a deployable system. With more testing and circuit reliability data, it could evolve into a strong local solution.
V. Bapat *et al.* 2017 [3]	Practical implementation using WSN; energy-efficient design; tested across scenarios	Limited scalability; lacks false-positive analysis; animal habituation to stimuli not addressed	I see this as a strong base model. Its field trials are commendable. However, success in small setups doesn't guarantee success at scale. It needs adaptive intelligence for long-term reliability.
N. V. Deshmukh *et al* 2021 [4]	Clear IoT architecture; good integration of sensors and alert systems; visual support enhances understanding	No power efficiency analysis; lacks testing across terrains and scales	This work sits in the sweet spot between feasibility and ambition. A bit more depth on energy planning and large-scale trials would make it very applicable for real farms.
A. L. Kadam *et al* 2020 [5]	Smart use of geofencing; accurate notifications; good user interface via mobile app; reduced false alarms	Ultrasonic range too narrow; centralized GPS logic may not scale; lacks deployment diversity	A forward-looking design with clear benefits in precision and ease of use. But for it to go beyond proof-of- concept, multi-node logic and terrain-adaptive algorithms must be included.
Kiruthika S *et al* 2023[6]	Integrates AI, image processing, and IoT; considers multi-dimensional farm issues like waterlogging; CNN-powered detection	Missing CNN training and dataset details; lacks performance metrics and testing	This paper excited me for its holistic thinking—combining vision and water monitoring—but it's incomplete without real model evaluations. The groundwork is strong, but needs rigor.
M. Gogoi *et al* 2015 [7]	Uses classical vision techniques (SIFT) effectively; decent object detection accuracy; practical for rural India	No quantitative metrics; untested in night or weather scenarios; scalability unclear	It's a good low-cost entry point for vision systems. While not cutting- edge, it's resourceful. With more robust environmental testing, it can be a dependable farmer's tool.
K. M. Lakshmi *et al* 2020 [8]	Accessible components (IR, GSM); virtual fencing logic; layered deterrents (alerts + shock)	Limited sensor range; unclear outdoor reliability; lacks intelligent detection	While the idea of a virtual fence is appealing, the execution is overly simplistic. Without real environmental testing and smarter intruder differentiation, it may produce more noise than value.

S. Shilaskar *et al* 2015 [9]	Strong ML algorithm comparison; excellent classification accuracy (Random Forest at 95.65%); thoughtful preprocessing	No environmental variability testing; dataset may not represent real conditions; lacks behavioural analysis	Among the strongest technically. I respect the rigorous algorithmic benchmarking, but real-time field testing and context-awareness must follow to make this applicable to live farms.
P. Marichamy *et al* 2023[10]	Uses deep learning (YOLO); integrates IoT for real-time deterrence; modern architecture	Confusing ML methodology; no performance benchmarks; weak technical depth	The paper feels ambitious but undercooked. It needs conceptual consistency (YOLO vs. SSD), technical details, and real deployment trials to move from idea to implementation.

Closing Reflections

In compiling this table, we've come to appreciate how wide the gap still is between theoretical promise and deployable precision agriculture solutions. Most of these papers highlight valuable innovations, yet they stop just short of the finish line—missing practical considerations like power autonomy, sensor maintenance, night detection, or weatherproofing.

A hybrid approach seems most promising—one that combines smart sensors, adaptive AI, scalable IoT communication, and ethical design. But this requires not just smart code, but smart engineering in the field, with farmers' feedback baked into the iteration process.

V. CONCLUSION

Analyzing the range of systems proposed for mitigating wildlife intrusion into farms reveals diverse methodologies driven by a shared goal: safeguarding crops ethically and intelligently. Most solutions shine in individual aspects—be it detection accuracy, cost, or power efficiency—but few offer holistic readiness for real-world deployment.

AI and machine learning models are increasingly outperforming traditional sensors in recognition accuracy, though power and data bandwidth constraints hinder their scalability. Conversely, sensor-based models offer affordability and ease but suffer from high false positives and limited adaptability.

The path forward calls for convergence: blending sensor simplicity with AI's decision-making, backed by energy-efficient communication and rigorous testing. Future designs must also address user interface simplicity for farmers, low-maintenance operation, and regulatory standards—especially for solutions involving tagged animals or deterrents.

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