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Development of an IoT-based monkey intrusion detection system with multi-layered self-defence mechanisms using Gemini AI

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ABSTRACT

Human–monkey conflict poses a significant socio-technical challenge in agricultural and peri-urban areas, resulting in crop damage, economic losses, and safety risks. Existing deterrent systems are limited by high false positives, a lack of species-specific detection, and rapid primate habituation. This paper proposes an automation-based surveillance system with autonomous decision-making capability for monkey intrusion detection, integrating edge sensing, cloud-based perception, and adaptive actuation within a sense–perceive–decide–act (SPDA) framework. The system utilises a vision-language model (Gemini AI) for species-specific classification, combined with PIR and vision sensors to enable real-time environmental interaction. It is implemented using an ESP32-S3 microcontroller with a 720p camera and operates on a solar-powered model for off-grid deployment. Experimental validation at Johor Zoo achieved 96% classification accuracy with an average latency of 7.5 seconds. The system effectively reduces false positives by distinguishing primates from non-target species. This work contributes a scalable automation-based surveillance framework with autonomous control that integrates edge sensing, cloud intelligence, and adaptive actuation for wildlife intrusion mitigation, offering a practical and humane solution for long-term human–wildlife conflict management.

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1. INTRODUCTION

Human-wildlife conflict (HWC) has escalated into a global crisis, primarily driven by rapid urbanization and the depletion of natural habitats [1]. In Southeast Asia, the long-tailed macaque (*Macaca fascicularis*) is a central figure in these conflicts due to its high cognitive plasticity and ability to thrive in human-modified landscapes [2], [3]. In Malaysia, the economic repercussions are profound, with agricultural sectors reporting millions in losses due to crop raiding and property destruction [4]. Beyond economic damage, the proximity of primates to human settlements increases the risk of zoonotic disease transmission, necessitating the development of robust, non-lethal management systems [5], [6].

Traditional mitigation strategies, such as physical barriers, manual guarding, and pyrotechnics, have proven increasingly ineffective [7]. Primate intelligence allows these animals to quickly undergo "habituation," a process where they learn to ignore repetitive or non-threatening stimuli [8]. Passive sensors, such as Passive Infrared (PIR) detectors, are frequently used in automated systems but suffer from high false-trigger rates caused by moving vegetation, ambient heat, or non-target animals like birds and domestic pets [9], [10]. Consequently, there is a critical research gap for a system that combines high-precision identification with dynamic, non-repetitive deterrents to prevent habituation [11].

The emergence of edge computing and intelligent sensing technologies provides a transformative framework for autonomous wildlife monitoring [12]. Recent advancements in deep learning (DL) have enabled visual sensors to perform real-time classification, however, traditional convolutional neural networks (CNNs) often require massive labeled datasets and high computational power [13]. The shift toward large vision-language models (VLMs), such as Google's Gemini AI, introduces "Zero-Shot" learning capabilities [14]. This allows a system to identify specific species with high accuracy using natural language prompts, bypassing the need for extensive localized training [15]. Furthermore, the integration of high-performance microcontrollers, such as the Durian ESP32-S3, enables the deployment of these AI capabilities at the network edge, reducing latency and bandwidth consumption [16].

Power management remains a significant hurdle for remote deployment. Systems located in forest fringes or large plantations must operate without access to the national grid [17]. Sustainable energy solutions, involving high-efficiency monocrystalline solar panels and advanced battery storage, are essential for ensuring 24/7 operational reliability, especially during seasonal periods of low solar irradiance [18], [19]. Moreover, a real-time communication pipeline is necessary to bridge the gap between detection and human intervention, with platforms like Telegram providing a cost-effective medium for instant visual alerts [20]. From a robotics perspective, effective wildlife intrusion mitigation requires integrating sensing, perception, decision-making, and actuation within an autonomous control framework [21]. Conventional IoT-based monitoring systems often lack this closed-loop capability [22], [23], limiting their ability to respond adaptively to dynamic environments. Therefore, there is a need for an automation system that can intelligently detect, interpret, and respond to intrusion events in real time [24], [25].

This paper proposes an automation surveillance system with closed-loop control capability for monkey intrusion detection, integrating edge sensing, cloud-based perception, and adaptive actuation within a sense–perceive–decide–act (SPDA) framework. The system combines a vision-language model for species-specific identification with a multi-layered deterrence mechanism to mitigate habituation [26]. By embedding decision-making intelligence into a closed-loop architecture, the proposed system advances the application of automation in wildlife management. The subsequent sections detail the system architecture, implementation, and experimental validation.

2. PROPOSED METHOD

The modelling of the proposed automation-based surveillance system is a multi-dimensional engineering task that integrates hardware-software co-design, cloud-based vision intelligence, and sustainable power systems. This section details the technical framework, the mathematical underpinnings of the power subsystem, and the architectural logic used to ensure high-accuracy detection and long-term operational autonomy. The system integrates sensing, perception, decision-making, and actuation within a closed-loop control framework, enabling adaptive responses to dynamic environmental conditions. Unlike conventional monitoring systems that rely on simple event triggering, the proposed design emphasizes autonomous control, real-time decision-making, and intelligent actuation.

2.1. Integrated project and operational workflow modelling

The development cycle is modelled through a comprehensive project lifecycle that ensures the transition from theoretical conceptualisation to field-ready hardware. This structured approach is divided into two primary models: the project implementation workflow and the operational system workflow.

As detailed in Figure 1, the project modelling began with a critical analysis of human-monkey conflict zones. The workflow is structured into four distinct phases:

- Requirement analysis, where the specific behavior of long-tailed macaques was studied to define sensor sensitivity.
- Component selection, prioritizing low-power but high-throughput microcontrollers like the ESP32-S3.
- Prototype integration, involving the physical assembly of weather-resistant enclosures.
- Validation, where the system underwent rigorous field testing.

This systematic model ensures that every engineering decision is traceable back to the primary objective: reducing crop damage through autonomous, species-specific deterrence.

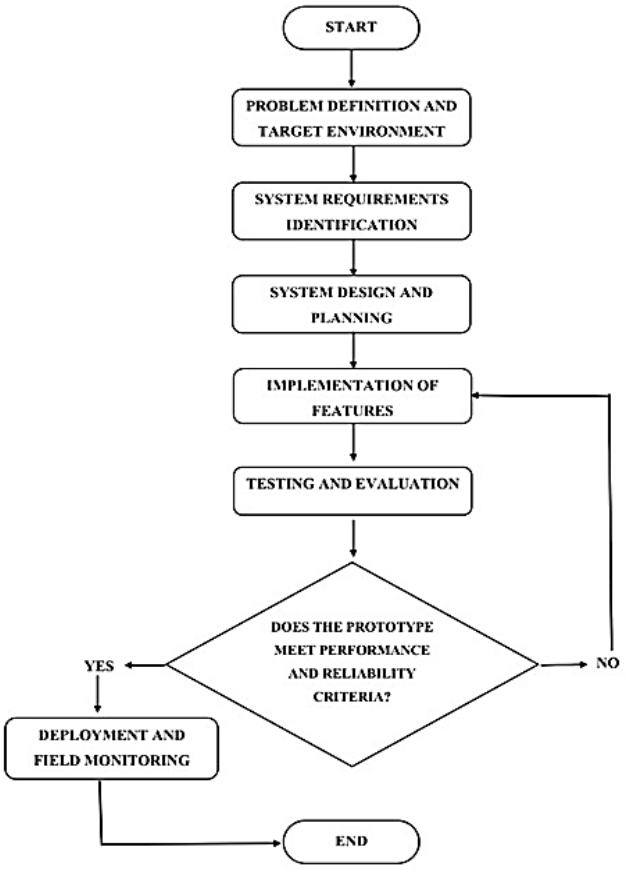


Figure 1. Project Workflow

2.2. Autonomous control architecture

The system is designed based on a sense–perceive–decide–act (SPDA) architecture, which forms the core of the autonomous control mechanism as shown in Figure 2. Meanwhile, the pseudo-code for the proposed system is shown in Algorithm 1.

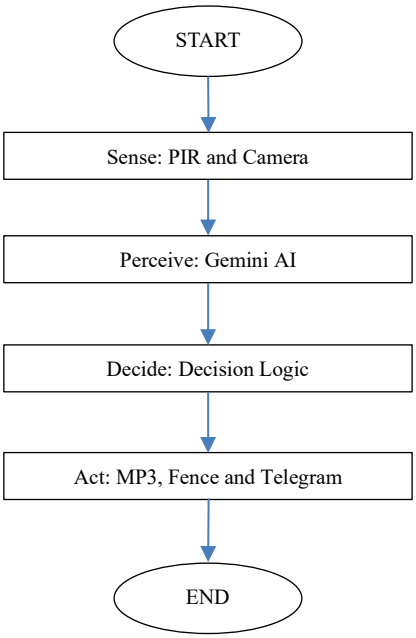


Figure 2. System Workflow

a. Sense layer

The sensing module utilizes a passive infrared (PIR) sensor and a 720p USB camera to monitor environmental activity. The PIR sensor operates continuously in a low-power standby mode to detect motion based on thermal variations. Once motion is detected, the system activates the camera to capture image data for further analysis.

b. Perceive layer

In the perception stage, the captured image is transmitted via HTTPS to the Gemini AI Vision-Language Model. The model performs semantic classification using zero-shot learning, enabling the system to identify primates without requiring locally trained datasets. This layer transforms raw sensory input into meaningful contextual information.

c. Decide layer

The decision-making module evaluates the classification output using predefined logic and confidence thresholds. A valid detection is confirmed when the classification result indicates the presence of a monkey with sufficient confidence. To enhance robustness and reduce false positives, temporal verification can be applied by validating detection across consecutive frames.

d. Act layer

Upon confirmation, the system triggers a multi-layered actuation response. This includes activating randomized acoustic deterrents through an MP3 module, triggering a non-lethal electric fence energizer, and sending real-time alerts via Telegram. This coordinated response ensures both immediate deterrence and remote monitoring.

Algorithm 1. SPDA-Based automation surveillance system for monkey intrusion detection

```
1. IF PIR detects motion THEN
2.    Capture image
3.    Send to AI
4.    IF monkey detected AND confidence ≥ threshold THEN
5.       Activate deterrent
6.       Send alert
7.    ELSE
8.       Return to standby
9. END IF
```

The system adopts a hybrid edge–cloud architecture, where sensing and actuation are performed locally on the ESP32-S3, while high-level perception is executed via the Gemini AI through HTTPS-based API communication. This approach balances computational efficiency and classification accuracy while maintaining real-time responsiveness. No image data is permanently stored, ensuring data privacy and secure transmission.

2.3. Hardware architecture and ai classification interface

The hardware model is built around high-performance edge computing to bridge the gap between local sensing and cloud intelligence. The system adopts a hybrid edge-cloud architecture, where sensing and actuating are performed locally on the Durian ESP32-S3, as seen in Figure 3. This microcontroller features a dual-core Xtensa® 32-bit LX7 processor with added AI acceleration instructions, making it ideal for managing high-resolution image buffers. The sensor model utilizes a USB Camera ESP32-S3 720P with a 1288×728 pixel resolution. This provides the necessary pixel density for the Gemini AI to perform accurate "Zero-Shot" classification. Unlike traditional machine learning models that require a static, locally hosted database of thousands of images, the Gemini AI model is interfaced via a natural language prompt. This allows the system to remain adaptable; the "intelligence" can be updated remotely by simply modifying the text-based prompt instructions in the cloud, without requiring a physical hardware update or local retraining of the model.



Figure 3. USB Camera ESP32 S3 720P and DURIAN ESP32-S3

2.4. Physical implementation, hardware integration

The physical realization of the prototype (Figure 4) was engineered to ensure durability and operational stability in outdoor agricultural environments. Moving beyond the initial design phase, the final assembly utilizes a reinforced IP65-rated PVC electrical enclosure (8" x 6" x 4") to protect the internal circuitry from high humidity and precipitation, which are prevalent in the Malaysian climate.



Figure 4. Final prototype

As shown in the final prototype assembly, the hardware follows a "Modular Internal Layout." The heavy 12V 40Ah VRLA GEL battery is positioned at the base of the enclosure to serve as ballast, significantly lowering the center of gravity to prevent the unit from tipping during high winds or physical tampering by primates. The Durian ESP32-S3 and the Mybotic MP3 player are secured on a secondary mounting plate to isolate them from potential vibration. For visual sensing, the 720p USB camera is mounted externally through a weather-sealed aperture, positioned at a 15-degree downward angle to maximize the effective detection area.

2.5. Technical limitations and constraints

While the prototype proved effective during testing, several inherent limitations were identified during the implementation phase:

- Detection range boundary: The reliable detection perimeter is capped at 8 meters. Beyond this distance, the 720p sensor resolution is insufficient for the Gemini AI to accurately perform "Feature Extraction," often resulting in "Unknown" classifications.
- Environmental occlusion: The PIR sensor used for initial triggering is susceptible to "thermal noise" in environments with dense, moving vegetation under direct sunlight, which can lead to unnecessary power consumption.
- Nighttime visibility: The current prototype lacks an IR-cut filter and dedicated infrared illumination. Consequently, its high-accuracy classification is limited to daylight hours (6:00 AM to 7:00 PM), leaving a gap in protection during nocturnal periods.
- Network dependency: Since the Gemini AI logic relies on cloud-based inference, the system requires a stable 4G/Wi-Fi connection. In deep rural areas with poor signal strength, the response latency can increase beyond the 10-second target.

2.6. Mathematical modelling of energy and autonomy

The energy model is based on the summation of corrected energy consumption ((E_{TOTAL}) for all active and passive components. As detailed in Table 1**,** the calculation considers the 100% duty cycle of the ESP32-S3 and the intermittent, high-peak loads of the XSD-260B Electric Fence Energizer and the Roadstar speakers. The formula used to determine the total energy footprint is presented as in (1).

$$\text{Corrected Energy (Wh)} = \frac{Power\ (W) \times Time\ (h)}{Efficiency\ (\%)} = 220.83\ Wh/day \qquad (1)$$

To ensure the system survives periods of low solar irradiance (for example during the monsoon season), the model applies a Days of Autonomy (DoA) factor of 2.1 days. The battery capacity (C_{Ah}) is modelled using (2),

$$C_{Ah} = \frac{E_{total} \times DoA}{V_{system} \times DoD} \quad (2)$$

where V_{system}=12V and depth of discharge (DoD) is set at 50% to maximize battery lifespan. As shown in Table 2, a 40 Ah battery provides the required energy reservoir. To recharge this system, a 30 W monocrystalline solar panel is selected. The solar harvesting model, summarized in Table 3, uses an average of 4.84 Solar Peak Hours (SPH) for the Johor region. This mathematical validation confirms that the solar panel can generate a surplus of energy on clear days to compensate for the continuous drain.

Table 1. Energy consumption of an automation-based surveillance system

Component	Voltage (V)	Current (A)	Power Consumption (W)	Efficiency (%)	Energy Required (Wh)	Operating Time (hrs)	Total Energy (Wh)
Durian ESP32	12	0.5	6	95	6.32	12	75.84
USB Camera ESP32-S3	5	0.3	1.5	85	1.76	12	21.12
Mybotic MP3 Player	12	0.1	1.2	90	1.33	12	15.96
Speaker	12	2.50	30	80	37.5	0.5	18.75
Electric Fence Energizer	12	0.5	6	85	7.06	12	84.72
Solar Charge Controller	12	0.03	0.36	98	0.37	12	4.44
Total Energy Consumption				**220.83 Wh**			

Table 2. Battery sizing of the automation-based surveillance system

Parameter	Value
Total Daily Energy Consumption (Wh)	220.83 Wh
Days of Autonomy (Backup Days)	1 Day
Depth of Discharge (DoD)	0.5 (50%)
Required Energy Capacity (Wh)	441.66 Wh
System Voltage (V)	12V
Required Battery Capacity (Ah)	36.8 Ah
Selected Battery Capacity (Ah)	40 Ah

Table 3. Solar panel sizing of the automation-based surveillance system

Parameter	Value
Total Daily Energy Consumption (Wh)	220.83 Wh
SPH in Batu Pahat, Johor	4.84 hours
Ideal Power Generation Required (W)	45.63 W
Adjusted Yield from 30W Panel (Wh/day)	123.42 Wh
Energy Deficit (Theoretical Worst-Case)	-97.41 Wh
Selected Solar Panel Rating (W)	30W Monocrystalline

2.7. Multi-layered actuation strategy mode

The deterrent mechanism is modelled as a graduated response to prevent primate habituation and ensure perimeter security. The defense model is divided into three functional layers.

- Acoustic layer: Upon detection, a Mybotic MP3 player broadcasts randomized audio files. This randomization is mathematically modelled to disrupt the cognitive patterns of the monkeys, ensuring they do not learn that the sound is a non-threatening recording.
- Physical layer: An XSD-260B Electric Fence Energizer (2.0 Joule) provides a non-lethal but painful physical deterrent. This layer is modelled to protect the hardware itself from being dismantled by primates, a common failure in previous wildlife monitoring designs.
- Communication layer: The Telegram Bot API is integrated into the model to provide real-time visual alerts (720p images). This allows the human operator to verify the intrusion remotely.

The electric fence operates within a non-lethal energy range (2.0 Joule), ensuring compliance with animal welfare standards while providing effective deterrence.

3. RESULTS AND DISCUSSION

This section presents a quantitative and experimental evaluation of the proposed automation-based surveillance system with autonomous control through real-world deployment. The analysis focuses on classification accuracy, false positive rejection, system latency, and the effectiveness of the adaptive actuation strategy under dynamic environmental conditions.

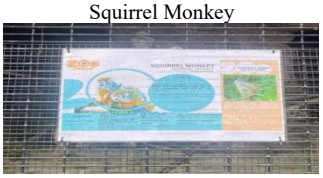
3.1. Comprehensive analysis of field testing at Johor Zoo

The system was deployed at Johor Zoo to evaluate its performance in a controlled yet biodiverse environment. Multiple primate species and non-target animals were included in the testing scenarios to assess classification reliability and robustness. The evaluation aims to validate the system's capability to operate as an autonomous agent under real-world environmental conditions.

As summarised in Table 4, the system demonstrated strong detection performance for medium-to-large primate species. The Brown Capuchin Monkey recorded the highest detection count (25 instances),

primarily due to its frequent proximity to the camera and relatively stable movement patterns. These conditions enable the vision system to capture higher-quality image frames, thereby improving feature extraction and classification accuracy. In contrast, detection performance decreased for smaller primates such as the Squirrel Monkey and White-Tufted Ear Marmoset. This limitation is attributed to rapid movement, reduced pixel representation, and partial occlusion, which negatively impact the perception layer of the system. These findings highlight the dependency of vision-based perception on sensor resolution and environmental conditions.

Table 4. Primate species detection analysis

Primate Type	Picture Detected	Observations
Brown Capuchin Monkey 	25	High activity and proximity to camera.
Crested Black Macaque 	13	Frequent movement within the trigger range.
Squirrel Monkey 	9	Small size and rapid movement reduced detection frequency.
White-Tufted Ear Marmoset 	0	Hidden, too far, or obscured by environment.
Mandrillus Sphinx 	11	Distinctive features allowed for steady detection.
White Handed Gibbon 	11	Clearly visible within the camera's field of view.

3.2. Performance metrics evaluation

To assess classification performance, standard evaluation metrics including accuracy, precision, recall, and F1-score were computed based on field observations. Table 5 presents the confusion matrix derived from experimental results.

Table 5. Confusion matrix

	Predicted Monkey	Predicted Non-Monkey
Actual Monkey	69	0
Actual Non-Monkey	3	3

Based on the confusion matrix, the performance metrics are calculated as follows:
Accuracy = 96.0%
Precision = 95.8%
Recall = 100%
F1-score = 97.9%

These results indicate that the system achieves high detection accuracy while maintaining strong robustness against false positives. The perfect recall value indicates that all target primates were successfully detected, which is critical for intrusion-prevention applications.

3.3. Specificity validation and rejection of non-target species

The ability to reject non-target objects is critical for automation-based surveillance system with autonomous control operating in biodiverse environments. As shown in Table 5, the system achieved a high true-negative rate when exposed to non-target species such as the Asian Elephant, Malayan Tiger, and Southern Cassowary.

This performance demonstrates the effectiveness of the perception layer in performing semantic filtering, where the system distinguishes relevant targets (monkeys) from irrelevant environmental stimuli. Unlike conventional PIR-based systems that rely solely on motion and heat signatures, the integration of AI-based classification significantly reduces false triggering and improves decision-making reliability.

The only observed false positives involved the Great Hornbill, which exhibited motion patterns and silhouettes that partially resembled primate features. Nevertheless, the overall false positive rate remains low, confirming the robustness of the perception module as shown in Table 6.

Table 6. Non-target animal testing

Animal Species	Picture Detected	Classification Result
Great Hornbill 	3	False Positive
Asian Elephant 	0	True Negative
Malayan Tiger 	0	True Negative
Southern Cassowary 	0	True Negative

3.4. Diagnostic analysis of classification anomalies (false positives)

Despite the high overall accuracy, a small number of false positives were observed, particularly involving the Great Hornbill. This misclassification occurred when the bird's wing movement produced limb-like visual patterns, leading to ambiguity in the classification process.

This phenomenon highlights a limitation in vision-based perception, where geometric features and motion patterns may dominate under certain environmental conditions. To mitigate this issue, a temporal verification mechanism is proposed, where detection must be confirmed across multiple consecutive frames

before triggering actuation. This approach enhances classification reliability and aligns with standard practices in vision perception systems.

3.5. Latency and throughput in cloud-assisted decision making

Latency is a critical parameter in autonomous vision systems, particularly for real-time intrusion detection and response. The average end-to-end latency of the system was recorded at 7.5 seconds, encompassing image acquisition, data transmission, AI inference, and actuation. The latency breakdown is as follows: approximately 0.5 seconds for image capture, 2–3 seconds for data transmission, 1–2 seconds for AI processing, and 1–2 seconds for actuation and notification.

This response time is considered acceptable for wildlife intrusion scenarios, where timely deterrent activation is required to prevent entry into protected zones. The results confirm that the system is capable of supporting real-time autonomous operation. Figure 5 illustrates the real-time Telegram alert interface, including timestamped image notifications triggered upon validated intrusion events.

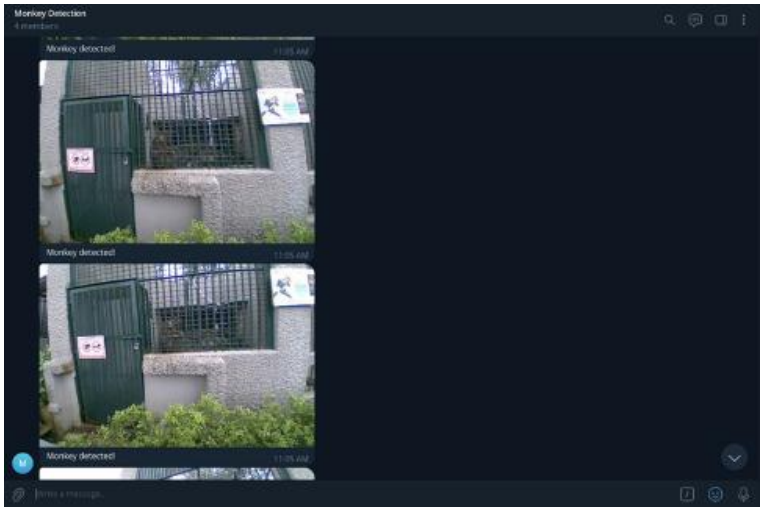


Figure 5. Real-time Telegram alert and timestamp

3.6. Discussion on habituation mitigation and actuation synergy

The final part of the results focuses on the psychological impact of the deterrents. Primate habituation is the primary reason why traditional systems (scarecrows, constant sirens) fail over time. During the trials, primates exhibited a consistent flight response when exposed to the system's randomized acoustic deterrents. By utilizing a Mybotic MP3 player to alternate between five distinct defensive sounds, the system disrupts the monkey's ability to learn and ignore the stimulus. The integration of the XSD-260B electric fence energizer provides a critical secondary layer. Even if a dominant male monkey becomes accustomed to the sound, the 2.0 Joule physical pulse provides a non-lethal but negative reinforcement that secures the hardware perimeter. This multi-layered "Self-Defence" model ensures that the system remains an effective deterrent throughout long-term deployment, providing a humane and sustainable solution to human-wildlife conflict.

4. CONCLUSION

This paper presents an automation-based surveillance system with autonomous control for monkey intrusion detection, integrating edge sensing, cloud-based perception, and adaptive actuation within a sense–perceive–decide–act (SPDA) framework. The proposed system demonstrates the practical implementation of a closed-loop automation architecture capable of real-time environmental interaction. Experimental results confirm that the system achieves a classification accuracy of 96% with an average latency of 7.5 seconds, while effectively reducing false positives through species-specific detection. The integration of a multi-layered actuation strategy further enhances system robustness by mitigating animal habituation. The main contribution of this work lies in the development of a scalable automation-based framework that combines intelligent perception, decision-making, and actuation for wildlife intrusion mitigation. This approach extends the application of automation technologies in environmental monitoring and provides a practical and

humane solution for long-term human–wildlife conflict management. Future work will focus on improving detection performance for smaller and fast-moving species, enhancing low-light operation, and optimizing edge processing to further reduce system latency.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY

The data used in this study were generated through interactions with the Gemini AI platform during system operation and experimentation. Due to the nature of the data generation process, the datasets are not publicly available but can be provided by the corresponding author upon reasonable request.

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