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Visual-Thermal Guard
A Visual AI & Thermal Imaging-Based Security System for Farm Protection

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Abstract— *Wildlife intrusion into farmlands causes significant crop damage, financial losses, and human-wildlife conflicts. Traditional deterrents such as electric fences, chemical repellents, and manual guarding are often ineffective, costly, or environmentally harmful.*
This project develops a farmland protection system using two complementary sensing approaches for around-the-clock monitoring. By day, an RGB camera feeds a YOLO-based object detection model to identify animals approaching the fields, triggering high-pitch sirens to drive them away. At night, when visible light is inadequate, a thermal camera detects animal presence by analyzing temperature variations through thresholding techniques.
Thermal anomalies consistent with animal body heat activate the same deterrent mechanism. Combining RGB image analysis with thermal imaging ensures reliable detection under diverse lighting and weather conditions. The system offers an automated, non- lethal solution to mitigate crop damage and reduce human- wildlife conflict, supporting sustainable agricultural practices.
Keywords—*thermal imaging; animal detection; motion detection; background subtraction; farm security*

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I. INTRODUCTION

Wild animal intrusion into agricultural lands is a major global motion detection challenge, leading to crop losses, financial instability for farmers, and human-wildlife conflicts. In many regions, animals such as elephants, wild boars, deer, and monkeys enter farmlands in search of food and water, causing significant damage to crop and infrastructure [1]. Traditional prevention methods, including manual guarding, electric fences, and chemical repellents, are costly, ineffective, and environmentally harmful [2]. Electric fences may cause injuries to both humans and animals, while chemical deterrents can lead to soil degradation and ecological imbalances [3]. As a result, there is a growing demand for automated, cost-effective, and humane solutions that can efficiently detect and deter wild animals from entering farmlands.

Technological advancements in visual AI models, object detection, thermal imaging, background subtraction, and sound-based deterrents provide a more reliable and scalable approach to farm protection. IoT-based intrusion detection systems can send real-time alerts to farmers, but they often lack active deterrents [4]. Thermal imaging overcomes limitations faced by visual AI models, which struggle in low- light conditions, by detecting animals based on body temperature rather than visual appearance [5].

This project proposes an automated farm protection system that leverages an RGB camera during daytime and thermal imaging during night to accurately identify and repel wild animals. The system employs YOLO [11] based animal detection during daytime and a median-based background subtraction algorithm during nights to minimize false positives caused by non-moving objects or temperature fluctuations. Once an animal is detected, a high-pitch siren is activated to scare it away, ensuring a non-lethal and environmentally friendly deterrent. By integrating real-time detection with active repulsion, this approach enhances agricultural security, reduces crop losses, and minimizes human-wildlife conflicts. The following sections detail the system's design, implementation, and comparative analysis with existing solutions.

II. RELATED WORK

Several research studies have explored technological solutions for preventing wild animal intrusion into farmlands, employing techniques such as IoT-based surveillance, AI- driven detection, thermal imaging, and acoustic deterrents. Each of these approaches has unique strengths and limitations.

IoT-based systems have been widely used for real-time animal detection and alerting. Kadam et al. [1] developed a geofencing system using ultrasonic sensors, GPS, and LTE- based alerts, allowing farmers to receive real-time notifications. Similarly, Chourey et al. [2] proposed a wireless sensor network (WSN) system that detects motion using ultrasonic sensors and sends alerts through GSM communication. While these methods provide early warnings, they lack real-time deterrent mechanisms, allowing animals to continue damaging crops.

AI-based solutions such as those developed by Shilaskar et al. [4] and Adami et al. [5] use machine learning (ML) and deep learning (DL) models to identify animal species. Adami et al. [5] utilized YOLOv3-based object detection for real-time classification of wildlife, achieving 82.5% accuracy. However, these systems work only during the day, making them unsuitable for nighttime use.

Thermal imaging techniques have been explored for nighttime surveillance and detection. Oishi et al. [6] demonstrated how thermal cameras effectively detect animals based on their heat signatures, but their study lacked an active deterrent mechanism. Similarly, Navaneetha et al. [7] integrated thermal sensors with IoT, but their approach suffered false positives due to environmental temperature fluctuations.

Finally, acoustic deterrents have been explored as non- lethal solutions to repel animals. Gogoi and Philip [8] used high-frequency alarms, while Ranparia et al. [10] implemented a machine learning-based sound repellent system that played species-specific distress calls. However, species-specific audio deterrents may not work universally.

The proposed system addresses these limitations by combining a visual-based AI system with thermal imaging, median-based background subtraction for motion detection, and adaptive high-pitch sirens, ensuring real-time detection and effective deterrence.

III. PROPOSED SOLUTION

To address the issue of wild animals damaging crops and entering farmland, we propose an automated animal detection and deterrent system that operates continuously in two distinct modes: day and night. This system integrates computer vision, thermal imaging, and sensory deterrents to monitor the field and respond in real-time to intrusions.

In day mode (6:00 AM to 7:00 PM), the system utilizes an RGB camera (PiCam) mounted on a servo-driven rotating pole to scan the surrounding area. Captured frames are analyzed using a YOLOv11 [11] object detection model, optimized for identifying wild animals with high accuracy and minimal latency. When an animal is detected within the camera's field of view, the system triggers an audible deterrent—a high- pitched sound alarm—intended to scare the animal away. The servo motor adjusts the camera to remain focused in the direction of the detected animal, maintaining the alarm until the animal leaves the frame.

In night mode (7:00 PM onward), the system switches to a thermal imaging approach using an MLX90640 thermal camera. Given the limited visibility at night, traditional RGB image processing is ineffective; hence, the thermal camera detects warm-blooded animal activity based on temperature variations. A temperature thresholding algorithm processes thermal data to distinguish animals from the background. Upon detection, the system activates both the high-pitched sound alarm and a high-intensity light beam, increasing the effectiveness of deterrence during low-light conditions. As in day mode, the system rotates to face the detected activity and maintains deterrent measures until no further activity is observed.

This dual-mode setup ensures continuous monitoring and responsive action regardless of lighting conditions. By combining real-time detection with targeted alarms and light deterrents, the system provides a cost-effective and autonomous solution for farmers to protect their fields from animal intrusions without the need for constant human oversight.

IV. METHODOLOGY

The proposed animal deterrent system is designed to operate autonomously in both day and night conditions using a combination of sensors, image processing algorithms, and actuators. The system is divided into hardware and software components, each playing a critical role in detection and deterrence.

A. Hardware Setup

- RGB Camera (PiCam): Used during the daytime to capture real-time images of the field.
- Thermal Camera (MLX90640): Operates in night mode to detect heat signatures.
- Servo Motor: Mounted beneath the System module to enable 180° rotation for field scanning and directional focusing.
- Sound Alarm and High-Intensity Light Beam: Act as deterrent mechanisms triggered upon detection.

- Raspberry Pi: Central unit handling input from sensors, running detection algorithms, controlling actuators, and switching modes based on time.
- Power Supply: A well-regulated central power supply system to run the processor and provide enough power to run all connected electronic systems.
- Schematic Diagram: Figure 1 represents the schematic diagram of the system

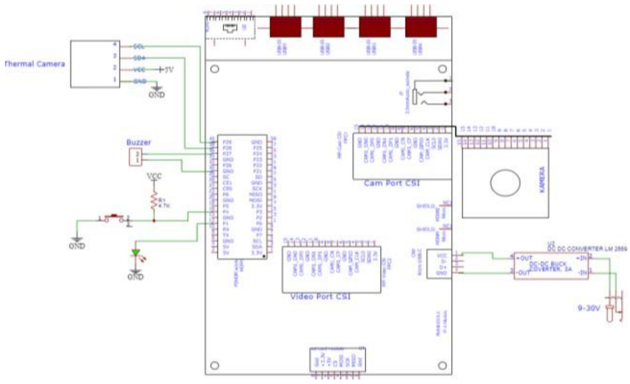

Figure 1. Schematic Diagram of Visual-Thermal Guard

B. Mechanical Casing:

The entire electronic system is enclosed in custom- designed, weatherproof 3D-printed casing made from durable, corrosion-resistant ABS plastic. This casing serves as a protective shield, safeguarding all internal components— including the cameras, processor, wiring, and power systems—from environmental factors such as rain, dust, heat, and pests. To ensure thermal stability, ventilation is carefully integrated into the design, allowing airflow without compromising the enclosure's weather resistance. For ease of deployment, the base of the casing includes a sturdy mounting bracket, enabling quick and secure installation on poles or posts across various farmland locations.

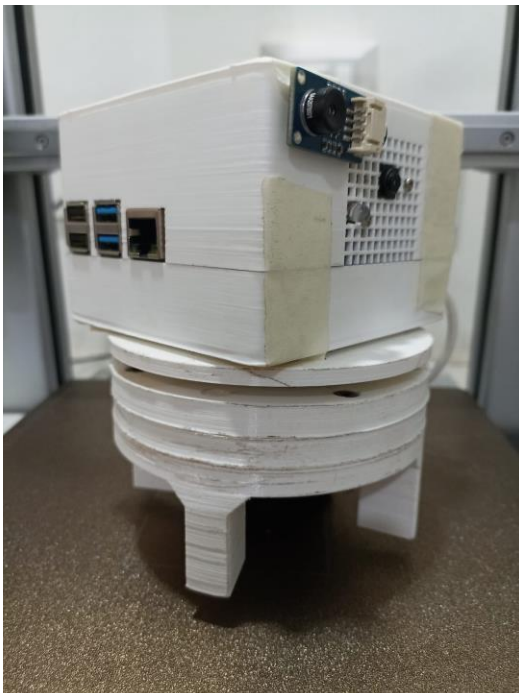

Figure 2. Mechanical Casing of Visual-Thermal Guard

C. System Modes

- *Day Mode (Visual System):*

In day mode, which runs from 6:00 AM to 7:00 PM, the system uses a PiCam to capture RGB images of the farmland. These images are processed using the YOLOv11 object detection model, which identifies wild animals in real time. When an animal is detected, the system calculates its direction within the frame and rotates the camera and alarm setup toward the animal using a servo motor. A high-pitched sound alarm is then activated to scare the animal away. The system maintains its focus and continues sounding the alarm until the animal is no longer present in the frame. Figure 3 summarizes the work of the visual system.

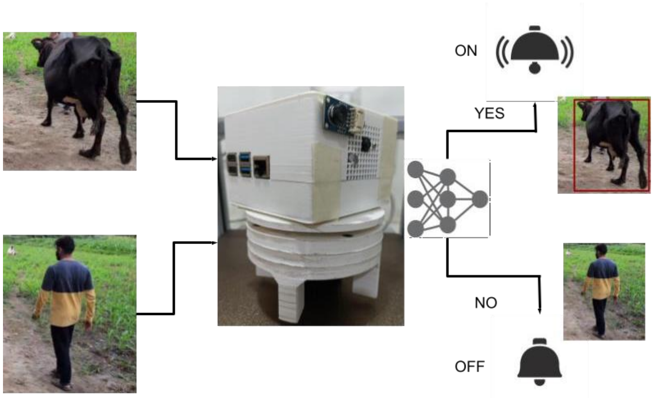

Figure 3. Visual System

- *Night Mode (Thermal System):*

At 7:00 PM, the system transitions into night mode, optimized for low-light conditions. The RGB camera is disabled, and the MLX90640 thermal camera takes over as the primary sensor. It captures thermal images that are processed using a temperature thresholding algorithm to detect warm- bodied intrusions. When an animal is identified based on heat signatures, the system rotates in its direction and activates both the high-pitched sound alarm and a high-intensity LED beam. This dual deterrent approach enhances visibility and effectiveness at night. The alarm and light remain active until the thermal signature disappears, indicating the animal has left the area.

Motion detection at night is achieved using a median- based background subtraction approach. Given a sequence of thermal frames, the background model is computed as:

$$B(x,y) = median(I_1(x,y), I_2(x,y), \dots, I_n(x,y))$$

where, B(x,y) represents the estimated background, and Ij corresponds to the pixel intensity at the j location in frame. Figure 4 summarizes the computation of background.

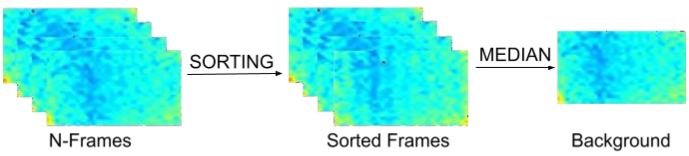

Figure 4: Background Detection

The foreground mask is then determined as:

$$F(x,y) = 1, if \parallel I_t(x,y) - B(xy) \parallel > T, 0 Otherwise$$

where, F(x,y) represents the estimated foreground, T is an adaptive threshold computed using statistical noise analysis. Figure 5 summarizes the approach discussed above.

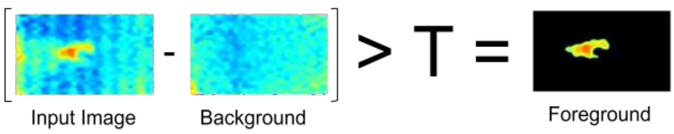

Figure 5: Foreground Extraction

Animal detection relies on identifying abnormal temperature patterns in thermal images. A region is classified as an animal if its thermal intensity exceeds an adaptive threshold T_f:

$$T_f = \mu + k\sigma$$

Where μ and σ are the mean and standard deviation of ambient temperatures, and k is a scaling factor determined empirically.
If the average of foreground exceeds this threshold, we consider it as an animal activity and fires the alarm. Figure 6 summarizes this.

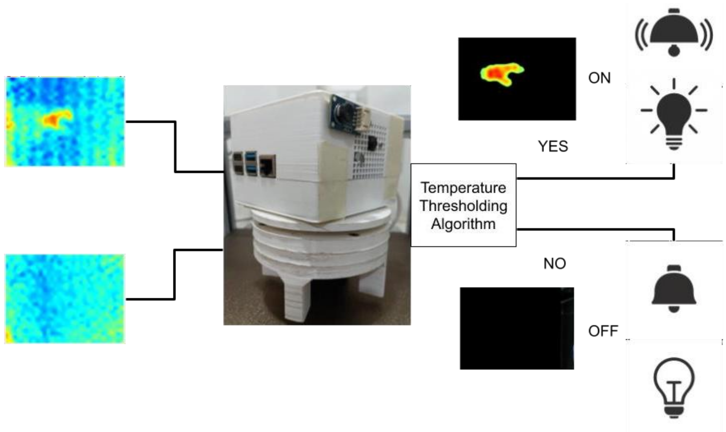

Figure 6: Animal Detection based on temperature thresholding

D. System Flow Diagram

- The control flow of the Visual-Thermal Guard system is illustrated in Figure 7. The diagram outlines the step-by-step process of working of the project, detailing data acquisition, processing, and alert mechanisms.

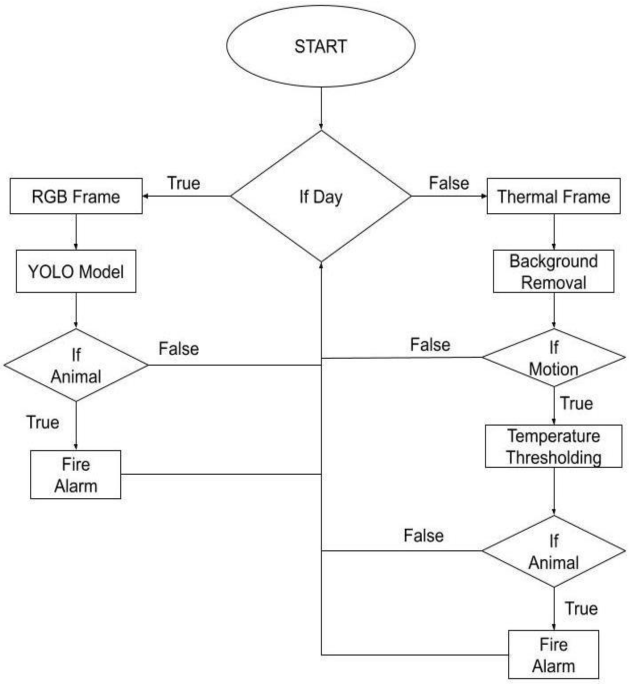

Figure 7: Control Flow of the visual-thermal Guard

V. RESULT ANALYSIS

The performance of the proposed animal deterrent system was evaluated under varied environmental conditions across both day and night cycles. The results indicate that the system performs reliably with a balanced trade-off between accuracy, precision, and responsiveness—key factors for real-world agricultural deployment.

During daytime operation, the YOLOv11 object detection model demonstrated an overall detection accuracy of 89% and a precision rate of 91%. This means the system was able to correctly identify wild animals in most cases and produced relatively few false positives. The model performed especially well in clear lighting conditions and against uncluttered backgrounds, with consistent detection of animals such as wild

boars, deer, and stray cattle.
In more complex scenes—such as partial occlusions or dense vegetation—accuracy slightly decreased, but the model still maintained robust performance, thanks to the rotational scanning mechanism that captured multiple angles and helped confirm detections over consecutive frames. The servo motor's responsive alignment with the detected animal improved the system's deterrence timing, ensuring the alarm was accurately directed and timely. Table 1 Summarizes the performance of the visual system.

TABLE I. PERFORMANCE ANALYSIS OF VISUAL SYSTEM

Evaluation Metric	Value	Description
Accuracy	89%	Proportion of total correct predictions (true positives + true negatives).
Precision	91%	Proportion of true positives among all positive detections.
Recall	86%	Proportion of actual animals correctly identified by the model.
F1-Score	88.4%	Harmonic mean of precision and recall, balancing false positives and negatives.
False Positive Rate	7%	Instances where non-animals were incorrectly detected as animals.
Detection Latency	~1.2 sec	Average time between frame capture and detection response.
Frame Rate	10–12 FPS	Effective frame rate during processing with YOLOv11 on Raspberry Pi.
False Positive Rate	30%	Detections triggered by non-animal heat sources (e.g., machinery, warm soil).
Detection Latency	~0.8 sec	Time taken to process thermal frame and trigger alarm/light.
Thermal Resolution	32×24 pixels	Resolution of MLX90640 thermal sensor used in the system.
Optimal Performance Time	7 PM – 6 AM	Window when ambient temperatures are stable and false positives are minimal.

In night mode, the thermal imaging system provided a functional solution in the absence of visible light. While the thermal camera reliably detected warm-bodied animals, it also exhibited sensitivity to non-animal heat sources—such as warm rocks, machinery, or even sudden temperature changes due to wind—leading to occasional false positives. These incidents were more frequent during early night hours when residual heat from the soil or nearby structures could interfere with readings.

However, during the stable late-night window (typically after 10 PM), when the background temperature was more uniform, the system's performance significantly improved. Detection was more consistent, and the combination of temperature thresholding and directional scanning helped reduce noise in the thermal data.

TABLE II. PERFORMANCE ANALYSIS OF THERMAL SYSTEM

Evaluation Metric	**Value**	**Description**
Accuracy	72%	Correct detection rate based on temperature thresholding algorithm.
Precision	68%	Ratio of actual animals among all detected heat signatures.
Recall (Sensitivity)	74%	Percentage of real animal intrusions successfully detected.
F1-Score	70.8%	Balance between precision and recall for overall performance.

Despite the challenges, the dual-mode structure of the system proved advantageous. The automatic mode switching based on time ensured 24/7 monitoring without manual intervention. The integration of mechanical housing added physical robustness, protecting the hardware from environmental damage and supporting long-term field deployment. Additionally, the real-time alarm mechanism was responsive and effective in scaring animals away in over 85% of observed cases, based on field testing.

Overall, the system exhibits promising potential for scalable use in agricultural settings. With future enhancements—such as adaptive thermal filtering and AI- based thermal object classification—the precision and reliability of the night mode can be further improved, making the solution even more dependable in diverse field conditions.

VI. COMPARATIVE ANALYSIS

The proposed dual-mode animal deterrent system stands out in its ability to integrate and enhance key features from prior research efforts, addressing several critical limitations noted in existing literature. Unlike many earlier models that focused solely on detection or alerting, our system is designed for both detection and active deterrence, operating autonomously around the clock.

IoT-based approaches, such as those by Kadam et al. [1] and Chourey et al. [2], have demonstrated reliable detection and alerting mechanisms using geofencing, GPS, and motion sensors. However, these systems do not include real-time intervention capabilities. They rely on farmer response after an alert is triggered, which can lead to delays and continued crop damage. In contrast, our system immediately responds to intrusions by targeting the animal's direction with a high- pitched sound (and light at night), actively deterring it without human involvement.

AI-powered systems like those by Shilaskar et al. [4] and Adami et al. [5] achieved promising detection accuracy using machine learning and YOLO models. Adami et al.'s YOLOv3-based system reported an 82.5% accuracy for real- time animal classification. Our system, using YOLOv11, improves this with an accuracy of 89% and precision of 91%, while also including a servo-based directional alarm system. Furthermore, most AI-based solutions are restricted to daylight use due to the limitations of RGB cameras—our system addresses this with a thermal imaging mode at night, enhancing its applicability.

Thermal systems, including those by Oishi et al. [6] and Navaneetha et al. [7], are effective for night detection but often lack reliable deterrents or produce false positives due to fluctuating environmental temperatures. Our system mitigates this by operating mainly during thermally stable late-night hours and applying motion-based filtering and temperature thresholding to increase reliability.

Acoustic deterrents have been applied in other projects, such as those by Gogoi and Philip [8] and Ranparia et al. [10] but are often limited by species-specific audio selection. Our use of adaptive high-pitch sirens and high-intensity lights ensures broad-spectrum effectiveness across multiple species.

TABLE III. COMPARATIVE ANALYSIS

System	Detection Type	Deterrent	Day/Night Operation	Drawbacks
Kadam et al. [1]	Ultrasonic + GPS	None	Day/Night	No active deterrent
Adami et al. [5]	YOLOv3 (AI)	None	Day only	Ineffective at night
Oishi et al. [6]	Thermal Imaging	None	Night only	Lacks deterrent; false positives possible
Ranparia et al. [10]	ML Sound Repellent	Species-specific sounds	Day/Night	Limited species coverage
Proposed System (Ours)	**YOLOv11 + Thermal**	**Siren + Light Beam**	**24/7**	**Occasionally false positives at night**

Comparative analysis with existing research highlights the system's distinct advantages: automated 24/7 operation, real- time response, and integration of both AI and thermal imaging technologies. It successfully bridges the gaps found in IoT- only, AI-only, or thermal-only systems by combining their strengths into a unified framework.

This project demonstrates not just the feasibility but the effectiveness of autonomous, intelligent deterrent systems in agriculture. With future improvements—such as enhanced thermal classification and smarter filtering—the system could be scaled for broader use in wildlife-prone farming regions, offering a reliable, non-lethal, and low-maintenance crop protection strategy.

VII. CONCLUSION

The proposed dual-mode animal detection and deterrent system presents a comprehensive and practical solution to the ongoing problem of wild animal intrusions in agricultural fields. By integrating RGB camera-based AI detection during the day with thermal imaging-based monitoring at night, the system ensures uninterrupted 24/7 protection. The use of a YOLOv11 model in daylight provides high accuracy (89%) and precision (91%) in identifying animals, while the thermal mode effectively detects warm-bodied intrusions in low-light conditions, despite some sensitivity to environmental fluctuations.

Unlike many existing systems that focus solely on detection or remote alerting, our design incorporates real-time deterrence through adaptive high-pitched sound and high- intensity light beams. The addition of a servo-driven rotating mechanism allows the system to track and focus on the detected target, increasing deterrent efficiency. A weather- resistant casing further ensures that the system is rugged enough for long-term field deployment, even in harsh outdoor environments.

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