Demo: From Pasture to Cloud: AI-Driven Predator Deterrence with Local Action and Cloud-Linked Alerts

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Abstract

With the growing population of wolves, attacks on livestock, particularly cattle, are becoming more frequent. This leads to increased concerns among farmers. Besides building expensive fences, traditional methods of managing this issue often focus on reducing wolf populations. To foster a non-lethal relationship between wolves, farmers and their livestock, alternative solutions are clearly needed to focus on early warning and deterrent systems.

This demo presents an innovative approach using AI-driven camera traps. The system can detect animals in real-time and activates deterrents to reduce the risk of an attack without harming the wolf. Notably, the solution is designed to operate without relying on constant internet access, making it suitable even for remote areas. However, when connectivity is available, the system also collects data about the sightings and can notify the person in charge, such as the farmer, of the potential attacks on their cattle by, for example, wolves.

Our demo gives a practical implementation of local predator detection, alerting, and data integration, offering a sustainable and effective way to live alongside wolves without lethal measures.

CCS Concepts

• **Hardware** → *Sensor applications and deployments*; • **Computing methodologies** → *Computer vision*; • **Computer systems organization** → *Distributed architectures.*

Keywords

Computer Vision, Animal Detection, Edge Computing, Deployment, Cloud Computing

1 Introduction and Motivation

In recent years, Germany has seen a rise in the number of predators, such as wolves and stray dogs, attacking livestock. The mAInZaun Project[1] aims to address this issue by enhancing traditional fences with artificial intelligence. The core idea is to integrate sensors that can detect the presence of a predator and activate deterrents to scare the animal away before it harms the livestock. Ideally, this system disrupts the predator and prevents an attack altogether.

One of the key challenges is that these systems must operate in remote, outdoor environments, often far from infrastructure or reliable connectivity. In our previous works[2, 3], we tackled these obstacles and developed strategies for overcoming them.

This demo represents an important step toward real-world deployment, focusing on meeting the practical needs of end users.

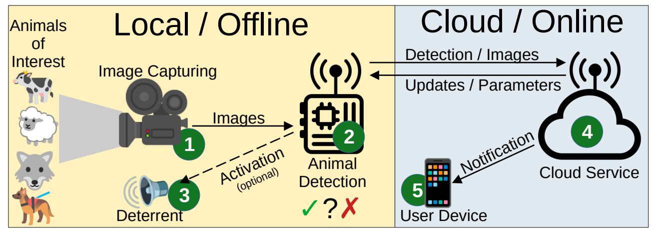

Figure 1: The camera (1) continuously monitors the environment and is connected to the embedded system (2), where the images are analyzed. If an animal of interest is detected, such as a predator, a deterrent (3) can be activated. This core functionality operates without the need for internet access. However, when a connection to our cloud service (4) is available, detection data can be transmitted to the end user device (5). The cloud service also provides system-wide management capabilities.

We demonstrate how the system detects animals, triggers deterrents, uploads images to a cloud service for further analysis, and sends real-time notifications to users. Additionally, it shows how the devices can be configured remotely via our cloud platform. We also require, that the system has to be able to perform fundamental operation without internet connectivity.

2 System Design

Our system design, as shown in Figure 1, consists of several interconnected components working together to provide real-time monitoring and protection for livestock. At the core of the system is the camera (1). Depending on the setup, we use either a USB camera (which is affordable and widely available but less suited for outdoor use) or a more durable, outdoor-rated surveillance camera connected and powered via Ethernet. The camera is linked to an embedded system (2), which runs an object detection algorithm directly on an edge device, such as a Raspberry Pi combined with Google Coral USB Accelerator. This enables fast and energy-efficient, on-site analysis of the images. In this demo, we use self-trained models based on YOLO[4] and run them using the TensorFlow[1] framework, allowing easy adaptation to other models. This setup processes approximately 10 frames per second allowing quick responses to detections.

When a critical animal, such as a wolf or other predator, is detected, the system triggers deterrents (3) to repel the threat. In the mAInZaun project, we are assuming deterrents such as sound (including ultrasound) and flickering lights, designed to make predators uncomfortable without causing harm. The specific deterrent

[1] https://intelligenter-herdenschutz.de/

can be customized based on environmental factors, target animals, budget, and other considerations. Technically, the system provides a switchable 12V power supply with up to 10A, supporting a variety of deterrent options suitable for field use.

Additionally, we integrated an e-paper display as a low-power status indicator, which shows essential system information such as time, detections, and device address. For real-world deployments, this offers the added benefit of easy readability, even in bright sunlight and gives important insights even for non-technical experts.

Communication between the detection system and the deterrents is handled via LoRa, a low-power, long-range communication protocol. For this project, we use plain LoRa to avoid reliance on the infrastructure and limitations required for LoRaWAN. This setup significantly reduces the energy consumption of the deterrents while providing a communication range of several hundred meters without complex network structures. By avoiding multi-hop networks, we reduce system complexity, lower costs, and improve reliability. Although this functionality is not part of our current demo, it is critical for real-world application, functioning entirely offline without requiring an internet connection

Once a detection is made and connectivity is available, the system transmits detection data, including the detected animal class and detection probability, to our cloud service (4) via an IP-based connection as, for example, 4G, 5G or WiFi. Depending on the available bandwidth, selected images are also uploaded for further analysis and training, allowing ongoing evaluation and validation to enhance the system's accuracy over time. The cloud service not only stores and processes this data but also serves as a control hub. Updates to the detection models can be sent from the cloud to the embedded system (4)→(2), enabling continuous learning and performance refinement. Additionally, key parameters of the edge device, such as sensitivity levels, activation triggers, can be remotely triggered and configured via the cloud, offering flexibility and reducing the need for physical maintenance.

For the end user, the system's primary function is to provide timely notifications and facilitate detailed analysis. When a relevant animal is detected, users are immediately alerted via their mobile phones (5), allowing them to take action if necessary. Beyond real-time notifications, the cloud service offers a comprehensive interface, providing users access to the full history of detections and their patterns. This enables users to monitor all detectors and deterrents in the system, gain insights into each detection event, and manage their livestock more effectively. This frontend of the cloud service is browser-based and compatible with both desktop and mobile devices.

3 Conclusion

The mAInZaun project addresses the growing challenge of livestock protection in regions facing increasing predator attacks. By integrating artificial intelligence with traditional fencing systems, we provide a smart, automated solution capable of detecting threats and triggering deterrents in real-time. Our design emphasizes flexibility and resilience, ensuring that the system can function autonomously, even in remote areas without reliable internet connectivity.

The demo we presented here highlights the essential features of the system, including real-time detection, cloud-based data exchange, user notifications, and remote configuration capabilities. Those are important steps for the mAInZaun project to move closer to practical deployment, offering farmers and livestock owners a powerful, AI-driven tool to safeguard their animals effectively. With some extension, it is also suitable for other applications like wildlife monitoring. Currently, we adapt the system to reduce the energy consumption and make it more self-sustaining for a real independent and long-lasting deployment.

4 Acknowledgments

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