Demo: InvisibleFence: Non-Lethal Edge-Optimized AI for Human Wildlife Coexistence and Crop Protection

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Abstract

Human-wildlife conflicts in residential/agricultural settings rely on ineffective deterrents like rodenticides or fences. We introduce InvisibleFence, a modular 3D-printed Vision Pod system with off-the-shelf deterrents. The Vision Pod fuses a 2K camera and 240° motion sensing with an edge-optimized pipeline trained on 44,000 wildlife images of eleven classes—achieving 86.7% mAP. Benchmarking YOLO variants (416p–2K) ensures performance. Upon detection, it sends MQTT commands to drive deterrent units—ultrasonic speakers or lighting/spray modules—that emit tones without affecting humans or pets. InvisibleFence creates adaptive zones that reduce false triggers and limit habituation.

CCS Concepts

• **Computing methodologies** → **Object detection**.

Keywords

Edge AI, Adaptive Wildlife Detection, Embedded Vision Systems, Computer Vision

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1 Introduction

Managing wildlife in residential and agricultural areas often stems from unresolved issues—gardeners abandon crops, and small-scale farmers reduce cultivation due to ineffective deterrents. Traditional solutions, such as rodenticides and lethal traps, prioritize immediate results over ecological sustainability, while motion-triggered systems frequently cause disturbances from high false-positive rates [2].

Community discussions with homeowners, gardeners, and farmers revealed dissatisfaction: generic deterrents lose efficacy once wildlife habituates, affecting household pets and non-target animals. These methods demand manual species identification, frequent reconfiguration, and continuous monitoring—leading to unsustainable, labor-intensive cycles [2].

Figure 1: (a) InvisibleFence: Vision Pod and Sound Pod (External deterrent modules); (b) The deployment of pods in a garden and their coverage.

We introduce *InvisibleFence*, an embedded ecological deterrence framework comprising a Vision Pod and external deterrent modules (for which we designed a prototype Sound Pod). InvisibleFence autonomously identifies wildlife and delivers targeted deterrence actions (Figure 1), reducing human oversight while mitigating ecological harm.

From our design and field experiences, we identify five key research challenges:

- **Robust Edge-based Classification:** A lightweight pipeline processes 2K input < 0.8s, correcting IR distortion and enhancing contrast for diverse conditions.
- **Modular Deterrence Integration:** Off-the-shelf deterrent units—ultrasonic speakers, lighting, spray modules—minimize habituation and limit effects on pets.

- **Low-latency, Power-efficient Coordination:** An MQTT-based, cloud-free system under 5 W, enabling 24/7 deployment with user privacy.
- **Adaptive Multi-sensor Integration:** A 240° tri-PIR array plus high-res camera reduces false triggers.
- **Curated Dataset:** A 44,000-image corpus of eleven species, having day/night & adverse weather settings.

These innovations form a scalable, ethically grounded solution for reliable, long-term wildlife coexistence.

2 System Design

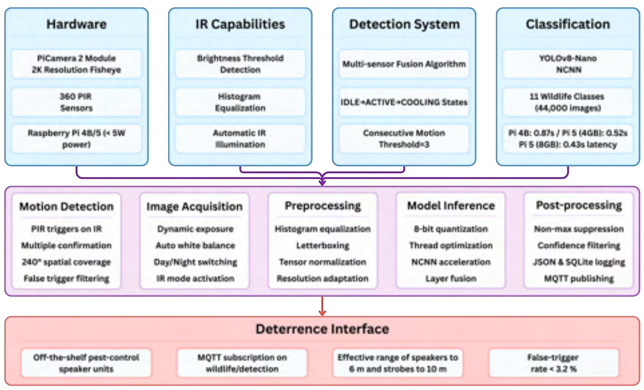

Figure 2: InvisibleFence system architecture overview.

InvisibleFence merges vision, edge computing, and external actuation into a unified system: a Vision Pod for detection/classification and modular deterrent units for response, coordinated over a cloud-free, low-latency MQTT protocol.

2.1 Vision Pod

Housed in a weatherproof 3D-printed enclosure, the Vision Pod combines a sub-5 W Raspberry Pi with a fisheye IR-capable camera (174° field of view, up to 2560 p resolution) for day/night wildlife detection. Upon confirmed motion, it transitions from IDLE to ACTIVE, avoiding wasted captures (e.g., rustling leaves). In low light, a night mode applies histogram equalization and color-shift compensation to mitigate IR artifacts (Figure 2). This state-machine approach minimizes power consumption while preserving accurate, high-resolution detection.

Images passing the motion filter undergo letterboxing, normalization, and exposure calibration before entering a YOLOv8-Nano NCNN inference pipeline (11.7 MB), achieving 86.7% mAP with sub-second latency on a Raspberry Pi [1]. Collected from farms and backyards, our 44,000-image dataset was augmented across color, shape, and scale, generating 33,500 synthetic variants for improved model robustness. Post-processing applies non-maximum suppression, bounding-box distance estimation, and MQTT metadata publication for real-time wildlife deterrent activation.

Table 1: Model performance and resource usage.

Model	Prec	Rec	F1	mAP	MB	Time (s)
YOLOv7-416	0.855	0.802	0.82	0.84	12.3	692.38
YOLOv7-640	0.856	0.811	0.83	0.855	12.3	699.52
YOLOv8-N NCNN	**0.868**	**0.811**	**0.83**	**0.867**	**11.7**	**157.09**
YOLOv11-S	0.889	0.804	0.87	0.893	19.2	1884.12
YOLOv11-S NCNN	0.889	0.804	0.87	0.893	36.1	325.37

2.2 Deterrence Interface

The Vision Pod streams detection events over a local, cloud-free MQTT network to drive external deterrence modules. Supported outputs include speaker units, programmable LED strobes, water-spray actuators, vibration motors. To avoid non-target activation, triggers are suppressed whenever human and dog/cat bounding boxes co-occur in the same frame. In bench tests, we integrated ultrasonic speaker modules—sold for bird/pest control—to validate message handling, power consumption, and latency.

2.3 Field Performance

Comparative demonstrations showed that off-the-shelf deterrence speakers such as X-octenol suffered from erratic triggering, frequent false activations, and a limited range of around 2 m, whereas InvisibleFence's Vision-driven modules consistently activated deterrents up to 6 m, reduced false alarms below 5%, and scale easily with additional units. These results confirm InvisibleFence as a scalable, autonomous, cloud-free solution offering superior operational efficiency.

3 Demo

In our demo, the Vision Pod distinguishes animals from humans in its 240° view. When an animal appears, it triggers an off-the-shelf speaker in a 3D-printed case to emit a human-audible tone; detection stops if a human enters the frame. A live dashboard displays what the pod sees, confidence scores, and distance to the target.

InvisibleFence's demo video: https://youtu.be/6DLVsTkO47E

References

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