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Smart Farm Fence Monitoring and Intrusion Detection System with AI-Based Location Tracking: A Review and Conceptual Architecture

Ghule Shubham Santosh, Prof. Bangar Abhishek Popat, Prof. S. B. Bhosale, Prof. Karad V. A.
Dept. of Computer Engineering,
Jaihind collage of Engineering, Pune, India

Abstract. Crop damage and theft caused by wild animals, stray animals and human intruders remain a persistent problem for farmers, and a passive fence neither detects nor reports a breach. This paper presents a focused narrative review of verified studies on intrusion detection, edge artificial intelligence (AI) and location tracking for farm protection, giving priority to IEEE journal publications and supplementing them with IEEE conference and open-access sources. Four themes are examined: camera-based AI detection and deterrence; low-cost sensor-triggered and LoRa-based fog or edge systems; GNSS and LoRa-based position tracking of animals; and validation practice. The reviewed work shows that lightweight deep-learning detectors can run on low-power edge devices, that a PIR-and-camera strategy has been reported to save energy, and that signal-strength information can reduce the energy spent on continuous GPS. However, the accessible evidence is dominated by prototype-scale studies, location tracking is rarely integrated with intrusion detection, and false-alarm rate, detection latency and independent validation are seldom reported. The paper contributes a comparative table of representative studies, a proposed seven-layer conceptual architecture for a smart farm fence that combines IR/PIR sensing, camera-based AI, GPS-collar tracking and geofencing, a leakage-resistant evaluation protocol, and a prioritised list of research gaps. The architecture is conceptual and has not been experimentally validated.

Keywords: Smart farm fence, intrusion detection, edge AI, TinyML, GPS tracking, geofencing, LoRa, Internet of Things

I. Introduction

Wildlife-induced crop damage and human loss impede food production and worsen supply and demand imbalances for farmers [1], and ungulate attacks in particular cause production losses that edge-AI crop-protection systems aim to reduce [2]. A passive fence cannot report that it has been crossed, so research has added sensing, analytics and alerting: low-cost PIR sensors, cameras and computer vision that detect intrusions and notify the farmer [3], and image classification that triggers a buzzer, a fence current and a message [4].

Farms also need to know where animals are. Energy-efficient GNSS-assisted and LoRa-based positioning has been studied for wildlife tracking [5], and received-signal-strength information has been used to avoid running GPS continuously on livestock collars [6]. In the literature reviewed here, however, intrusion detection and location tracking are developed largely as separate strands.

This review is motivated by an academic project that targets a 200 ft × 200 ft plot (about 61 m × 61 m, roughly 244 m of perimeter) and combines IR/PIR sensing, camera-based AI detection and GPS-collar tracking with a geofencing application. Its objectives are to (i) synthesise detection, deterrence and tracking approaches, (ii) compare their methods and limitations, (iii) propose a literature-grounded conceptual architecture and an evaluation protocol, and (iv) identify research gaps.

II. Review Methodology

A focused narrative review was carried out. Candidate studies were identified through web searches of publisher platforms, DOAJ-indexed journals, institutional repositories and DOI metadata, using combinations of animal intrusion, wildlife intrusion, smart fence, virtual fence, crop protection, edge AI, TinyML, YOLO, LoRa, GNSS, GPS tracking and geofencing. IEEE journal articles were prioritised, together with publications from 2021 to 2025; IEEE conference papers and open-access journal papers were retained for context where they addressed the same problem.

Each record was checked against a DOI or a publisher or repository record. Direct logged querying of IEEE Xplore, Scopus and Web of Science was not performed, so the review is narrative rather than systematic and study counts are not reported. For two sources [5], [9] only the bibliographic record was accessible, and statements about them are limited to their titles and venues. Performance figures are reproduced as stated in the accessible records and were not re-analysed.

III. Intrusion Detection and Deterrence

1. Camera-Based AI Detection at the Edge

Reddy et al. [1] combine tinyML-based deep learning with IoT for animal intrusion detection and deterrence. Their system integrates a laser detection system and an AI camera running lightweight deep-learning algorithms, proposes a compact classification model named EvoNet, and adds an IoT rover with which the farmer can assess the situation remotely. With pruning and quantization the model is reported to give comparable accuracy at file sizes as low as 1.63 MB, which is directly relevant to constrained hardware.

Adami et al. [2] build a virtual fence from computer vision and ultrasound. They evaluated a Raspberry Pi with and without a neural compute stick and an NVIDIA Jetson Nano running YOLO and Tiny-YOLO models with custom training, and report that detectors can run on power-efficient edge devices without compromising mean average precision while meeting real-time requirements. They also provide a cost/performance analysis and CPU-temperature measurements, and generate ultrasonic signals tailored to each species.

Other studies follow a similar pattern at an earlier stage. Girish and Rohith [7] describe a crop-guard system in which an AI camera running MobileNet-based models recognises humans, birds, pets and wildlife in live video and triggers responses. Kiruthika et al. [4] segment images, extract features and use a CNN to decide whether the land is empty or contains animals; on detection a buzzer sounds, a light electric current is passed to the fence and a message is sent to the farmer. Tamburello et al. [8] describe a platform of OpenMote devices on a 6LoWPAN mesh, connected to an FPGA-based board that processes camera data and activates ultrasonic jammers when an animal is detected.

A consistent feature is the coupling of detection to an actuator (ultrasound [2], [8], buzzer or fence current [4]) and to a farmer alert [1], [4]. Because actuators act on animals, they should be non-harmful and lawful, and decision logic should state its confidence rather than force a label.

2. Sensor-Triggered and LoRa-Based Systems

Miao et al. [3] propose a fog-based smart agriculture infrastructure that integrates edge computing with LoRa communication to address latency, bandwidth consumption and rural Internet disconnections. Low-cost PIR sensors, cameras and computer vision detect intrusions pre-emptively, identify the intruder, forecast its movement and alert the farmer, and the authors report significant energy savings when comparing power consumption with other approaches. “LoRa Agri” [9] likewise addresses agriculture automation and intruder detection with IoT and LoRa; only its title and venue were verified here. These results are consistent with triggering the camera from a low-power sensor instead of running it continuously, which is the logic adopted in the proposed architecture.

IV. AI-Based Location Tracking

1. Position of Tagged Animals

Animal position tracking is dominated by GNSS, whose energy cost shapes most design choices. Lopez-Escobar et al. [5] address energy-efficient GNSS-assisted and LoRa-based positioning for wildlife tracking in IEEE Sensors Journal; only the bibliographic record was accessible for this review. Muñoz et al. [6] study livestock monitoring with LoRaWAN and GPS and propose estimating the animal's distance to a gateway from the received signal strength indicator (RSSI) so that GPS need not run continuously; duty cycles vary with the RSSI zone, and experiments showed an important reduction in the energy consumed by the microcontroller. Lam et al. [10] propose two RSSI-based LoRa localization algorithms for very noisy outdoor environments, building on earlier findings that LoRa networks are suitable for outdoor localization.

2. Location of Intruders

For untagged intruders, location is inferred from the sensing infrastructure. In [3], detections from PIR sensors and cameras are used to identify the intruder and to predict its future location. None of the accessible records describes combining intruder localisation with tagged-animal tracking in a single system.

3. Where AI Enters

In the reviewed set, AI appears mainly in perception, that is, classifying what triggered the sensor [1], [2], [4], [7], and in movement prediction [3], whereas tagged-animal positioning relies on GNSS and signal-strength processing [5], [6], [10]. An AI-based location-tracking capability for a farm fence therefore has to be assembled from these parts: classify the intruder, localise it to a fence zone, track tagged animals against a geofence, and reduce position-update energy with signal-strength information.

V. Edge Deployment and Energy

Hardware choices in the reviewed work span tinyML models for constrained devices [1], single-board computers and Jetson-class modules [2], FPGA-based boards [8] and LoRa-linked sensor nodes [3], [9]. Energy is a recurring concern: power-efficient inference [2], energy savings from sensor-triggered operation [3] and reduced GPS usage [6]. For a plot of about 61 m × 61 m with roughly 244 m of perimeter, per-zone sensing nodes and a single gateway appear feasible; the choice between Wi-Fi, GSM and LoRa is a trade-off between coverage, power and recurring cost that the reviewed studies do not settle for plots of this size.

VI. Comparative Analysis

Table I summarises ten representative sources in chronological order. Values are reproduced from the accessible records and are not directly comparable. 'NR' denotes information not reported in the accessible record.

Table 1: Comparison of Representative Farm-Intrusion and Location-Tracking Studies

Study (year)	Venue	Focus and method	Reported outcome	Limitation noted
Lam et al., 2018 [10]	IEEE COMPSAC (conf.)	RSSI-based LoRa localization for very noisy outdoor environments	Two new localization algorithms proposed to improve accuracy	Not animal-specific; abstract-level
Adami et al., 2021 [2]	IEEE Access (journal)	Virtual fence: YOLO/Tiny-YOLO on Raspberry Pi, compute stick and Jetson Nano, plus ultrasound	mAP maintained and real-time needs met on edge devices; cost, performance and CPU-temperature data	Ungulate focus; hardware benchmarking; no location tracking
Tamburello et al., 2022 [8]	IEEE MELECON (conf.)	OpenMote 6LoWPAN mesh with FPGA camera processing; ultrasonic jammers	Architecture for reliable, energy-efficient detect-and-repel	NR (architecture-level)

Study (year)	Venue	Focus and method	Reported outcome	Limitation noted
Kiruthika et al., 2023 [4]	E3S Web Conf.	Segmentation and CNN classification (empty vs animal); buzzer, fence current, message	Detection-to-alert-and-deterrence chain	NR (quantitative results)
Preksha D et al., 2023 [9]	IEEE CCEM (conf.)	LoRa-based agriculture automation and intruder detection (title only)	NR	Only bibliographic record reviewed
Reddy et al., 2024 [1]	IEEE Access (journal)	tinyML edge AI; laser detection and AI camera; EvoNet model; IoT rover	Comparable accuracy with model files as small as 1.63 MB after pruning and quantization	Field results not stated in abstract
Miao et al., 2024 [3]	Future Internet (open access)	Fog and LoRa system; PIR, camera and computer vision; future-location prediction	Pre-emptive detection, identification, movement forecasting; significant energy savings reported	Numeric results not in accessible abstract
Girish and Rohith, 2025 [7]	IEEE ICKECS (conf.)	AI camera with MobileNet-based models; humans, birds, pets, wildlife	Live-video detection with triggered responses	NR (quantitative results)
Muñoz et al., 2025 [6]	IEEE Access (journal)	LoRaWAN and GPS livestock monitoring; RSSI zones with variable duty cycle	Important reduction in microcontroller energy use	Controlled environment; monitoring, not intrusion
Lopez-Escobar et al., 2025 [5]	IEEE Sensors J. (journal)	GNSS-assisted and LoRa-based positioning for wildlife tracking (title only)	NR	Only bibliographic record reviewed

Three observations follow from Table I. First, edge detection is supported by IEEE journal evidence [1], [2] and location-energy reduction by [6], but the two strands are not combined in any one system. Second, many supporting records are conference papers, proceedings or abstracts with limited quantitative detail [4], [7]–[9]. Third, the accessible records do not report false-alarm rate or detection latency, which determine whether farmers will trust an alerting system.

VII. Proposed Conceptual Architecture

Fig. 1 presents a proposed seven-layer architecture derived from Sections III–V. It has not been implemented or experimentally validated. Solid arrows show operational data flow; the dashed arrow shows the gated model-update loop.

- Layer 1 – Farm environment. The monitored system is a 200 ft × 200 ft plot with a perimeter fence, possible intruders (wild or stray animals, humans) and tagged animals wearing GPS collars.
- Layer 2 – Sensing. IR/PIR sensors along the fence provide a low-power trigger [3]; a camera with night capability supplies images for classification [1], [2], [7]; a GPS collar module reports the position of tagged animals [6]. Optional vibration, light and temperature/humidity sensors can help explain transient signals.
- Layer 3 – Data acquisition and link. An ESP32- or Arduino-class microcontroller reads the sensors, timestamps records from a real-time clock, checks them for range and integrity, and buffers them locally so that loss of connectivity does not lose data. Wi-Fi, GSM or LoRa links [3], [9] carry summaries to the application.
- Layer 4 – Edge AI perception. A lightweight detector, for example a tiny YOLO or MobileNet-class model [1], [2], [7], runs when a trigger fires and classifies the event as animal, human or other. Pruning and quantization [1] can reduce model size. Outputs carry a calibrated confidence; below a threshold the layer reports UNCERTAIN instead of forcing a label.

- Layer 5 – Location tracking and geofencing. The collar's GNSS fix is compared with the geofence boundary, and RSSI-assisted duty cycling [6] can lower GPS energy use. Intrusions are localised to the fence zone whose sensor or camera fired, and the recent sequence of zones can be used to estimate the direction of movement [3].
- Layer 6 – Decision and alerts. A rule engine applies thresholds with persistence (an alarm only after repeated confirmations) and hysteresis to limit false alarms. Local buzzer or light output works without connectivity; SMS or application notifications are sent when a link exists [1], [4]. Deterrent actuators such as ultrasound [2], [8] should be non-harmful and lawful, and every alert should recommend inspecting the relevant zone rather than assert a diagnosis.
- Layer 7 – Monitoring application and validation loop. A dashboard shows the map, event log and device health. Field inspection of alerts produces verified labels, and a retrained model is released to Layer 4 only after independent re-testing on events not used for training [11].

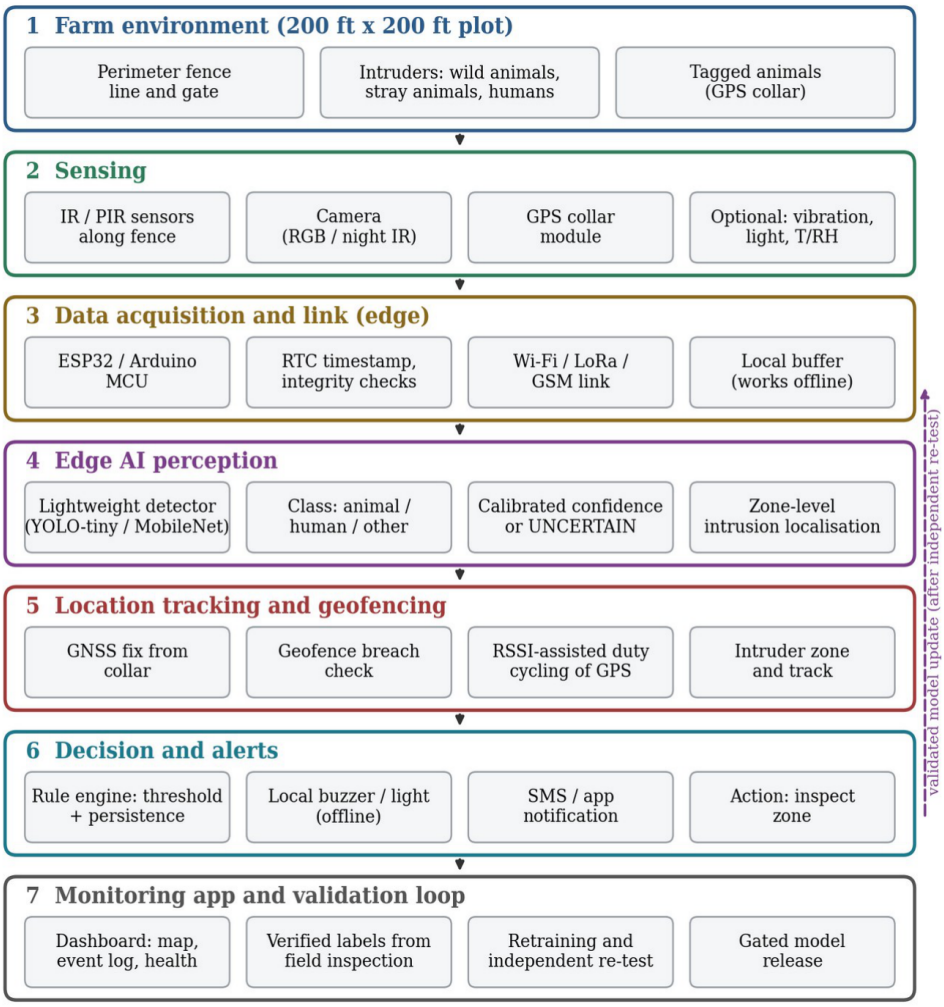


Fig. 1. Proposed conceptual seven-layer architecture for AI-based smart farm fence monitoring, intrusion detection and location tracking (conceptual, not experimentally validated).

VIII. Proposed Evaluation Protocol

Because no experimental data are reported here, this section proposes a protocol for a future prototype; no metric values are claimed. Table II lists suggested metrics.

Table 2: Proposed Evaluation Metrics

Metric	Why it matters
Precision	Share of alarms that are real intrusions
Recall (miss rate)	Share of real intrusions detected; main loss-related metric
False alarms per night	Determines farmer trust and workload
Detection-to-alert latency	Time from intrusion onset to notification
GPS position error	Collar fix versus surveyed reference points
Geofence-breach delay	Time from boundary crossing to alert
Energy per day	Feasibility of battery or solar operation
Model size, inference time	Feasibility on the chosen microcontroller or board
Cross-site and cross-season performance	Decisive test of deployability

Real intrusions are rare compared with empty periods, so accuracy alone is misleading; precision, recall and false alarms per night should be reported together. Frames or readings from the same intrusion event are strongly correlated, so random frame-level splits would place near-duplicates in both training and test sets and inflate results [11]. Splits should be grouped by event, night, site and season, with preprocessing fitted on training data only, and the final test should use an entirely independent site or season.

Research Gaps and Future Directions

Gaps supported by the reviewed evidence. (i) Detection and tracking are developed separately: detection studies [1]–[4], [7], [8] and tracking studies [5], [6], [10] do not share an architecture. (ii) Field evidence is thin in the accessible records: quantitative results from operating farms are not stated for [1], [4], [7], [8]. (iii) Alert-quality metrics (false alarms, latency, recall) are not reported in the accessible records. (iv) Energy is optimised in parts, namely inference [2], trigger logic [3] and GPS [6], but not jointly across camera, GPS and radio. (v) Leakage-resistant, grouped validation is not described [11].

Directions requiring investigation. Priorities include a multi-season field trial on the target plot with inspected and labelled events; a joint energy model for camera, GPS and radio; fusion of intruder localisation with tagged-animal geofencing; shared labelled datasets of farm-intrusion events; evaluation of non-harmful deterrents; and a usability study of alert channels (SMS or application, local language) with farmers.

Limitations of this review. Logged database queries of IEEE Xplore, Scopus and Web of Science were not possible, so relevant studies may have been missed. Only bibliographic records were accessible for [5] and [9], and several others were assessed from abstracts alone. Reported figures are not re-analysed.

IX. Conclusion

Edge-AI detectors, sensor-triggered LoRa systems and energy-aware position tracking have each been demonstrated at prototype scale for farm protection. The accessible evidence does not yet show them combined, validated in operating farms, or reported with false-alarm and latency figures. The proposed seven-layer architecture joins IR/PIR sensing, camera-based AI, GPS-collar tracking with geofencing, offline-capable alerts and a gated validation loop. Before it can be trusted, it must be built and evaluated with grouped, multi-season field trials on the target plot.

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[To be completed by the authors.]

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