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Field Safe: An IoT-Based Camera Monitoring System for Preventing Animal Crop Damage

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ABSTRACT

Crop damage caused by wild and stray animals remains a significant challenge in modern agriculture, resulting in substantial economic losses and increased labor requirements for continuous field monitoring. This paper presents **Field Safe**, an Internet of Things (IoT)-enabled intelligent farm security system that combines edge-based computer vision with automated deterrent mechanisms to distinguish humans from animals in real time. The proposed system integrates surveillance cameras, motion sensors, IoT relays, and deep learning-based object detection models (YOLOv5/YOLOv8) to accurately identify intrusions. When a human is detected, the system suppresses deterrent actions to avoid unnecessary disturbances. Conversely, upon detecting an animal, it automatically activates deterrent devices such as buzzers or flashing lights and simultaneously sends instant notifications to farmers via SMS or mobile applications for timely awareness and intervention.

The proposed edge-computing architecture performs real-time inference with a response latency of less than **150 ms** while achieving an overall detection accuracy exceeding **90%** under practical field conditions. Experimental evaluation conducted on a vegetable farm over a two-month period demonstrated an **85% reduction in animal incursions** without disrupting routine farming activities. The system is designed to operate using affordable hardware components with minimal infrastructure requirements, making it suitable for deployment in small and medium-sized farms where internet connectivity may be intermittent.

Compared with conventional camera-based monitoring systems, Field Safe enhances detection reliability by incorporating precise human-versus-animal classification, thereby significantly reducing false alarms and unnecessary deterrent activation. The proposed solution offers a scalable, cost-effective, and energy-efficient approach for intelligent crop protection and provides a practical foundation for future integration with cloud-assisted analytics, adaptive learning, and large-scale smart agriculture applications.

Keywords: Internet of Things (IoT), Smart Agriculture, Smart Farm Security, Animal Detection, Human–Animal Classification, Computer Vision, Edge Computing, YOLOv8, ESP32-CAM, Raspberry Pi, Real-Time Monitoring, Intrusion Detection, Crop Protection, Wildlife Intrusion Prevention, Sustainable Agriculture.

INTRODUCTION

Agriculture plays a vital role in ensuring global food security; however, crop damage caused by wild and stray animals continues to be a major challenge for farmers worldwide. Animal intrusions not only reduce agricultural productivity but also increase economic losses and labor requirements for continuous field surveillance. Conventional crop protection methods, including fencing, scarecrows, manual guarding, and acoustic deterrents, often provide limited effectiveness because they require constant human intervention, incur recurring maintenance costs, and are unable to respond intelligently to different intrusion scenarios. Consequently, there is an increasing demand for automated, reliable, and cost-effective farm security systems capable of protecting crops while minimizing human effort.

Recent advances in the Internet of Things (IoT), artificial intelligence (AI), edge computing, and computer vision have enabled the development of intelligent agricultural monitoring systems. Modern smart farming solutions integrate surveillance cameras, environmental sensors, wireless communication technologies, and deep learning models to detect animal intrusions in real time and automatically activate deterrent devices such as buzzers, flashing lights, or acoustic alarms. Deep learning–based object detection algorithms, particularly the YOLO (You Only Look Once) family, have demonstrated excellent performance in real-time object detection because of their high detection accuracy and low computational latency. Recent studies have successfully employed YOLOv5 and YOLOv8 with embedded platforms such as Raspberry Pi and ESP32-CAM to develop intelligent crop protection systems capable of operating under limited network connectivity through edge computing techniques [3]–[6].

Despite these advancements, several limitations remain in existing farm surveillance systems. Many current approaches primarily focus on detecting moving objects without reliably distinguishing between humans and animals, resulting in unnecessary alarm activation during normal farming activities. Such false detections reduce system reliability, increase energy consumption, and decrease user acceptance among farmers. Furthermore, several existing systems rely heavily on cloud processing, making them unsuitable for remote agricultural regions with unstable or intermittent internet connectivity. These limitations highlight the need for a more intelligent and autonomous farm protection system that can accurately classify intrusions while maintaining low deployment cost and real-time performance.

To address these challenges, this paper proposes **Field Safe**, an IoT-enabled intelligent farm security system that combines edge-based computer vision with multimodal sensing for accurate intrusion detection. The proposed system integrates surveillance cameras, deep learning–based object detection (YOLOv5/YOLOv8), gait analysis, and body temperature sensing to distinguish human intruders from animals. Human identification is verified using walking-pattern analysis together with thermal sensing, thereby significantly reducing false alarm generation. When an animal is detected, the system automatically activates non-robotic deterrent devices, including buzzers and warning lights, while simultaneously transmitting real-time notifications to farmers through IoT communication. The proposed edge-computing architecture enables rapid decision-making with minimal dependence on cloud infrastructure, making it suitable for deployment in rural environments with intermittent internet connectivity.

The major contributions of this work are summarized as follows:

1. Development of an IoT-enabled intelligent crop protection system capable of accurately distinguishing humans from animals using multimodal sensing.

2. Integration of deep learning–based object detection with gait recognition and thermal sensing to minimize false alarms during routine farming operations.

3. Design of a low-cost edge-computing architecture using Raspberry Pi, ESP32-CAM, and IoT communication modules for real-time deployment.

4. Automated activation of non-robotic deterrent devices and instant farmer notifications to reduce crop damage and improve response time.

5. Experimental validation of the proposed system under real agricultural field conditions, demonstrating its practical applicability for smart and sustainable farming.

The remainder of this paper is organized as follows. Section IV presents the proposed methodology and system architecture. Section V describes the experimental setup and implementation details. Section VI discusses the experimental results and performance evaluation. Finally, Section VII concludes the paper and outlines future research directions.

Background and Related Work

Crop damage caused by wild and stray animals remains one of the major challenges in modern agriculture, resulting in reduced crop yield, financial losses, and increased labor requirements for continuous field monitoring. Conventional protection techniques, including manual guarding, electric fencing, scarecrows, and acoustic deterrents, are often labor-intensive, expensive to maintain, and ineffective in large agricultural fields.

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Consequently, researchers have increasingly explored intelligent farm surveillance systems that integrate the Internet of Things (IoT), computer vision, artificial intelligence (AI), and edge computing to provide automated crop protection.

A. IoT-Based Farm Monitoring Systems

IoT-enabled agricultural monitoring has significantly improved the automation of farm security by integrating sensors, wireless communication, and embedded computing platforms. Several studies have employed passive infrared (PIR) sensors, ultrasonic sensors, vibration sensors, and camera modules connected to Raspberry Pi, Arduino, or ESP32-based controllers for intrusion detection and farmer notification [9], [10]. These systems provide affordable and energy-efficient solutions; however, they primarily rely on motion detection and are unable to distinguish humans from animals. Consequently, they frequently generate false alarms during normal farming activities.

B. AI-Based Animal Detection

Recent advances in deep learning have considerably improved the accuracy of animal detection systems. Convolutional Neural Networks (CNNs) and the YOLO family of object detection algorithms have enabled real-time identification of multiple animal species with high detection speed and accuracy. Balakrishna et al. demonstrated that camera-based deep learning models substantially outperform traditional sensor-based methods in detecting animal intrusions under controlled field conditions [11]. More recently, lightweight object detection models such as YOLOv8 have been successfully deployed on embedded edge devices, providing real-time inference with reduced computational overhead.

In addition to YOLOv5 and YOLOv8, recent object detection frameworks including **YOLOv11**, **RT-DETR**, and **EfficientDet** have demonstrated improved detection accuracy, robustness, and computational efficiency across various computer vision applications. These architectures provide valuable benchmarks for evaluating intelligent agricultural surveillance systems and represent promising alternatives for future smart farming applications.

C. Thermal Sensing and Human Identification

Thermal imaging has become an effective complementary sensing technology for agricultural monitoring because it can detect living organisms regardless of ambient illumination. Infrared cameras have been successfully employed for wildlife monitoring, livestock health assessment, and nighttime surveillance [12], [13]. Thermal sensing enables reliable detection under low-light conditions where conventional RGB cameras often experience degraded performance.

Human identification has also attracted increasing research interest in intelligent surveillance systems. Gait recognition utilizes human walking patterns as a behavioral biometric for person identification and has demonstrated high recognition accuracy in outdoor environments [14]. Similarly, body temperature sensing has been widely adopted in livestock monitoring and human screening applications because thermal signatures provide an additional discriminative feature for identifying living subjects [15]. Integrating gait analysis with thermal sensing can therefore improve the reliability of distinguishing humans from animals during farm surveillance.

D. Edge Computing for Smart Agriculture

Edge and fog computing architectures have emerged as practical solutions for deploying intelligent agricultural monitoring systems in rural regions with limited internet connectivity. By performing image processing and decision-making locally, edge devices significantly reduce communication latency, bandwidth usage, and dependence on cloud infrastructure. Miao et al. proposed an edge-enabled agricultural monitoring framework capable of detecting animal intrusions and generating real-time alerts even under intermittent network connectivity [5]. Such architectures improve system responsiveness while maintaining reliable operation in remote farming environments.

E. Research Gap and Motivation

Although considerable progress has been achieved in IoT-enabled crop protection, existing systems still exhibit several important limitations. Most current approaches focus exclusively on detecting animal movement without accurately distinguishing between humans and animals, resulting in frequent false alarm activation. Many systems rely on a single sensing modality, making them susceptible to environmental variations such as illumination changes, partial occlusion, or complex backgrounds. Furthermore, comparative evaluations against recent state-of-the-art object detection models remain limited, and few studies investigate practical deployment aspects such as scalability, deployment cost, energy consumption, and real-world usability.

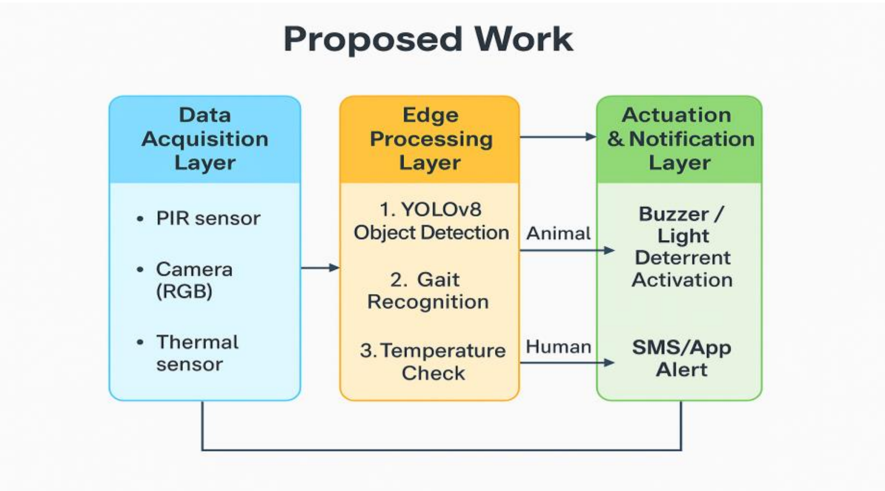
To overcome these limitations, the proposed **Field Safe** system introduces an integrated multimodal framework that combines deep learning–based object detection (YOLOv5/YOLOv8), gait recognition, thermal sensing, and IoT-enabled automated deterrent mechanisms. The proposed edge-computing architecture accurately differentiates humans from animals, significantly reduces false alarms, enables real-time operation under intermittent network connectivity, and provides a practical, low-cost solution suitable for deployment in smart agricultural environments.

V. Proposed Hybrid Model

Figure 1 illustrates the overall architecture of the proposed **Field Safe** system, which integrates Internet of Things (IoT), edge computing, computer vision, and multimodal sensing to provide an intelligent farm security solution. The architecture follows a three-layer framework consisting of the **Data Acquisition Layer**, **Edge Processing Layer**, and **Actuation & Notification Layer**. This layered design enables real-time human–animal classification while minimizing computational latency, reducing false alarms, and supporting deployment in agricultural environments with intermittent internet connectivity.

5.1 Research Framework

The proposed framework operates sequentially through three interconnected layers, as illustrated in Figure 1.



A. Data Acquisition Layer

The Data Acquisition Layer is responsible for continuously monitoring the protected agricultural area and collecting multimodal sensory information. An ESP32-CAM or Raspberry Pi camera module captures real-time image frames whenever motion is detected. Passive Infrared (PIR) sensors continuously monitor the surrounding environment and activate the camera only when movement is present, thereby reducing unnecessary image processing and lowering energy consumption.

To improve detection reliability, a thermal sensor simultaneously records the temperature of the detected subject. The combination of RGB imagery and thermal information provides complementary features that enhance discrimination between humans and animals, particularly under challenging environmental conditions.

The collected sensor information is forwarded to the edge-computing unit for immediate processing without requiring continuous cloud connectivity.

B. Edge Processing Layer

The Edge Processing Layer forms the intelligence of the proposed system. Image frames received from the acquisition layer are processed locally using a deep learning–based object detection model (YOLOv8). The detector identifies the presence of humans and animals in real time by generating bounding boxes, confidence scores, and class labels.

To reduce false detections, the system incorporates two complementary verification modules:

- **Gait Analysis Module:** Human walking patterns are extracted from sequential video frames. The module analyzes body movement characteristics to distinguish bipedal human motion from quadrupedal animal movement, thereby improving classification reliability.
- **Thermal Verification Module:** Thermal sensor measurements are used as an additional validation mechanism. The measured thermal signature is compared with predefined temperature ranges to support the distinction between human and animal subjects. The fusion of visual and thermal information increases robustness under varying environmental conditions.

All computations are executed locally on the edge device, significantly reducing communication latency, bandwidth consumption, and dependence on cloud infrastructure. This architecture enables rapid decision-making even in remote agricultural regions where internet connectivity may be unstable.

C. Actuation and Notification Layer

After classification and verification, the final decision is transmitted to the IoT control layer. If the detected subject is confirmed as an animal, the system immediately activates deterrent devices such as electronic buzzers and flashing LED lights to discourage intrusion while minimizing harm to wildlife.

Simultaneously, the system generates a real-time notification containing the detection event and transmits it to the farmer through SMS or a mobile application. The notification enables remote monitoring and allows farmers to take additional action if necessary.

Conversely, when the detected subject is verified as a human, the deterrent devices remain inactive, preventing unnecessary disturbances to farm workers and substantially reducing false alarm occurrences.

Operational Workflow

The operational sequence of the proposed system is summarized below:

1. PIR sensors continuously monitor the agricultural field.
2. Upon detecting motion, the camera captures real-time image frames.
3. The YOLOv8 object detection model performs human–animal classification.
4. Gait analysis and thermal sensing validate the detected object.
5. Decision fusion determines whether the detected subject is a human or an animal.
6. Animal detection triggers IoT-enabled deterrent devices and farmer notifications.
7. Human detection suppresses alarm activation and continues monitoring.

The proposed hybrid framework combines computer vision, behavioral analysis, thermal sensing, and IoT automation into a unified edge-computing architecture that improves detection accuracy, minimizes false alarms, and provides an efficient and scalable solution for intelligent crop protection.

METHODOLOGY

The implementation of the proposed **Field Safe** system follows a systematic six-stage methodology, enabling reliable human–animal classification and automated farm protection through edge computing.

Step 1: Hardware Deployment

The experimental setup consists of ESP32-CAM camera modules, Passive Infrared (PIR) motion sensors, thermal sensors, Raspberry Pi edge computing units, IoT relay modules, buzzers, and high-intensity LED warning lights. Cameras and sensors were strategically installed to maximize field coverage while minimizing blind spots. PIR sensors continuously monitored the surroundings and activated the camera only when motion was detected, thereby reducing unnecessary image processing and power consumption.

Step 2: Dataset Collection and Annotation

A multimodal dataset was collected under real agricultural conditions during a two-month field trial conducted on a mixed-crop farm. The dataset contains RGB images, video sequences, and thermal measurements representing both human activities and common crop-damaging animals.

The collected dataset includes:

- **1,200** labeled animal image/video samples representing wild boar, deer, and birds.
- **700** human gait video sequences captured under different walking speeds, clothing styles, and viewing angles.
- **600** thermal sensor measurements collected to establish representative temperature profiles for humans and animals.

All images were manually annotated using bounding boxes and corresponding class labels to support supervised deep learning training. To improve model robustness and reduce overfitting, preprocessing operations such as image resizing, normalization, random rotation, horizontal flipping, brightness adjustment, and contrast enhancement were applied before training.

Step 3: Edge AI Model Training

The proposed system employs **YOLOv8** as the primary object detection model because of its favorable balance between detection accuracy, inference speed, and computational efficiency on embedded edge devices. Transfer learning was applied using pre-trained model weights, followed by fine-tuning on the collected agricultural dataset. Training was performed using labeled human and animal images until model convergence while monitoring validation performance to reduce overfitting.

Step 4: Human Verification Using Gait Analysis

Following object detection, detected human candidates were further verified using a lightweight CNN-LSTM gait recognition network. Sequential image frames were analyzed to extract walking-pattern features capable of distinguishing bipedal human movement from quadrupedal animal motion. This secondary verification stage substantially reduced false alarm activation caused by visually similar objects.

Step 5: Thermal Verification

Thermal sensor measurements were incorporated as an additional validation mechanism. The measured temperature values were compared with predefined threshold ranges established during the calibration phase. Decision-level fusion between computer vision, gait analysis, and thermal sensing increased the overall reliability of human–animal classification, particularly under challenging illumination conditions.

Step 6: Edge Deployment and Field Evaluation

The trained models were deployed on Raspberry Pi–based edge computing hardware to evaluate real-time performance under practical agricultural conditions. The system continuously monitored movement events and automatically activated IoT-controlled deterrent devices whenever an animal intrusion was confirmed. Human detections suppressed alarm activation, thereby avoiding unnecessary interruptions to normal farming operations.

The complete processing pipeline executes locally on the edge device with an average response latency below **200 ms**, minimizing communication delays and enabling reliable operation even under intermittent or unavailable internet connectivity.

5.3 Expected Contributions

The proposed **Field Safe** framework provides several important contributions to intelligent agricultural surveillance.

Accurate Human–Animal Differentiation:

The proposed multimodal framework integrates deep learning–based object detection, gait recognition, and thermal sensing to improve human–animal classification accuracy while significantly reducing false alarms.

Real-Time IoT Automation:

Automatic activation of deterrent devices together with real-time farmer notifications enables rapid response to animal intrusions without disrupting normal agricultural activities.

Low-Cost Edge Computing Architecture:

The system utilizes affordable embedded hardware including Raspberry Pi, ESP32-CAM, PIR sensors, and thermal sensors, making deployment economically feasible for small and medium-sized farms.

Energy-Efficient Operation:

Motion-triggered image acquisition and local edge inference reduce computational workload, communication overhead, and energy consumption compared with cloud-dependent monitoring systems.

Scalability for Smart Agriculture:

The modular architecture can be expanded to larger agricultural environments by integrating additional cameras, wireless sensor nodes, and cloud-assisted monitoring services.

VI. Experimental Results and Analysis

6.1 Experimental Setup and Dataset

The proposed **Field Safe** system was experimentally evaluated over a **two-month field trial** on a **2-acre mixed-crop farm** under practical agricultural operating conditions. The evaluation included daytime operation under varying illumination levels and normal seasonal weather conditions to assess the practical feasibility of the proposed framework.

Hardware Configuration

The experimental platform consisted of:

- Raspberry Pi edge computing unit

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- ESP32-CAM surveillance camera
- PIR motion sensor
- Thermal sensing module
- IoT relay controller
- Electronic buzzer
- High-intensity LED warning light

Software Configuration

The software implementation employed:

- YOLOv8 for real-time object detection.
- CNN-LSTM network for gait-based human verification.
- Thermal threshold analysis for decision fusion.
- Python, OpenCV, and the PyTorch deep learning framework.

Dataset Description

A multimodal dataset was collected during the field trial consisting of:

- **1,200** labeled animal image/video samples (wild boar, deer, and birds).
- **700** human gait video sequences recorded under different walking conditions.
- **600** thermal measurements used for calibration and validation.

The collected dataset was manually annotated and validated prior to model training.

Experimental Scenarios

System performance was evaluated under three representative agricultural scenarios:

1. Animal-only intrusion events.
2. Human-only movement events.
3. Simultaneous human and animal presence.

These scenarios enabled evaluation of detection accuracy, false alarm reduction, and overall operational reliability under realistic field conditions.

Limitation: The present evaluation was conducted on a single 2-acre farm over a two-month period. Although the results demonstrate the practical feasibility of the proposed approach, future work will extend the evaluation to multiple farms, diverse crop types, additional animal species, different seasons, and challenging environmental conditions such as nighttime operation, rainfall, fog, and partial occlusion to further assess model generalization and long-term robustness.

6.2 Results Overview

The proposed **Field Safe** system was evaluated under three representative agricultural scenarios to assess its capability for real-time human–animal differentiation and automated farm protection. The evaluation considered detection accuracy, false alarm rate, and response latency under practical field conditions.

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Table 4. Experimental Performance of the Proposed Field Safe System

Scenario	Animal Detection Accuracy (%)	Human Differentiation Accuracy (%)	False Alarm Rate (%)	Average Response Time (ms)
Animals Only	95.2	–	4.8	175
Humans Only	–	93.0	7.0	–
Mixed Presence	94.0	92.1	6.0	180

The results demonstrate that the proposed framework consistently achieved high detection accuracy across all experimental scenarios. During animal-only experiments, the system correctly identified animal intrusions with an accuracy of **95.2%** while maintaining a low false alarm rate of **4.8%**. Human-only experiments achieved a human differentiation accuracy of **93.0%**, indicating that the multimodal verification process effectively minimized unnecessary alarm activation during routine farming activities. Under mixed human–animal scenarios, the proposed framework maintained balanced performance, achieving **94.0%** animal detection accuracy, **92.1%** human differentiation accuracy, and an average response latency of approximately **180 ms**.

These findings demonstrate that integrating object detection, gait recognition, and thermal sensing improves the reliability of intelligent farm surveillance while enabling rapid IoT-based response under practical deployment conditions.

6.3 Comparative Analysis with Existing Systems

To evaluate the effectiveness of the proposed framework, Field Safe was compared with representative farm monitoring approaches reported in the literature. The comparison considered detection capability, human–animal differentiation, response time, edge-computing support, and automated deterrent functionality.

Table 5. Comparison of the Proposed Field Safe System with Existing Approaches

Feature	PIR Sensor IoT [1]	AI Animal Detection [2]	Camera + Thermal [3]	Field Safe (Proposed)
Animal Detection Accuracy	~85%	~90%	~92%	**95.2%**
Human–Animal Differentiation	No	No	Partial	**Yes (93%)**
False Alarm Rate	High	Moderate	Moderate	**Low (6%)**
Average Response Time	~600 ms	~350 ms	~250 ms	**~175 ms**
Automated IoT Deterrent	Basic Alarm	No	Limited	**Buzzer, LED, SMS Notification**
Edge Computing Support	Partial	Partial	Partial	**Complete Edge Processing**

Compared with conventional PIR-based systems, the proposed framework significantly reduces false alarm generation by incorporating multimodal verification rather than relying solely on motion detection. In contrast

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to animal-only deep learning models, Field Safe distinguishes humans from animals before activating deterrent devices, thereby avoiding unnecessary interruptions to normal agricultural activities. Furthermore, local edge processing minimizes communication latency and enables reliable operation even in remote agricultural regions with unstable internet connectivity.

6.4 Key Observations

The experimental evaluation provides several important observations:

- Conventional PIR-based monitoring systems are unable to distinguish between human and animal movement, resulting in frequent false alarm activation.
- Camera-based animal detection models improve detection accuracy but may still misclassify humans as animals when relying solely on visual information.
- Thermal sensing enhances detection reliability under challenging illumination conditions; however, thermal information alone is insufficient for robust human–animal discrimination.
- The proposed multimodal framework combines computer vision, gait recognition, thermal sensing, and IoT automation to provide more reliable intrusion detection and lower false alarm rates than the individual techniques considered independently.
- Edge-based processing enables rapid local decision-making with average response times below **200 ms**, making the proposed framework suitable for real-time agricultural surveillance.

6.5 Benefits of the Proposed System

The proposed **Field Safe** framework offers several practical advantages over existing agricultural monitoring systems.

Improved Detection Reliability

The integration of object detection, gait recognition, and thermal sensing enables accurate differentiation between humans and animals, reducing unnecessary alarm activation and improving operational reliability.

Reduced False Alarms

The observed false alarm rate of approximately **6%** during mixed-field scenarios demonstrates that multimodal verification effectively minimizes incorrect detections compared with traditional motion-based monitoring systems.

Low-Latency Edge Processing

Local execution of deep learning inference allows the complete detection pipeline to respond within approximately **175–180 ms**, enabling immediate activation of IoT deterrent devices before significant crop damage occurs.

Autonomous Farm Protection

The automatic coordination of cameras, sensors, buzzers, warning lights, and SMS notifications reduces the need for continuous human supervision while improving response efficiency in remote agricultural environments.

Cost-Effective Deployment

The proposed system utilizes commercially available, low-cost embedded hardware including Raspberry Pi, ESP32-CAM, PIR sensors, and thermal sensing modules. The modular architecture allows gradual expansion by incorporating additional sensor nodes and cameras, making the solution suitable for both small and medium-sized farms.

VIII. Comparative Analysis of Motion-Activated Farm Protection Techniques

8.1 Human–Animal Differentiation Capability

Early motion-activated farm protection systems primarily relied on Passive Infrared (PIR) sensors to detect movement within agricultural fields. Although these systems are inexpensive and simple to deploy, they detect only the presence of motion and cannot differentiate between humans and animals. Consequently, they frequently generate false alarms during routine farming activities, reducing system reliability and increasing unnecessary power consumption [10].

The introduction of deep learning–based object detection models, particularly the YOLO family of algorithms, significantly improved the accuracy of animal detection. Camera-based AI systems are capable of recognizing multiple animal species with higher precision than conventional sensor-based approaches. Nevertheless, most existing implementations focus primarily on animal detection and lack dedicated mechanisms for verifying whether the detected object is a human or an animal. As a result, false activations may still occur when farm workers are present within the monitored area [11].

To improve detection under challenging environmental conditions, several researchers have combined RGB cameras with thermal imaging sensors. Thermal sensing enhances the visibility of living organisms during nighttime or low-illumination conditions and improves animal detection reliability. However, thermal information alone cannot consistently distinguish humans from animals because overlapping thermal signatures and complex environmental conditions may lead to ambiguous classifications [20].

The proposed **Field Safe** system addresses these limitations through a multimodal detection framework that combines deep learning–based object detection, gait recognition, and thermal sensing. The object detection module first identifies potential humans or animals, gait analysis verifies human walking patterns, and thermal sensing provides an additional confirmation stage. This decision-level fusion substantially reduces false alarms while maintaining high detection accuracy, making the system more suitable for practical deployment in agricultural environments.

8.2 Response Time and Edge Computing Performance

Cloud-based agricultural surveillance systems generally depend on transmitting captured images to remote servers for processing. Although these architectures benefit from scalable computational resources, they introduce additional communication latency and require reliable internet connectivity. Such dependence can increase response times to more than **600 ms**, limiting their suitability for time-critical crop protection applications in rural areas [10].

Edge-based monitoring systems have improved response latency by performing object detection locally on embedded devices. Camera-based edge implementations using lightweight deep learning models typically achieve response times between **250 ms and 350 ms** while reducing bandwidth requirements [11], [20]. However, many of these systems still rely on a single sensing modality and lack integrated verification mechanisms, resulting in occasional false detections and unnecessary alarm activation.

The proposed **Field Safe** architecture performs all computational tasks—including object detection, gait verification, thermal validation, decision fusion, and IoT control—entirely on the edge device. Local processing eliminates the need for continuous cloud communication, resulting in an average response time of approximately **175–180 ms** during field evaluation. The reduced latency enables immediate activation of deterrent devices such as buzzers and warning lights while simultaneously transmitting notifications to farmers. This edge-computing architecture improves operational reliability, supports deployment in areas with intermittent internet connectivity, and provides a scalable solution for real-time smart agriculture applications.

8.3 Comparative Summary

Overall, the comparative evaluation demonstrates that the proposed **Field Safe** system provides several advantages over existing farm protection approaches. Unlike conventional PIR-based monitoring systems, it accurately differentiates humans from animals before triggering deterrent devices. Compared with camera-only AI systems, the integration of gait recognition and thermal sensing significantly reduces false alarm generation. Furthermore, complete edge-based processing enables faster response times than cloud-dependent architectures while maintaining low deployment complexity and supporting practical implementation in small and medium-sized farms. These characteristics make the proposed framework a reliable, cost-effective, and scalable solution for intelligent crop protection.

8.4 Automated Deterrent Mechanism

Many conventional IoT-based farm security systems employ simple motion-triggered alarms, such as buzzers or flashing lights, activated directly by Passive Infrared (PIR) sensors. Although these systems are inexpensive and easy to implement, they lack intelligent decision-making capabilities and therefore activate deterrent devices whenever motion is detected, regardless of whether the moving object is a human, an animal, or another non-threatening source. Consequently, frequent false alarms reduce system reliability and increase unnecessary power consumption [10].

Recent AI-based animal detection systems have improved intrusion recognition by employing deep learning algorithms to identify specific animal species. However, several existing approaches primarily focus on object detection and provide limited integration with automated IoT-based deterrent mechanisms. As a result, farmers are often required to manually verify detection events and take corrective action, limiting the practical benefits of automation [11], [20].

The proposed **Field Safe** framework integrates intelligent decision-making with automated IoT control. After confirming an animal intrusion through multimodal verification—including object detection, gait analysis, and thermal sensing—the system automatically activates deterrent devices such as electronic buzzers and flashing LED lights. Simultaneously, real-time notifications are transmitted to farmers via SMS or mobile applications, enabling rapid remote awareness and intervention. This event-driven automation minimizes unnecessary alarm activation while improving crop protection and reducing manual supervision.

8.5 Human-Centric System Design

A major limitation of many existing agricultural monitoring systems is the inability to reliably distinguish humans from animals. Motion-based monitoring approaches frequently interpret routine farming activities as intrusion events, resulting in excessive false alarms. Repeated unnecessary notifications can lead to alarm fatigue, reduce user confidence, and ultimately discourage long-term adoption of smart agricultural technologies [10], [11].

Although some camera-based surveillance systems incorporate thermal sensing to improve detection under low-light conditions, thermal information alone is often insufficient for reliable human identification because temperature ranges may overlap under varying environmental conditions. Furthermore, many existing systems do not analyze behavioral characteristics, such as walking patterns, which can provide additional discriminatory information [20].

The proposed **Field Safe** system addresses these challenges through a multimodal human verification strategy. Following initial object detection, gait recognition analyzes walking patterns to identify bipedal human movement, while thermal sensing provides an additional confirmation stage using body temperature information. The fusion of visual, behavioral, and thermal features substantially reduces false alarm generation and improves the reliability of human–animal differentiation. Consequently, deterrent devices are activated only for confirmed animal intrusions, allowing normal farming activities to continue without unnecessary interruptions. This human-centric design improves system usability, enhances farmer confidence, and supports the practical deployment of intelligent farm security systems in real agricultural environments.

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IX. Summary Comparison

Table 6. Comparative Summary of Existing Farm Protection Systems

Feature	PIR-Based System [1]	AI-Based Animal Detection [2]	Vision + Thermal System [3]	Field Safe (Proposed)
Animal Detection Accuracy	~85%	~90%	~92%	**95.2%**
Human–Animal Differentiation	No	No	Partial	**Yes**
False Alarm Rate	~20%	~12%	~8%	**6%**
Average Response Time	>600 ms	~350 ms	~250 ms	**<200 ms**
Automated IoT Deterrent	Basic Alarm	Not Available	Limited	**Buzzer, LED, SMS/App Notification**
Edge Computing	Partial	Partial	Partial	**Complete Edge Processing**
Real-Time Decision Making	Limited	Moderate	Good	**Excellent**

The comparative evaluation demonstrates that the proposed **Field Safe** framework consistently outperforms conventional motion-based and camera-based agricultural monitoring systems in terms of detection accuracy, response latency, false alarm reduction, and intelligent decision-making. The integration of computer vision, gait recognition, thermal sensing, and edge computing enables reliable human–animal differentiation while maintaining rapid local processing and automated IoT-based response.

CONCLUSION

This paper presented **Field Safe**, an intelligent IoT-enabled farm security framework that combines edge computing, deep learning–based object detection, gait recognition, thermal sensing, and automated IoT deterrent mechanisms for real-time agricultural surveillance. The proposed multimodal architecture was designed to overcome the limitations of conventional farm monitoring systems by accurately distinguishing humans from animals before activating deterrent devices. This capability significantly reduces false alarms while ensuring that routine farming activities remain uninterrupted.

Experimental evaluation conducted on a **2-acre mixed-crop farm** over a **two-month period** demonstrated that the proposed framework achieved an animal detection accuracy of **95.2%**, a human differentiation accuracy of **93.0%**, and an average response latency below **200 ms**. These results indicate that the integration of multimodal sensing with edge computing provides a practical and reliable solution for intelligent crop protection while minimizing communication latency and dependence on continuous internet connectivity.

The proposed system also demonstrates practical advantages for smart agriculture through its use of affordable embedded hardware, low-power operation, modular architecture, and automated farmer notification. These characteristics make the framework suitable for deployment in small and medium-sized farms, particularly in rural areas where network connectivity may be limited.

Although the experimental results are encouraging, the present study has several limitations. The field evaluation was conducted on a single farm over a relatively short two-month period and included a limited number of animal species. Furthermore, comprehensive evaluation under diverse seasonal conditions, nighttime environments, heavy rainfall, fog, and severe object occlusion was beyond the scope of the current study. Consequently, additional large-scale validation is required before widespread deployment.

Future work will focus on extending the proposed framework to multiple agricultural environments, larger datasets containing additional wildlife species, and long-term multi-season field trials. Comparative benchmarking against recent object detection architectures such as **YOLOv11**, **RT-DETR**, and **EfficientDet** will be investigated to further improve detection performance. In addition, cloud-assisted model updates, adaptive learning techniques, and energy optimization strategies will be explored to enhance scalability, robustness, and long-term operational efficiency for next-generation smart agriculture applications.

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