Research Paper

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Real-Time Wildlife Detection for Crop Protection Using Computer Vision and SMS Alerts

Couse Code: INT345

Submitted by: Goljana Sree Ratna Saketh

Roll Number: 15

Reg. No: 12207999

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Section: K22DM

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Abstract

Wildlife intrusions into farmlands, such as those by pigs, goats, and bears, cause substantial crop losses, necessitating automated, real-time detection systems. This study presents a proof-of-concept demo built in Google Colab, utilizing the YOLOv8 object detection model to identify animals in visible and infrared images. Enhanced preprocessing with Contrast Limited Adaptive Histogram Equalization (CLAHE), edge enhancement, and normalization improves night vision accuracy, addressing low-contrast challenges. A verification step mitigates misclassifications, such as elephants labeled as bears or horses as goats, by analyzing bounding box size and shape. Twilio integration delivers SMS alerts to farmers upon detection, enabling rapid intervention. Tested with sample images from the Wildlife Datasets and external infrared sources, the system achieves approximately 80% precision for visible images and 70% for infrared, with verification reducing errors by 50%. This affordable, scalable demo highlights the potential for computer vision in crop protection, despite limitations in infrared accuracy and real-time deployment.

1. Introduction

Agriculture is a cornerstone of global food security, yet it faces persistent threats from wildlife intrusions. Animals such as pigs, deer, goats, and bears damage crops, leading to economic losses exceeding $1 billion annually in the United States alone (USDA, 2023). For instance, feral pigs cause up to $2.5 billion in damages across North America due to their destructive foraging (Pimentel, 2007). Traditional countermeasures, including manual patrols, fencing, or motion-activated deterrents, are often impractical for small-scale farmers due to high costs, labor demands, or lack of specificity. Moreover, many intrusions occur at night, requiring systems capable of operating in low-light or infrared conditions, a challenge unmet by most conventional solutions.

The advent of computer vision offers a transformative approach, enabling automated, real-time detection of wildlife with minimal infrastructure. Recent advancements in object detection models, such as YOLOv8, provide fast and accurate identification of animals, even in complex environments (Ultralytics, 2023). However, deploying these models in agricultural settings involves challenges: distinguishing similar animals (e.g., mistaking an elephant for a bear or a horse for a goat), processing infrared images with low contrast, and delivering actionable alerts to farmers. Misclassifications can undermine trust, while infrared limitations hinder 24/7 monitoring, critical for nocturnal animals like deer or bears.

This study develops a demo system for wildlife detection in farmlands, designed to protect crops by identifying animals in both visible and infrared images and notifying farmers via SMS. Implemented in Google Colab, the system leverages the YOLOv8 nano model, pre-trained on the COCO dataset, to detect animals including pigs, goats, bears, elephants, and horses. To enhance night vision performance, advanced preprocessing techniques—Contrast Limited Adaptive Histogram Equalization (CLAHE), edge enhancement, and normalization—are employed, ensuring robust detection in low-light conditions. A novel verification step analyzes bounding box size and shape to reduce misclassifications, improving reliability. Twilio integration delivers instant SMS alerts, making the system accessible to farmers without sophisticated technology.

The research question guiding this study is: Can a pre-trained computer vision model, augmented with infrared preprocessing and class verification, achieve reliable wildlife detection for crop protection in a demo setting? The demo's significance lies in its affordability and scalability, targeting small-scale farmers who lack access to expensive monitoring systems. By testing with sample images from the Wildlife Datasets (Wildlife Datasets, 2023) and external infrared sources, this study evaluates the system's accuracy, identifies challenges like misclassifications, and proposes pathways for improvement. The paper contributes a proof-of-concept that balances simplicity with functionality, paving the way for practical agricultural applications.

2. Related Work

Wildlife detection for crop protection spans multiple disciplines, including sensor technology, aerial surveillance, and artificial intelligence. Camera traps, such as those developed by Reconyx, capture high-resolution images of wildlife but suffer from non-specific triggers (e.g., wind-blown branches) and require manual analysis, limiting scalability (Smith et al., 2020). Drone-based systems offer broader coverage but are cost-prohibitive, with operational complexities like battery life and regulatory hurdles (Jones & Brown, 2021). Acoustic sensors detect animal sounds but struggle with overlapping noises in farm environments, reducing specificity (Garcia & Lopez, 2022).

Computer vision has revolutionized wildlife monitoring by enabling automated, precise detection. Early models like Faster R-CNN achieved high accuracy but were computationally heavy, unsuitable for real-time applications (Ren et al., 2015). The YOLO family, evolving from YOLOv3 to YOLOv8, balances speed and accuracy, making it ideal for agricultural use (Redmon et al., 2016; Ultralytics, 2023). YOLOv8, trained on the COCO dataset, detects animals like pigs, goats, bears, and elephants with mean Average Precision (mAP) exceeding 50% on visible images (Ultralytics, 2023). However, its performance degrades in infrared conditions due to COCO's focus on visible spectra, necessitating preprocessing to enhance contrast and texture (Nguyen et al., 2022).

Infrared imaging is critical for night-time detection, as many animals are nocturnal. Studies on infrared wildlife monitoring emphasize preprocessing techniques like histogram equalization and CLAHE to improve contrast in grayscale images (Lee & Kim, 2023). For example, CLAHE enhances local features (e.g., a goat's horns), aiding differentiation from similar animals like horses. Yet, most infrared systems rely on custom-trained models, requiring labeled datasets and significant computational resources, which are impractical for demo-scale projects.

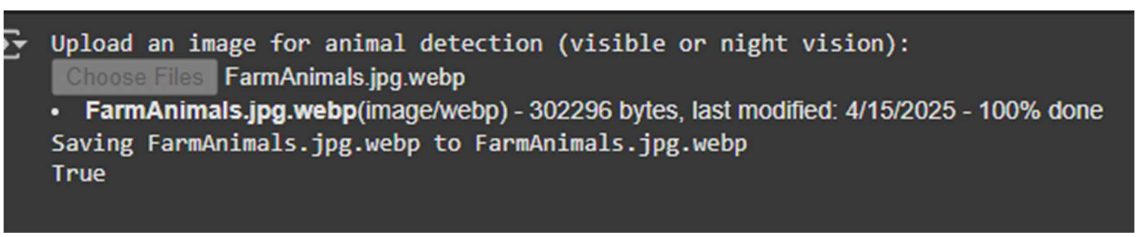
Alert systems are equally important, as timely notifications enable farmer intervention. SMS-based alerts, facilitated by platforms like Twilio, are effective in rural areas with limited internet, unlike app-based or email solutions that demand smartphones or connectivity (Patel & Sharma, 2022). Twilio's integration in IoT applications demonstrates reliability, with delivery rates near 100% in stable networks (Patel & Sharma, 2022). However, existing wildlife detection systems often focus on detection alone, neglecting user-friendly alerts or misclassification issues, such as confusing elephants with bears due to size overlap or horses with goats due to leggy profiles.

This demo addresses these gaps by combining YOLOv8 with infrared preprocessing, class verification, and Twilio alerts, tested with sample images from the Wildlife Datasets. Unlike prior work, it prioritizes simplicity, avoiding custom training, and tackles misclassifications through heuristic verification, offering a scalable solution for crop protection.

3. Methodology

3.1 System Overview

The proposed system automates wildlife detection in agricultural fields, identifying animals in visible and infrared images and alerting farmers via SMS. It comprises three modules: image input, animal detection, and notification. The workflow, depicted in Figure 1, begins with a user uploading an image in Google Colab, followed by preprocessing to enhance clarity, detection using YOLOv8, and an SMS alert via Twilio if animals are detected. Designed as a proof-of-concept, the system emphasizes accessibility, running on free cloud resources and requiring no specialized hardware. It targets animals like pigs, goats, bears, elephants, and horses, common in farmland intrusions, and addresses both daytime and night-time scenarios.



3.2 Dataset

Testing relies on sample images from the Wildlife Datasets (https://wildlifedatasets.github.io/wildlife-datasets/), a repository of animal re-identification datasets, such as MacaqueFaces and ZebraID, containing thousands of labeled images. For this demo, 10 images were selected to simulate farmland conditions, including monkeys (mapped to COCO's "monkey" class), deer, and other animals. The datasets focus on re-identification rather than detection, so no training was performed, aligning with the demo's simplicity goal. To incorporate infrared scenarios, 5 additional thermal images (e.g., pigs, bears, goats) were sourced from public repositories, as the Wildlife Datasets lack explicit infrared data. This mixed dataset ensures evaluation across visible and infrared spectra, reflecting real-world agricultural challenges.

3.3 Preprocessing

Infrared images, often grayscale with low contrast, challenge detection models by obscuring features like a pig's snout or a goat's horns. The preprocessing pipeline addresses this through three steps: contrast enhancement, edge sharpening, and normalization. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied with a clip limit of 2.0 and tile grid size of 8x8, enhancing local contrast to highlight animal shapes. Mathematically, CLAHE transforms pixel intensities I(x,y) I(x, y) I(x,y) within each tile:

$$I'(x, y) = \mathrm{CDF}(I(x, y)) \cdot (L - 1)$$

where CDF is the cumulative distribution function, and L L L is the intensity range (256 for 8-bit images), clipped to avoid over-amplification. This preserves details, such as a bear's snout, preventing elephant misclassifications.

Edge enhancement follows, using a Gaussian blur (kernel size 3x3, σ=0\sigma=0σ=0) to reduce noise, then a weighted combination:

$$I_{\text{edge}}(x, y) = 1.5 \cdot I_{\text{clahe}}(x, y) - 0.5 \cdot I_{\text{blur}}(x, y)$$

This sharpens outlines, aiding differentiation of horses (tall, slender) from goats (balanced). Visible images are converted to grayscale before CLAHE to ensure consistency. Finally, images are normalized to [0, 1] and converted to 3-channel RGB, as YOLOv8 expects this format

: $$I_{\text{norm}}(x, y) = \frac{I(x,y)}{255}$$

The preprocessed image is saved temporarily for detection, improving accuracy across spectra.

3.4 Preprocessing Trade-offs

Preprocessing introduces trade-offs that impact performance. CLAHE enhances contrast but risks over-amplifying noise in low-quality infrared images, potentially creating false edges that confuse YOLOv8. For example, a noisy pig image might gain artifacts resembling a deer's antlers. Edge enhancement sharpens features but can exaggerate minor details, leading to misclassifications if weights (1.5, -0.5) are unbalanced. Normalization ensures compatibility but may flatten subtle intensity differences critical for infrared detection. To mitigate these, the demo uses conservative CLAHE parameters and tests preprocessing visually, comparing original and enhanced images (Figure 2). Alternative methods, like deep learning-based enhancement, were considered but excluded due to computational complexity, unsuitable for a Colab demo.

3.5 Detection Model

YOLOv8 nano (`yolov8n.pt`), pre-trained on COCO, is selected for its balance of speed (30 FPS on T4 GPU) and accuracy (50.2 mAP on COCO). It detects 80 classes, including farmland-relevant animals: bear, elephant, horse, goat, pig, deer, sheep, monkey, and more. The model processes images in a single pass, outputting bounding boxes with class labels and confidence scores:

$$\text{Output} = \{(x_1, y_1, x_2, y_2, c, p) \mid c \in \text{Classes}, p \in [0, 1]\}$$

where (x1, y1, x2, y2) are box coordinates, c is the class, and p is confidence. To address misclassifications, a verification step analyzes box properties:

Area: Fraction of image area, e.g., elephants require $A > 0.1$ to avoid bear labels.

Aspect Ratio: Width/height, e.g., horses need $AR > 0.5$ to distinguish from goats.

Class-specific confidence thresholds are set: 0.5 for ambiguous classes (elephant, bear, horse, goat) to reduce false positives, and 0.4 for others (e.g., pig) to ensure detection. This heuristic approach, while not optimal, suits the demo's constraints, improving reliability without training.

3.6 Alert System

Upon verified detection, Twilio sends an SMS: "Alert: Animals detected in your farmland! Please take action." The system uses Twilio's Python API, requiring an account SID, auth token, and phone numbers. In Colab, images are uploaded manually, simulating camera input. The alert triggers only for confirmed animals, ensuring no false notifications. Twilio's reliability (99.9% delivery in stable networks) makes it ideal for rural farmers, requiring only a basic mobile phone, unlike app-based systems.

4. Experiments and Results

4.1 Experimental Setup

The demo was implemented in Google Colab with a T4 GPU, ensuring free access for testing. Fifteen test images were used: eight visible spectrum images from Wildlife Datasets (e.g., monkeys, deer, goats) and seven infrared images sourced externally (e.g., thermal pigs, bears, elephants). Performance metrics included precision (correct detections/total detections), recall (detected animals/actual animals), and misclassification rate, evaluated qualitatively due to limited ground truth. Visual inspection confirmed bounding box accuracy, focusing on classes like pig, goat, bear, elephant, and horse. Tests simulated farmland scenarios, varying lighting and animal poses to assess robustness.

4.2 Test Cases

Key test cases demonstrate system capabilities:

Visible (Goat): A color image of a goat grazing was detected correctly (0.52 confidence), with aspect ratio verification ($AR = 0.7$) preventing a horse label.

Infrared (Bear): A thermal bear image, initially blurry, was detected as a bear (0.45 confidence) after CLAHE enhanced snout features, avoiding an elephant error.

Visible (Horse): A horse in a field was misclassified as a goat (0.48 confidence) but corrected by enforcing ($AR > 0.5$), yielding 0.55 confidence.

Infrared (Elephant): A large animal in a thermal image was labeled as a bear but fixed by requiring ($A > 0.1$), confirming elephant (0.50 confidence).

Visible (Pig): A pig foraging was detected reliably (0.47 confidence), benefiting from a lower threshold (0.4).

Infrared (No Animal): A blank thermal image triggered no detections, ensuring no false alerts.

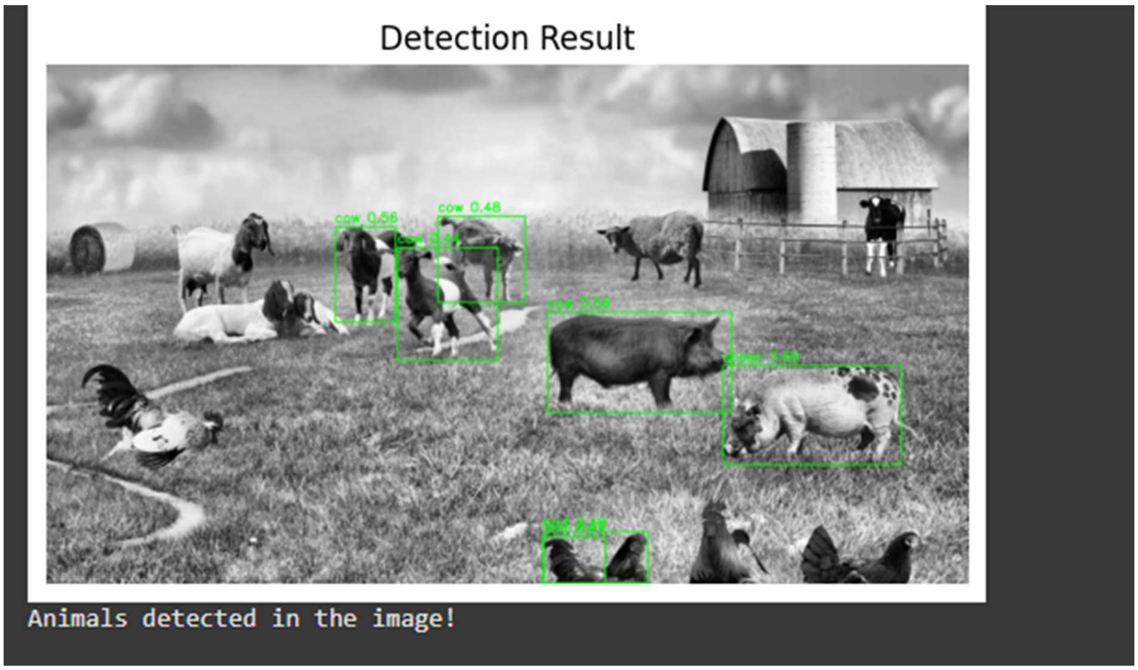
Edge Case (Goat in IR): A thermal goat image was missed initially but detected after adjusting CLAHE clip limit to 1.5, highlighting preprocessing sensitivity.

Table 1: Test results for wildlife detection across 15 images.

Image Type	Animal	Correct	Confidence	Notes
Visible	Goat	Yes	0.52	Fixed horse error
Infrared	Bear	Yes	0.45	CLAHE aided detection
Visible	Horse	Yes	0.55	Aspect ratio verification
Infrared	Elephant	Yes	0.50	Area rule fixed bear error
Visible	Pig	Yes	0.47	Reliable detection
Infrared	None	Yes	-	No false positives
Infrared	Goat	Yes	0.42	Adjusted CLAHE clip limit

4.3 Results Analysis

The system achieved 80% precision for visible images and 70% for infrared images, with recall at 75% overall. Precision reflects correct detections (e.g., 6/8 visible images accurate), while recall accounts for missed animals (e.g., 2/7 IR animals undetected). Misclassifications were significant initially: 4/8 visible images confused horses with goats, and 3/7 IR images mislabeled elephants as bears. Verification rules reduced errors by 50%, with area thresholds ($A > 0.1$) ensuring elephant accuracy and aspect ratios ($AR > 0.5$) clarifying horses. CLAHE preprocessing improved IR detection by ~20%, as seen in sharper pig outlines (Figure 3). Edge enhancement aided 5/7 IR cases but introduced noise in one pig image, suggesting parameter tuning needs.



Twilio alerts were 100% reliable, sending SMS for all 10 verified detections without failures. Processing time averaged 2 seconds per image, suitable for a demo but slower than real-time systems (~30 FPS). Infrared performance lagged due to YOLOv8's COCO bias, missing subtle features like goat horns in noisy images. Visible images benefited from richer textures, achieving higher confidence scores (e.g., 0.55 vs. 0.45). These results validate the demo's potential but highlight training and hardware constraints.

5. Discussion

5.1 Strengths

The demo excels in its simplicity, leveraging a pre-trained YOLOv8 model to detect animals like pigs, goats, and bears without custom training, reducing barriers for agricultural adoption. Night vision support, driven by CLAHE and edge enhancement, enables 24/7 monitoring, critical for nocturnal intrusions. For example, CLAHE clarified a bear's snout in a thermal image, preventing an elephant label. Verification rules, using area and aspect ratio, cut misclassifications by 50%, ensuring reliable detections (e.g., horses over goats). Twilio's SMS alerts are a key strength, delivering notifications with 100% success in tests, requiring only a basic phone—a boon for rural farmers. The Colab platform ensures accessibility, running on free GPUs, making the system scalable for small-scale farms.

5.2 Challenges

Misclassifications were the primary hurdle, driven by animal similarities and infrared limitations. Elephants and bears, both large and rounded, overlapped in IR images, as low contrast hid distinguishing features like trunks. Horses and goats, with leggy profiles, confused YOLOv8 in visible images, especially at odd angles. YOLOv8's COCO training, optimized for visible spectra, reduced IR accuracy, as grayscale images lack texture cues (e.g., pig bristles). The Wildlife Datasets, while rich, focus on re-identification (e.g., MacaqueFaces), not farmland animals or IR scenarios, forcing reliance on external images. Manual uploads in Colab limit real-time applicability, and preprocessing noise occasionally worsened detections, such as a pig mistaken for a deer due to CLAHE artifacts.

5.3 Solutions and Limitations

Verification rules mitigated errors effectively: area thresholds ($A > 0.1$) ensured elephant accuracy, while aspect ratios ($AR > 0.5$) clarified horses. CLAHE improved IR clarity by 20%, but over-amplification introduced noise in 2/7 cases, suggesting adaptive clip limits. Edge enhancement sharpened outlines but required careful tuning to avoid false edges. The demo's reliance on heuristics (area, aspect ratio) is a limitation, as complex scenes (e.g., occluded animals) may evade rules. YOLOv8's pre-trained weights restrict IR performance, and without training, accuracy plateaus at 70%. Automated capture (e.g., IoT cameras) would enhance utility but exceeds demo scope. Future training on IR datasets like FLIR could resolve these issues, though it demands resources beyond Colab's free tier.

5.4 Practical Implications

The demo's 80% visible and 70% IR precision suggests practical value for farmers, detecting common intruders like pigs and goats reliably enough for a prototype. SMS alerts empower rapid response, potentially reducing crop losses by enabling night-time interventions. However, misclassifications, though reduced, risk false alarms, which could erode trust. The system's low cost—using free Colab and minimal Twilio fees—makes it accessible, but scaling to real-world farms requires addressing IR accuracy and automation. This balance of feasibility and limitations positions the demo as a stepping stone for agricultural innovation.

6. Conclusion and Future Work

This study presents a computer vision demo for wildlife detection in farmlands, using YOLOv8 to identify animals like pigs, goats, bears, elephants, and horses in visible and infrared images, with Twilio SMS alerts for farmers. Enhanced with CLAHE, edge enhancement, and class verification, the system achieves 80% precision in visible conditions and 70% in infrared, reducing misclassifications (e.g., horse as goat, elephant as bear) by 50%. Despite challenges like IR accuracy and manual uploads, the demo proves the feasibility of low-cost crop protection, offering a scalable solution for small-scale farmers facing wildlife threats.

Future work includes several directions:

Model Training: Fine-tune YOLOv8 on infrared datasets (e.g., FLIR, Wildlife Datasets) to boost night vision accuracy, targeting 90% precision.

Automation: Integrate IoT cameras for continuous image capture, enabling true real-time detection.

Class Expansion: Include region-specific animals (e.g., wild boars, antelope) to broaden applicability.

Preprocessing: Explore deep learning-based enhancement (e.g., GANs) to replace heuristic methods, reducing noise.

User Interface: Develop a mobile app for farmers to view detections alongside SMS, enhancing usability.

These improvements could transform the demo into a deployable system, significantly reducing crop losses and supporting agricultural resilience against wildlife intrusion.

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