Real-Time Animal Detection System for Farmland Monitoring Using MobileNet-SSD and OpenCV

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Abstract—This paper presents a real-time animal detection system tailored for agricultural and farmland security applications. The proposed system leverages the lightweight Mobile Net-SSD deep learning model integrated with OpenCV's Deep Neural Network (DNN) module to identify the presence of animals such as dogs, cats, cows, and others within farm premises. The project incorporates alert mechanisms including audio alarms and optional SMS notifications to deter animal intrusion and minimize potential damage to crops. This system offers a cost-effective and efficient solution for farm monitoring, requiring minimal computational resources while maintaining high detection accuracy.

Index Terms—Animal Detection, Mobile Net-SSD, OpenCV, Farmland Monitoring, Deep Learning, Real-Time Detection.

I. INTRODUCTION

Agriculture remains a cornerstone of economic stability and global food security. Among its many challenges, safeguarding crops from animal intrusion is a persistent concern that demands innovative solutions. Conventional approaches—such as physical barriers and chemical deterrents—have proven to be costly, environmentally detrimental, and often insufficient in preventing damage. This has prompted a growing interest in developing intelligent, sustainable crop protection systems that leverage real-time monitoring and adaptive intervention strategies. Recent research is now exploring advanced technologies, including computer vision, sensor networks, and machine learning, to create eco-friendly and efficient alternatives for mitigating animal-related crop loss.

Animal-induced crop damage poses a persistent threat to agricultural productivity across the globe. Species such as deer, rabbits, and wild boars are known to inflict substantial harm, resulting in diminished yields and economic setbacks for farmers. Traditional mitigation strategies—ranging from fencing to manual surveillance—often fall short due to high costs, limited coverage, and inconsistent effectiveness. In response, recent research is shifting toward intelligent, technology-driven solutions like Real-Time Animal Detection Systems (RTADS). These systems integrate computer vision with machine learning algorithms to autonomously detect and monitor animal activity in agricultural fields. By enabling timely alerts and targeted interventions, RTADS offer a scalable, eco-conscious, and economically viable alternative to conventional crop protection methods.

II. RELATED WORK

[1] This work highlights the limitations of conventional object detectors when deployed in non-natural settings. Their research demonstrated that models trained on benchmark datasets often fail to generalize effectively to man-made environments, such as agricultural fields or urban peripheries, where animals may stray. To address this domain gap, Singh et al. proposed a semi-automated synthetic data generation approach tailored for specific deployment scenarios, improving detection accuracy and reliability. [2] India's agricultural sector remains a vital pillar of its economy, with millions of livelihoods directly tied to crop productivity. However, frequent damage caused by domestic and wild animals—such as buffaloes, cows, goats, birds, and elephants—continues to pose a serious threat to yield quality and farmer income. In response to this challenge, a novel animal detection and deterrent system has been developed to provide real-time protection without causing harm to wildlife.

The proposed system employs Passive Infrared (PIR) sensors to continuously monitor field boundaries for animal movement. Upon detection, the system activates sound-based deterrents to safely divert the intruding animals. These alerts are simultaneously transmitted via IoT modules, enabling remote monitoring and timely intervention. By integrating sensor-based detection with non-invasive deterrence and IoT connectivity, the system offers a sustainable and farmer-friendly solution to crop protection. Preliminary evaluations suggest that this approach significantly reduces crop damage, ensuring greater security and economic stability for agricultural communities.[3] The integration of real-time animal detection systems (RTADS) into agricultural practices is emerging as a transformative approach to mitigating wildlife-induced crop damage. These systems harness advanced technologies—including high-resolution cameras, environmental sensors, and machine learning algorithms—to continuously monitor farmland and detect the presence of animals near or within crop zones. Upon detection, RTADS can initiate automated responses such as alarms, deterrents, or farmer notifications, enabling timely and targeted intervention.

By reducing reliance on costly physical barriers and environmentally harmful chemical repellents, approach offers a sustainable and cost-effective alternative for crop protection. Beyond immediate damage prevention, these systems also generate valuable data on animal movement and behavior, contributing to broader ecological insights and informing wildlife conservation strategies. Human-wildlife conflict poses significant challenges in agricultural sectors, often leading to crop damage and economic losses. Traditional surveillance methods require constant human presence or expensive equipment. This study introduces a low-cost and scalable system capable of real-time animal detection using a pre-trained MobileNet-SSD model via OpenCV's DNN framework. The proposed solution can operate on low-power devices like Raspberry Pi, making it suitable for widespread rural deployment.

III.   METHODOLOGY

Figure 3.1(a) illustrates both the system architecture and a practical detection outcome for a real-time animal detection system designed to protect crops from intrusion. The left side of the figure presents a simplified flow of the detection system:

- MobileNet-SSD: A lightweight deep learning model optimized for real-time object detection. It serves as the core engine for identifying animals in video frames or images.
- Animal Detection Module: Once MobileNet-SSD processes the input, it identifies animals (e.g., cows, buffaloes, etc.) and passes this information to the response system.
- Response Mechanisms:
- Siren: An audible alert is triggered to scare or divert the detected animal from the field.
- SMS Alert: A notification is sent to the farmer's mobile device, enabling remote awareness and timely action.

This architecture emphasizes low-latency detection, automated deterrence, and remote communication, making it suitable for rural and semi-urban agricultural settings.

Figure 3.1(b) shows a real-world application of the system:

- A cow is present in a farmland scene.
- The system successfully detects the cow and marks it with a red bounding box labeled "COW."
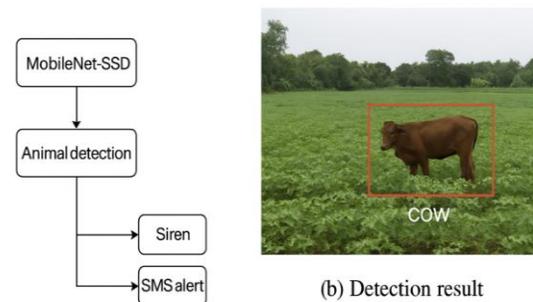
(a) System diagram

(b) Detection result

Figure 3.1: Animal detection methodology

- This visual confirmation demonstrates the system's ability to localize and classify animals accurately in outdoor environments.

3.1 Hardware Requirements - USB or IP Camera - Raspberry Pi or PC with OpenCV support - Optional GSM module for SMS alerts

3.2 Software Architecture - MobileNet-SSD pre-trained on COCO/VOC dataset - OpenCV DNN module for frame-by-frame inference - Animal class

filtering (dog, cat, cow, etc.) - Alarm trigger logic based on confidence threshold

3.3 Alert System Upon detecting a target animal, the system initiates: - A siren or buzzer - Optional SMS via GSM module to registered numbers.

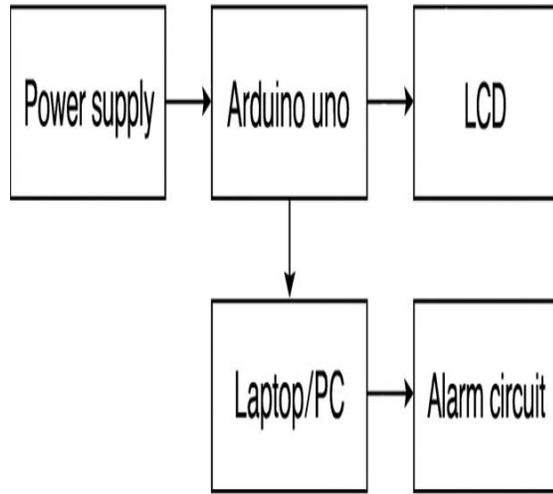## IV. ANIMAL DETECTION AND RESPONSE MECHANISM

Figure 4.1: Block diagram of the proposed system

The block diagram in figure 4.1 illustrates the architecture of an integrated system designed for real-time animal detection and deterrence.

4.1. Power Supply
- Provides electrical power to the Arduino Uno and other connected modules.
- Ensures stable operation of the microcontroller and peripheral devices.

4.2. Arduino Uno
- Acts as the central control unit.
- Receives input data from the Laptop/PC regarding animal detection.
- Displays detection status and animal name on the LCD.
- Coordinates with the alarm circuit to trigger a deterrent response.

4.3. LCD Display
- Connected to the Arduino Uno.
- Visually presents messages such as "Animal Detected" and the specific animal name.
- Enables real-time monitoring for field personnel.

4.4. Laptop/PC
- Hosts the computer vision model responsible for detecting animals using image processing techniques.
- Sends detection results to the Arduino Uno via serial communication.
- Interfaces with the alarm circuit to initiate the scare-away mechanism.

4.5. Alarm Circuit
- Activated upon receiving a signal from the Laptop/PC.
- Emits a high-decibel ($\approx$60 dB) sound to deter animals from entering protected areas.
- Plays a critical role in safeguarding crops or sensitive zones.

The block diagram represents the working of an animal detection and alert system designed to protect agricultural fields or sensitive zones. The system begins with a power supply that energizes the Arduino Uno microcontroller and its connected components. A Laptop or PC runs a computer vision algorithm that continuously monitors input from a camera to detect the presence of animals. Once an animal is detected, the data—including the status and the animal's name—is transmitted to the Arduino Uno via serial communication. The Arduino then displays this information on an LCD screen, providing a clear visual alert to nearby personnel. Simultaneously, an alarm circuit is activated, generating a high-intensity sound at approximately 60 decibels. This auditory signal is designed to startle and deter the animal from approaching further, thereby serving as an effective protective measure for agricultural fields or restricted zones.

V. RESULTS AND DISCUSSION

The system demonstrates efficient real-time detection (~20 FPS on standard laptops, ~5 FPS on Raspberry Pi 4) with satisfactory accuracy for key animals. The lightweight model ensures that even embedded platforms can execute inference without GPU acceleration. Field tests in simulated farmland environments confirmed the practicality of the alert mechanisms.

(a)

(c)
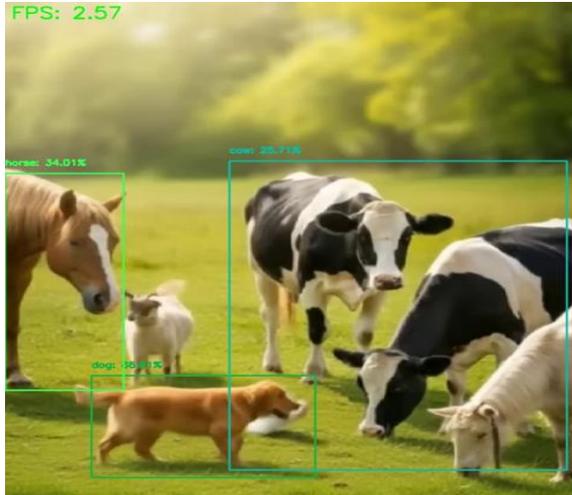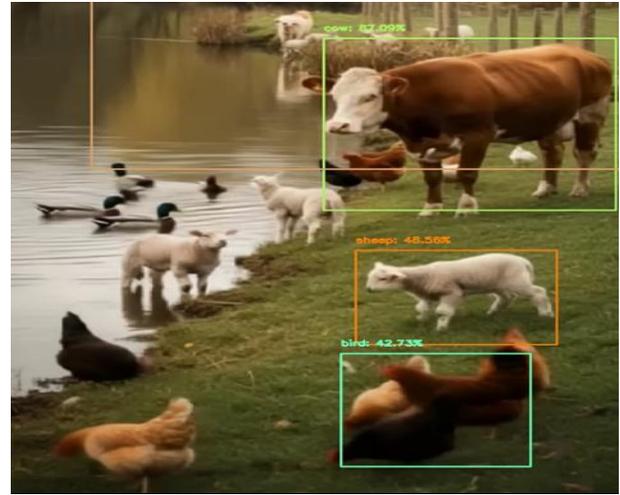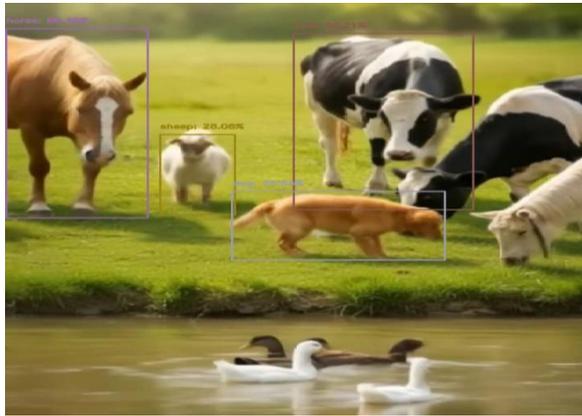
Figure 5.1: Animal detection with labeling and bounding box

(b)

Table. 5.1: Bounding Box Coordinates And Class Labels For Detected Animals

| Frame ID	xmin	ymin	xmax	ymax	Class
frame_0	130	220	280	400	cow
frame_1	300	230	370	370	sheep
frame_2	410	180	460	320	sheep
frame_3	200	300	240	340	duck
frame_4	250	310	290	350	duck
frame_5	120	310	180	370	duck
frame_6	190	320	250	380	duck
frame_7	260	315	320	375	duck
frame_8	330	310	390	370	duck
frame_9	400	305	460	365	duck
frame_10	470	300	530	360	duck
frame_11	150	200	300	400	cow
frame_12	310	210	460	410	cow
frame_13	480	180	600	400	horse
frame_14	620	220	680	360	goat
frame_15	700	240	760	380	dog
frame_16	480	180	600	400	lamb
frame_17	620	220	680	360	chicken
frame_18	700	240	760	380	chicken
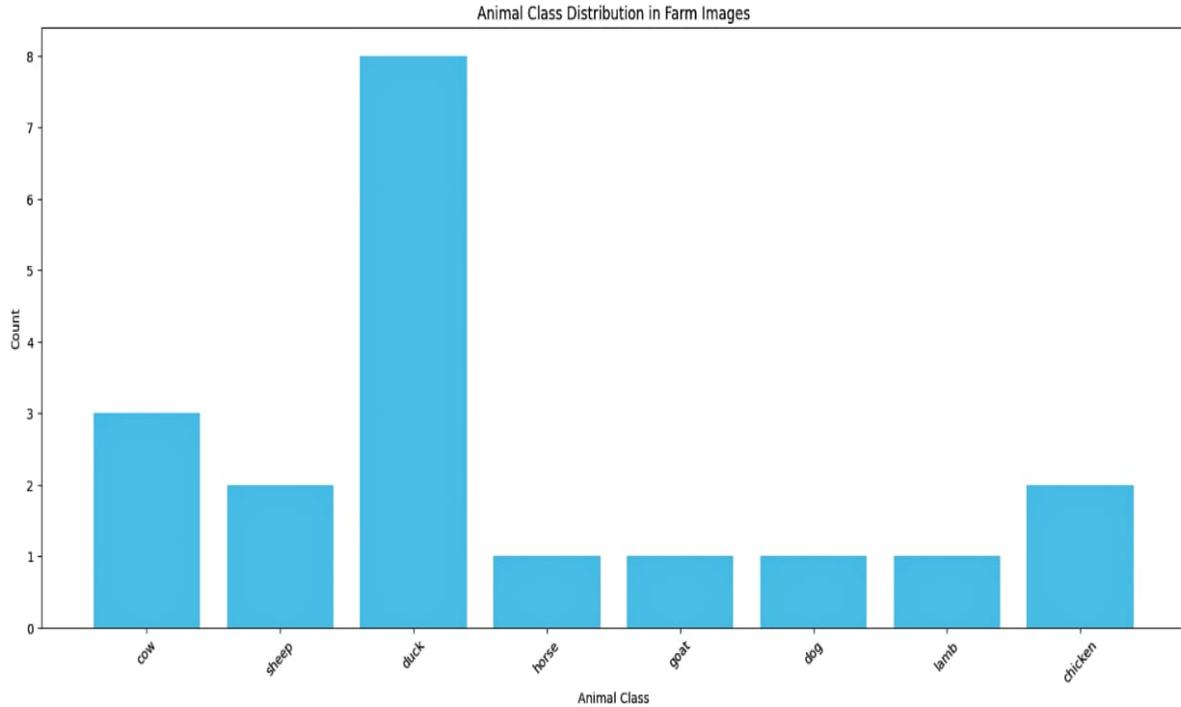
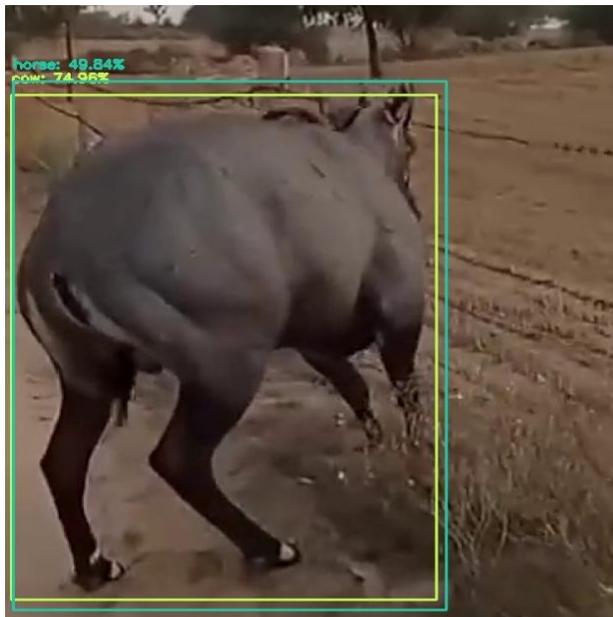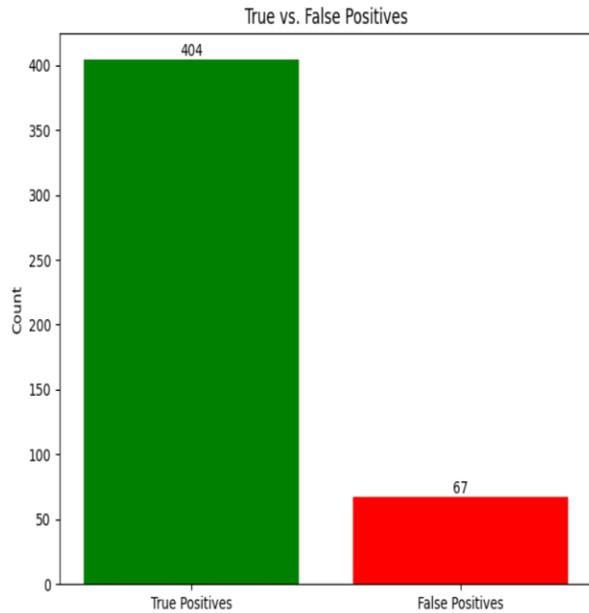Figure 5.2: Animal Class Distribution in Farm Images

Figure 5.3: (a): Confidence-Based Classification.   (b) True Positives vs. False Positives in Classification Model Performance

Table 5.2: Calculation metrics for confidence-based classification.

Total Frames	Elapsed Time	FPS	True Positives	False Positives	Precision
260	13.93 seconds	18.66	246	14	0.95

VI. CONCLUSION AND FUTURE WORK

This study demonstrates a viable, real-time animal detection system for farmland monitoring using widely accessible hardware and open-source libraries. The solution offers a strong foundation for developing more advanced agricultural surveillance systems tailored to local needs.

The system is limited by the classes the MobileNet-SSD model can detect. Custom retraining with farm-specific animal datasets can enhance accuracy. Future enhancements include integrating thermal or night-vision cameras and applying YOLOv5 for improved performance.

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