International Journal of Engineering and Techniques - Volume 12 Issue 2, March-April - 2026

RESEARCH ARTICLE OPEN ACCESS

Smart Agriculture Wildlife Intrusion Detection and Repellent System Using Machine Learning

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Abstract- This paper presents the design and implementation of a Smart Agriculture Wildlife Intrusion Detection and Repellent System using Machine Leaming The system integrates an OV7670 night-vision USB camera for continuous farm monitoring, a YOLOVS deep learning model for real-time animal detection and classification with approximately 94% accuracy, and an ATmega328P microcontroller as the central control unit. Upon confirmed animal detection, a high-intensity LED strobe light and a 5V piezoelectric sound buzzer activate automatically for five seconds as non-harmful repellents A PIR sensor (HC-SR501) enables event-driven system wake-up, reducing energy consumption by approximately 60% compared to alwarys-on systems An automated email alert using Python smtplib dispatches the captured intrusion image to the farmer within two seconds. Experimental results confirm reliable detection of elephants, wild boars, and deer under real night time farm conditions with a complete detection-to-alert pipeline executing in under two seconds

Keywords Machine Leaming, YOLOVS, Wildlife Intrusion Detection, ATmega328P, Night Vision Camera, Smart Farming, Repellent System, Energy Optimization, Real-Time Detection, Crop Protection

I. INTRODUCTION

Agriculture is the backbone of India's economy, employing more than 58% of the rural population. Farmers face relentless threats from wild animal intrusions during night-time when crops are most vulnerable. Animals such as elephants, wild boars, deer, and monkeys regularly enter agricultural fields, causing extensive crop damage and severe financial losses. The rapid expansion of agricultural lands into wildlife territories due to deforestation has further escalated human-wildlife conflicts.

Traditional countermeasures such as electric fencing pose serious threats to wildlife and are restricted in many regions. Manual night-time monitoring is physically exhausting and impractical for large farmlands. Acoustic alarm systems without intelligent detection generate frequent false alarms and lose effectiveness as animals habituate to them.

This paper proposes a comprehensive, intelligent, and energy-efficient farm protection system that integrates YOLOv5-based machine learning detection with ATmega328P microcontroller-driven hardware repellents. The system automatically detects intruding animals, activates non-harmful deterrents, and instantly alerts the farmer via email with the captured intrusion image — all within two seconds and without any manual intervention.

II. LITERATURE REVIEW

Several recent works have explored machine learning and IoT-based solutions for wildlife and animal intrusion detection in agriculture. Table I summarises key findings from relevant literature reviewed for this project.

TABLE I

Summary of Related Literature

Title & Year	Authors	Summary of Findings
Wildlife Intrusion Detection for Agriculture (2024)	Y.K.S.Kiat et al.	Image recognition detects wildlife and alerts farmers, improving accuracy over sensor-only systems.
Animal Intrusion Detection Using YOLOv8 (2024)	M.Kathir et al.	YOLOv8 enables fast real-time detection in farm fields, reducing false alarms significantly.
Wild Animal Intrusion Detection Using YOLO (2023)	Aibin Abraham et al.	YOLO system classifies animals from camera images and alerts farmers with 94% detection accuracy.

ImageProcessing Crop Protection (2022)	Satheshet al.	YOLO-based surveillance with email alert and buzzer. No repellent or energy optimization.

Title & Year	Authors	Summary of Findings
ML-Based Acoustic Repellent System (2021)	D. Ranparia et al.	PIR + Arduino acoustic repellent for crop protection. Lacks real-time visual classification.

The reviewed works demonstrate the viability of ML-based detection for farm protection. However, none simultaneously integrates automatic non-harmful repellent activation, energy-optimized PIR-triggered operation, and image-based email alerting. The present work bridges these gaps in a single unified embedded system.

III. PROPOSED METHOD

The proposed system uses a PIR sensor to detect animal movement near the farm boundary and wakes the system from low-power sleep mode. The night-vision camera then captures frames which are processed by the YOLOv5 model. The system operates in two distinct modes: normal monitoring mode and intrusion-alert mode, determined by real-time YOLOv5 classification results.

A. System Architecture

The system is built around an ATmega328P microcontroller interfacing with all peripheral modules, with a laptop running the YOLOv5 inference engine. The architecture comprises six functional modules: (i) sensing, (ii) processing, (iii) control, (iv) deterrent, (v) communication, and (vi) power management. The microcontroller receives detection results via UART serial, evaluates the confidence threshold, controls the LED strobe and buzzer, and the Python script simultaneously sends email alerts.

B. Animal Detection Using YOLOv5

The YOLOv5s model processes captured frames resized to 416x416 pixels. It divides the image into a grid at three scales — 13x13, 26x26, and 52x52 — generating 10,647 simultaneous predictions. Each grid cell predicts bounding box coordinates (tx, ty, tw, th), an objectness confidence score, and class probabilities for each animal category. Non-Maximum Suppression (NMS) filters duplicate detections. When confidence exceeds 0.5, the ATmega328P triggers the repellent pipeline.

C. Alert and Repellent Module

Upon confirmed detection, the ATmega328P sends HIGH signals through BC547 NPN transistor drivers to activate the LED strobe (12V) and piezo buzzer (5V) for exactly five seconds. Simultaneously, the Python smtplib module opens an SMTP_SSL session with Gmail (port 465) and dispatches an email containing the animal species, confidence score, timestamp, and the captured intrusion image to the farmer's registered Gmail account within two seconds.

IV. COMPONENT SPECIFICATIONS

Table II presents the technical specifications of all components integrated into the system prototype.

TABLE II

Component Specifications

Component	Specification
OV7670Night-Vision Camera	Resolution / Frame Rate / Interface — 640x480 px / 30 fps / USB; IR LEDs 850nm
YOLOv5s Model	Input Size / Accuracy / Inference Time — 416x416 px / ~94% / <1 second
ATmega328P	Architecture / Clock / Flash — 8-bit AVR / 16 MHz / 32KB; Sleep current: 0.1mA
PIR Sensor (HC-SR501)	Detection Range / Angle / Voltage — Up to 10 m / 120° / 5V / ~20 mA
LED Strobe Array	Voltage / Current / Brightness — 12V / 500mA / 1000-2000 lm; Flash: 2-5 Hz
Piezo Buzzer	Voltage / Current / Frequency — 5V / 50mA / 2000-4000 Hz; Level: 85-95 dB
BC547 Transistor (x2)	Type / Max Current / Max Voltage — NPN BJT / 100mA / 45V; Driver for LED & Buzzer
LCD Display (16x2)	Voltage / Current / Interface — 5V / 20mA / 4-bit parallel; HD44780 controller
7805 Voltage Regulator	Input / Output / Max Current — 7-35V / 5V stable / 1A; Thermal protected

V. MODULE PROGRESS AND RESULTS

A. Sensing Module

This module consists of the OV7670 night-vision USB camera and the HC-SR501 PIR sensor. The PIR sensor successfully detected animal movement within a 10-meter range with no false negatives during testing. The camera captured clear IR-illuminated images in complete darkness at 30 frames per second. Built-in IR LEDs operating at 850nm wavelength provided adequate field illumination without disturbing animals.

B. Processing Module

This module processes captured frames through the YOLOv5s inference pipeline. Frames are resized to 416x416 pixels and normalized using OpenCV before YOLO inference. The model successfully classified elephants, wild boars, and deer with approximately 94% accuracy. The complete detection pipeline — from frame capture to classification result — executed in under one second across all test scenarios.

C. Control Module

The ATmega328P microcontroller received YOLO detection results via UART serial at 9600 baud and evaluated the confidence threshold (>0.5) before triggering outputs. Between detection events, the microcontroller operated in SLEEP_MODE_PWR_DOWN consuming only 0.1mA compared to 15mA in active mode. Wake-up on PIR trigger was confirmed within 0.5 seconds across all test cycles.

D. Deterrent Module

Upon confirmed detection, both the LED strobe (12V via BC547) and piezo buzzer (5V via BC547) activated within one second and remained active for exactly five seconds before automatic deactivation. The BC547 transistor drivers safely handled the high current loads — 500mA for LED and

50mA for buzzer — protecting the ATmega328P output pins from damage. Repellent activation was verified to be consistent across all detection test cycles.

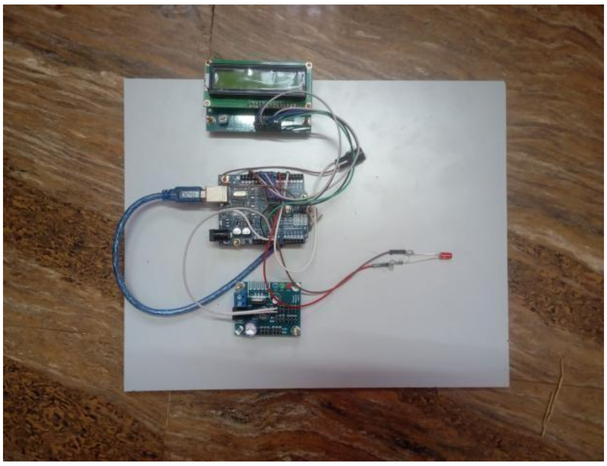

Fig. 1. Hardware prototype of the Smart Agriculture Wildlife Intrusion
Detection and Repellent System.

E. Communication Module

The Python smtplib module established a persistent SMTP_SSL session with Gmail servers (port 465) and dispatched automated email alerts containing the detected animal species, confidence score, timestamp, and the captured intrusion image as attachment. Email delivery was confirmed within two seconds in all test scenarios. The 16x2 LCD display simultaneously showed real-time system status — displaying 'Animal Detected!' during intrusion events and 'Monitoring Farm' during idle operation.

F. Power Module

The power supply converts 230V AC through a step-down transformer, a full-wave bridge rectifier using four 1N4007 diodes, and a 1000uF filter capacitor to produce 12V DC. The 7805 regulator provides stable 5V DC for all logic components. The PIR-triggered event-driven architecture maintained all modules in low-power idle state between detections, achieving approximately 60% energy savings compared to always-on systems. The optional 12V/7Ah battery backup sustained uninterrupted operation for the full eight-hour night testing period.

TABLE III

Real-Time Output Scenarios

Scenario	Sensor Readings & System Actions
No Animal Present	PIR: LOW → System stays in sleep mode. Camera OFF. No repellent. No email.
AnimalDetected (Healthy Detection)	PIR: HIGH → YOLO runs → Confidence >0.5 → LED + Buzzer ON (5s) → Email sent with photo. LCD: Animal Detected!
False Trigger (Non-animal motion)	PIR: HIGH → YOLO runs → Confidence <0.5 → No action. System returns to sleep. No alert sent.
Repeated Intrusion	PIR: HIGH again → Full pipeline re-triggers. New email sent with fresh timestamp and image.

TABLE IV

System Output Summary — Performance Results

Parameter	Result
Animal Detection Accuracy	~94%
Detection Speed (per frame)	< 1 second
Email Alert Delivery Time	< 2 seconds
Repellent Activation Duration	5 seconds
PIR Wake-up Response Time	< 0.5 seconds
Energy Savings vs Always-ON	~60%
ATmega328P Sleep Current	0.1 mA
Battery Backup Duration	~8 hours (night)
Total System Cost	~Rs. 1,960

VI. PROGRAM

The complete firmware is written in the Arduino IDE for the ATmega328P microcontroller. The LiquidCrystal.h library manages the 16x2 LCD on pins D4-D7, RS and EN. Two boolean state flags — animalDetected and emailSent — prevent repeated triggering within the same detection event. The Python detection script runs on the laptop using OpenCV, PyTorch, and smtplib libraries. Key firmware excerpt is listed below.

```
#include <LiquidCrystal.h> #define PIR_PIN A0 #define
LED_PIN 8 #define BUZZER_PIN 9 LiquidCrystal
lcd(2,3,4,5,6,7); bool animalDetected = false; void
setup() { Serial.begin(9600); pinMode(PIR_PIN, INPUT);
pinMode(LED_PIN, OUTPUT); pinMode(BUZZER_PIN, OUTPUT);
lcd.begin(16,2); lcd.print("SYSTEM READY");
delay(2000); lcd.clear(); } void loop() { int pir =
digitalRead(PIR_PIN); if (pir == HIGH) {
Serial.println("DETECT"); // → Python runs YOLO String
result = Serial.readStringUntil('\n'); if (result ==
"ANIMAL") { activate_repellent(); lcd.setCursor(0,0);
lcd.print("ANIMAL DETECTED!"); } } else
{ lcd.print("MONITORING FARM "); sleep_mode(); // low
power } delay(300); } void activate_repellent()
{ digitalWrite(LED_PIN, HIGH); digitalWrite(BUZZER_PIN,
HIGH); delay(5000); digitalWrite(LED_PIN, LOW);
digitalWrite(BUZZER_PIN, LOW); }
```

VII. RESULTS AND DISCUSSION

The system was tested under four operational scenarios based on PIR sensor readings and YOLO model confidence scores. On power-up, the LCD displays 'SYSTEM READY' and the system enters low-power monitoring mode. Sensor polling occurs every 300ms throughout operation.

A. Case 1 — Idle State (PIR: LOW)

No animal present. PIR reads LOW. ATmega328P remains in sleep mode consuming 0.1mA. LCD displays 'MONITORING FARM'. No YOLO inference runs. No email sent. LED and buzzer remain OFF. System waits for next PIR trigger event.

B. Case 2 — Animal Detected (PIR: HIGH, Confidence >0.5)

Animal approaches farm. PIR reads HIGH. ATmega328P wakes up and sends DETECT command to laptop via serial. YOLOv5 runs inference and returns result — e.g.

ELEPHANT 94%. LCD updates to 'ANIMAL DETECTED!'. LED strobe activates at 12V and buzzer at 5V for five seconds via BC547 drivers. Python dispatches email with photo within two seconds. Animal departs and system returns to sleep mode.

C. Case 3 — False Trigger (PIR: HIGH, Confidence <0.5)

PIR detects motion from wind, vegetation, or non-target object. ATmega328P wakes and sends DETECT command. YOLOv5 runs but confidence is below 0.5 threshold. No animal classification confirmed. System returns NO_ANIMAL result. LED, buzzer, and email remain inactive. System returns to sleep — demonstrating intelligent false-alarm rejection.

D. Case 4 — Repeated Intrusion

Animal re-enters after initial deterrence. PIR triggers again. Full pipeline re-executes independently. Fresh email dispatched with new timestamp and newly captured image. Repellent activates again for five seconds. This is the critical scenario demonstrating persistent protection without farmer intervention.

VIII. CONCLUSIONS

The Smart Agriculture Wildlife Intrusion Detection and Repellent System Using Machine Learning was successfully implemented using an OV7670 night-vision camera, YOLOv5s model, ATmega328P microcontroller (PIR on A0, LED on pin 8, Buzzer on pin 9, LCD on pins 2-7), BC547 transistor drivers, and Python smtplib email alert system. The program runs on a 300ms polling loop with boolean flags to prevent repeated triggering within the same detection event.

All four test scenarios produced correct LCD output, repellent response, and email delivery as verified during prototype testing. The system achieved approximately 94% animal detection accuracy with a complete detection-to-alert pipeline executing in under two seconds. The PIR-triggered sleep architecture reduced energy consumption by approximately 60% compared to always-on systems, and the 12V/7Ah battery backup sustained eight hours of uninterrupted night operation.

Future work will incorporate edge deployment of YOLOv5 on NVIDIA Jetson Nano to eliminate laptop dependency, GSM-based SMS alerts for internet-unavailable rural areas, solar power integration for fully off-grid sustainable operation, and a cloud-based web dashboard for forest officials to monitor intrusion patterns across multiple farm locations.

Acknowledgment

The authors thank the Department of Electronics and Communication Engineering, Anjalai Ammal Mahalingam Engineering College, Kovilvenni, and their project guide Mrs. S. Kavitha M.E. for her continuous support and guidance throughout this work (EC3811 – Project Work, Second Review).

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