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Design and Development of a Low-Power Embedded Edge Computing Framework for Real- Time Wildlife Monitoring and Deterrence

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Abstract - In modern agriculture, protecting crops from animal intrusions is a major challenge. This project presents a real-time wildlife monitoring and deterrence system using the YOLO V8 object detection algorithm. The system employs AI-based image processing with OpenCV for pre processing and integrates automatic notification and control mechanisms for enhanced farm security. A camera continuously captures images, and YOLO V8 detects and classifies animals in real time. Detected images are uploaded to a remote server for analysis and then deleted to save storage. Pre-processing steps like noise reduction, resizing, and normalization improve detection accuracy, while compression and feature extraction ensure real-time performance. When an animal is detected, the system sends an email alert with the timestamp and type of animal, activates a buzzer, and displays details on an LCD screen. LED floodlights turn on in low light to increase visibility and deter nocturnal animals. The YOLO V8 model is continuously refined for accuracy and adaptability, offering a practical, efficient solution for smart farm wildlife monitoring and deterrence.

Keywords: Smart Agriculture, Wildlife Monitoring System, Animal Intrusion Detection, YOLOv8 Object Detection, Computer Vision in Agriculture

I. INTRODUCTION

In recent years, technological advancements in agriculture have led to the development of intelligent systems aimed at improving efficiency, security, and farm management. A significant challenge faced by farmers, particularly in rural or remote areas, is protecting crops from intruding animals, which can cause substantial damage and financial losses. Traditional methods, such as physical barriers, fencing, and manual monitoring, are often labor-intensive, costly, and not always effective. With the increasing size and complexity of modern farms, continuous human surveillance is impractical, highlighting the need for automated and efficient solutions.

This has led to the emergence of intelligent wildlife monitoring and deterrence systems that leverage machine learning, artificial intelligence (AI), and image processing techniques to detect, recognize, and respond to animal intrusions in real time. The proposed system addresses this challenge by developing a robust and efficient real-time animal detection system using the YOLO V8 (You Only Look Once) object detection framework. YOLO V8 is a deep learning-based model capable of detecting objects in images with high accuracy and speed. Unlike traditional detection methods, which process images in multiple steps, YOLO V8 analyzes an entire image in one pass, making it highly suitable for real-time applications.

The system integrates YOLO V8 with a camera-based monitoring setup that continuously captures images of the farm environment. When an animal is detected, 2 the image is uploaded to a server for further analysis. Images are pre- processed using OpenCV, applying techniques such as resizing, noise reduction, and color adjustments to enhance quality and improve detection accuracy. Compression methods, including dimensionality reduction and feature fusion, are applied to reduce computational load and storage

requirements, enabling efficient real-time operation even in resource-constrained environments.
YOLO V8 detects and identifies animals based on a trained dataset of labeled images encompassing various species, including cattle, deer, and other common intruders. Feature extraction and fusion techniques enhance the model's ability to distinguish animals from other objects, minimizing false positives. Once an animal is detected, the system triggers automated responses, such as sending email notifications to the farmer with details of the detection and activating a buzzer to deter the animal.

The buzzer can also be remotely controlled through web or mobile interfaces, providing flexible management of the system. Operating in real-time, the system minimizes crop damage by promptly detecting intrusions without requiring constant human oversight. Images are temporarily stored and deleted after analysis, ensuring efficient data management and avoiding excessive storage consumption. The system is scalable and adaptable, suitable for farms of varying sizes, and can be fine-tuned to detect different species of animals. Continuous updates and model training ensure effectiveness as animal behavior and environmental conditions evolve.

This system combines state-of-the-art AI technologies such as YOLO V8 and OpenCV with practical response mechanisms to provide an efficient, user-friendly solution for real-time wildlife monitoring and deterrence. By automating animal detection and response, the system improves crop protection, farm security, and overall agricultural productivity.

II. LITEREATURE REVIEW

A. Review Stage

The proposed system presents a robust edge-based solution for real-time wildlife detection using YOLOv8 deployed on a Raspberry Pi 5. Designed to address the increasing threat of wildlife intrusion in agricultural and rural areas, the architecture integrates a Pi Camera for continuous video capture and a custom-trained YOLOv8 model tailored to region-specific animal species. The Raspberry Pi performs local inference, enabling rapid detection of animals such as elephants, lions, leopards, and monkeys without relying on cloud resources. Upon detection, the system activates audio-visual alarms and sends real-time alerts to relevant authorities, facilitating prompt intervention. A lightweight web dashboard supports live monitoring, while Python scripts manage frame processing and alert logic. The emphasis on low power consumption, standalone operation, and internet- independent functionality makes this setup ideal for deployment in remote landscapes. Overall, the system enhances situational awareness, minimizes human-animal conflict, and demonstrates the efficacy of YOLOv8 in delivering fast, accurate, and energy-efficient wildlife detection at the edge.

The smart wildlife detection and alert system described in this study is designed to address the persistent issue of animal intrusion in rural and agricultural regions, especially those adjacent to forested areas. By deploying a network of IoT sensors, motion detectors, and cameras along farmland boundaries, the system ensures continuous surveillance of wildlife movement. Data captured from these devices is processed either locally at the edge or via cloud servers, depending on network availability. A machine learning model classifies the detected animals and evaluates the threat level.

When a potential danger is identified, the system promptly sends alerts through SMS and mobile applications, while also activating deterrents such as sirens or lights. The architecture emphasizes energy efficiency and remote operability, with support from renewable sources like solar panels.Illustrates this workflow, showing how sensor data flows through AI-based detection layers, is securely stored in the cloud, and triggers real-time alerts for rapid response. The system has been validated through community-level testing, demonstrating its reliability across varying environmental conditions and its potential to reduce human-wildlife conflict effectively.

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The AI-driven wildlife behavior monitoring system outlined in this study is tailored to mitigate nighttime agricultural losses caused by animal intrusions. It employs a combination of surveillance cameras and infrared sensors to capture real-time footage around farmland boundaries. The core of the system is a hybrid machine learning model that integrates Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), enhancing detection accuracy under low-light conditions. Trained on locally sourced datasets, the model effectively distinguishes between wildlife and benign movements. Upon detection, a microcontroller activates deterrent mechanisms such as sirens and lights, while GSM modules dispatch SMS alerts to farmers. Additionally, intrusion data is stored in the cloud for behavioral analysis and system refinement. As illustrated in the architecture includes preprocessing, object detection, and behavior analysis modules, which collectively interpret animal activity and generate alerts for abnormal or critical patterns. Field trials further optimize sensor placement and detection thresholds, ensuring high reliability and minimal false positives in diverse environmental conditions.

The Animal Guard system introduces a CNN-driven, IoT-based wildlife monitoring solution tailored for village communities near forest boundaries. To address the limitations of manual surveillance over large terrains, the system deploys low-power motion and ultrasonic sensors along with camera nodes to form a detection perimeter. These devices communicate via a LoRa wireless network, enabling long-range and energy-efficient data transmission. A central gateway processes incoming data using a rule- based decision model to classify movement as harmless or dangerous. Upon detecting a threat, the system activates sirens and sends alerts through mobile applications and emails.

Figure 2.4 illustrates the PLC layout, where an ESP8266 microcontroller receives input from ultrasonic sensors and controls a relay for visual alerts via a bulb. The connected PC processes data from the ESP8266 and webcam, generating real-time sound and email notifications. The system is designed for offline operation with backup power, ensuring reliability in connectivity- challenged rural areas. Community participation is emphasized to optimize sensor placement and maximize coverage, enhancing early warning capabilities and promoting safe coexistence with wildlife.

The animal deterrence system described in this study leverages thermal imaging and computer vision to detect elephant intrusions in forest-adjacent agricultural zones. Designed for high night-time reliability, the system uses thermal cameras to capture heat maps of moving objects, which are then analyzed using thresholding and shape- based image processing techniques. By calibrating the system to recognize heat intensity and body mass signatures, it effectively distinguishes elephants from other entities like cattle or humans. Alerts are issued through speakers and mobile notifications, enabling villagers to take timely preventive action. As the YOLO architecture processes input images through convolutional layers to extract features, followed by prediction and output layers for real-time object detection. The system is powered by solar energy, ensuring uninterrupted operation in remote areas. Field tests confirm its robustness under low-light, foggy, and dense vegetation conditions. However, limitations include high implementation costs, the need for expert calibration, and restricted detection capabilities beyond elephants.

The system described in this study introduces edge intelligence to wildlife camera traps using hyperdimensional computing, aiming to enhance conservation efforts in threatened habitats. It integrates AI with IoT-based wearable sensors to monitor animal health, detect poaching activities, and identify forest hazards such as fires. The wearable modules include heartbeat and temperature sensors, with data collected via an ESP32 microcontroller and transmitted to a central server. An accelerometer tracks abnormal movements, while a camera module performs image analysis to detect unauthorized activities. AI algorithms assess risk levels and trigger automated alerts to forest officials, including activating a water pump for fire suppression. As illustrated in the system comprises a Smart Camera Trap with HD and SD cameras, motion detection, compute and storage modules, and a Wi- Fi unit, all powered by a solar-based Power Supply Unit. This setup ensures autonomous, energy-efficient operation in remote environments. The system enables real-time monitoring, early threat detection, and reduced reliance on manual patrolling, thereby supporting sustainable wildlife management. However, limitations include potential discomfort from wearable sensors, battery constraints, dependence on strong network coverage, weather-sensitive camera performance, and AI misclassification risks in complex scenarios.

The Parabraksh v3.5 system is a solar-powered, autonomous animal repellent solution designed to mitigate human-wildlife conflict in forest-adjacent rural areas. It uses a dual-stage detection model: first, Local Binary Patterns (LBP) and AdaBoost algorithms identify regions of interest; then, a CNN classifies the animal species. Real- time images are captured via camera, and alerts are triggered through mobile messages, alarms, or deterrent devices. Powered by an Arduino Uno and solar energy, the system integrates PIR, laser, and LDR sensors to detect motion and environmental cues. It achieves 85% accuracy, minimizes false alarms, and operates efficiently in remote terrains. However, its performance may degrade in extreme weather, struggles with rare species and multiple animal detection, and requires retraining for new locations.

The Agro Guard Edge AI system presents a sustainable and solar-powered solution for mitigating wildlife intrusion in rural and forest-bordering agricultural zones. It combines basic deterrence mechanisms with edge-based image classification to protect crops from animals such as boars, deer, and monkeys. The system uses a solar panel to charge a battery that powers a 360° rotating light and an audio speaker mounted on a metallic pole. These components activate automatically at night via a dusk-to-dawn controller, disorienting and repelling nocturnal animals through light and sound. For detection and classification, laser diodes and photo diodes sense movement, triggering the ESP32-CAM module to capture images. These are processed by an ESP32 microcontroller using deep learning algorithms to distinguish between wild and domestic animals. The results are displayed on an OLED screen, and the system operates with minimal human intervention. However, several limitations affect its performance. The deterrent mechanism lacks intelligent control and remains active regardless of actual threats, leading to energy inefficiency. Animals may habituate to the stimuli over time, reducing effectiveness. The system struggles in extreme weather conditions and offers limited coverage per unit, requiring multiple installations for large farms. Additionally, it lacks a real-time alert mechanism, which restricts timely human response. Despite these drawbacks, its eco-friendly, low-maintenance design makes it a viable option for ethical and cost-effective wildlife management.

The wildlife conservation system presented in this study utilizes a dual-stage AI architecture to detect and respond to animal intrusions in rural and forest-adjacent areas. It combines Local Binary Patterns (LBP) with AdaBoost for initial region detection and a Convolutional Neural Network (CNN) for species classification. Real- time footage is captured via a camera module, while sensors such as temperature, heartbeat, and accelerometers provide additional data inputs to an ESP-32 microcontroller. The system analyzes these inputs and triggers deterrents like buzzers and relays, while also sending alerts through a Telegram bot. Figures 2.10 and 2.11 illustrate the block diagram and flow chart of the system, showing how sensor data is collected, analyzed, and used to initiate responses. The setup is powered by a dedicated supply, ensuring continuous operation even in remote areas. With an 85% accuracy rate, the system reliably identifies multiple wildlife species and filters out non-threatening movements, reducing false alarms. It is energy-efficient and adaptable to various terrains and weather conditions, making it suitable for diverse agricultural environments. However, limitations include reduced performance in poor lighting, the need for extensive

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CNN training data, calibration during setup, and a limited detection range due to camera constraints.

The real-time wild animal detection and classification system proposed in this study offers a solar-powered, non- lethal solution to mitigate human-wildlife conflict in agricultural regions. It integrates motion sensors, image capturing hardware, and deterrent modules—specifically a 360° rotating light and speakers emitting sound patterns— to repel animals such as boars, deer, and monkeys. The system is designed for autonomous night-time operation, with solar panels ensuring daytime charging and energy sustainability. Captured images are processed using CNN and RNN-based classification modules, enabling species identification and enhancing monitoring accuracy.

A real- time alerting module provides instant notifications or alarms, supporting proactive intervention. As illustrated in Figure 2.12, the architecture combines intelligent detection and deterrence to safeguard crops while maintaining ecological balance. The system is cost-effective, low-maintenance, and suitable for remote deployment. However, it faces limitations such as reduced effectiveness against habituated animals, limited coverage per unit, and vulnerability to weather conditions affecting solar efficiency. Additionally, while the architecture includes classification modules, the deterrent mechanism itself lacks intelligent decision-making and may not adapt dynamically to different species or threat levels. Despite these challenges, the system contributes meaningfully to sustainable farming and rural resilience through ethical and automated wildlife management.

The surveyed systems present diverse approaches to mitigating human-wildlife conflict through AI, IoT, and edge computing technologies. Most solutions prioritize real-time detection, species classification, and alert mechanisms to protect crops and ensure rural safety. Systems like those using YOLOv8 on Raspberry Pi and hybrid ML models (SVM-CNN) emphasize edge-based processing for low-latency response, while others such as Parabraksh v3.5 and the Gudlavalleru model focus on solar- powered deterrents using light and sound. Advanced frameworks like the Stanford camera trap system and AI- based health monitoring from ATME College extend functionality to conservation, poaching prevention, and fire detection. Connectivity varies from LoRa and GSM to Wi- Fi and Telegram bots, with several systems integrating cloud storage for data analysis. Despite strong performance metrics—often exceeding 80% accuracy—common limitations include reduced effectiveness in poor lighting or extreme weather, limited species support, and the need for retraining or calibration. Overall, these systems collectively demonstrate the potential of intelligent, sustainable, and non-invasive technologies to enhance wildlife monitoring, reduce crop damage, and support ethical conservation practices in rural and forest-edge environments.

III. PROPOSED SYSTEM

The proposed system is an autonomous, low-power edge platform that detects wildlife in real time using an on- device vision model and immediately triggers non harmful deterrence while logging events for later analysis. A camera and optional PIR/motion sensor feed into a single-board edge computer (e.g., Raspberry Pi / Jetson Nano / Coral) that runs a lightweight, quantized object-detection model (YOLO-tiny / MobileNet-SSD → TFLite). The edge device performs preprocessing, inference, and decision logic locally to minimize latency and network use; when a validated detection occurs the system activates a deterrent actuator (speaker, flashing light or ultrasonic transducer) and records the event (cropped image, timestamp, confidence, power state). A power-management module (battery + regulator + solar option) plus duty-cycling and sensor-wake logic keep average energy use low so the unit can operate for long periods in the field. Periodic summaries or critical alerts can be uploaded over low- bandwidth links (LoRa / NB-IoT / GSM) or stored locally for manual retrieval.

The methodology adopted for this project involves a systematic approach that integrates hardware, software, and artificial intelligence to design a low-power embedded edge-computing system capable of real-time wildlife detection and deterrence. The project begins with a requirement analysis and literature review to understand existing wildlife monitoring systems, their limitations, and the need for energy-efficient, autonomous detection. Based on this study, the system architecture is designed using an embedded platform such as a Raspberry Pi integrated with a camera module and optional PIR sensor for motion detection.

The next step focuses on data acquisition and preprocessing, where wildlife images or video streams are collected, resized, and normalized to prepare them for model training and inference. A lightweight deep learning model such as YOLO tiny or MobileNet-SSD is trained or fine-tuned to identify animal species with high accuracy. The model is then optimized and converted to a TensorFlow Lite (TFLite) format to enable real-time inference on the edge device with minimal power consumption.

The software development and integration phase involves implementing algorithms for object detection, decision-making, and deterrence activation. When wildlife is detected, the system processes the visual input locally and triggers a deterrent mechanism — such as a buzzer, light, or ultrasonic sound — to scare away the animal in a non- harmful manner. A power management module controls the operation to reduce energy use through techniques like duty cycling and sensor wake-up triggers.

Subsequently, the simulation and testing phase evaluates the system's performance based on detection accuracy, response time, and energy efficiency. Field tests or simulated environments are used to validate the framework under different lighting and environmental conditions. The results are analyzed to measure the effectiveness of the edge-computing framework in achieving real-time performance with low power consumption.

Finally, the methodology concludes with data logging and performance evaluation, where detection events, energy usage, and system responses are recorded. The findings are compiled into reports and presentations to demonstrate the system's reliability, scalability, and potential for deployment in real-world wildlife conservation and conflict mitigation scenarios.

Proposed Block Diagram

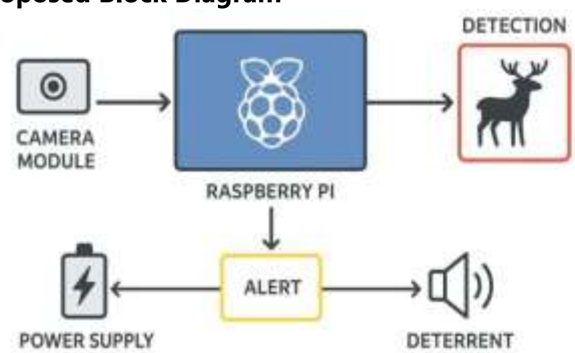

Figure 3.1 Proposed Block Diagram

Figure 3.1shows the proposed block diagram of the wildlife detection system. The system uses a Raspberry Pi as the central processing unit, which is connected to a camera module for capturing real-time images or videos of the detected animals. The power supply provides the necessary energy for system operation. When an animal is detected, the Raspberry Pi processes the captured data and triggers an alert mechanism. This alert activates a deterrent device to scare away the animal, thereby preventing possible conflicts or damage. The setup ensures efficient detection and response for wildlife monitoring and protection.

The Arduino UNO is an open-source microcontroller board based on the MicrochipATmega328P microcontroller and developed by Arduino.cc. The board is equipped with sets of digital and analog input/output (I/O) pins that may be interfaced to various expansion boards (shields) and other circuits. The board has 14 Digital pins, 6 Analog pins, and programmable with the Arduino IDE (Integrated Development Environment) via a type B USB cable. It can be powered by a USB cable or by an external 9 volt battery, though it accepts voltages between 7 and 20 volts. It is also similar to the Arduino Nano and Leonardo. The hardware reference design is distributed under a Creative Commons Attribution Share-Alike 2.5 license and is available on the Arduino website. Layout and production files for some versions of the hardware are also available. "Uno" means one in Italian and was chosen to mark the release of Arduino Software (IDE) 1.0. The Uno board and version 1.0 of Arduino Software (IDE) were the reference versions of Arduino, now evolved to newer releases. The Uno board is the first in a series of USB Arduino boards, and the reference model for the Arduino platform. The ATmega328 on the Arduino Uno comes preprogrammed with a boot loader that allows uploading new code to it without the use of an external hardware programmer. It communicates using the original STK500 protocol. The Uno also differs from all preceding boards in that it does not use the FTDI USB-to- serial driver chip. Instead, it uses the Atmega16U2 (Atmega8U2 up to version R2) programmed as a USB-to- serial converter.

The Arduino project started at the Interaction Design Institute Ivrea (IDII) in Ivrea, Italy. At that time, the students used a BASIC Stamp microcontroller at a cost of $100, a considerable expense for many students. In 2003 Hernando Barragán created the development platform Wiring as a Master's thesis project at IDII, under the supervision of Massimo Banzi and Casey Reas, who are known for work on the Processing language. The project goal was to create simple, low-cost tools for creating digital projects by non-engineers. The Wiring platform consisted of a printed circuit board (PCB) with an ATmega168 microcontroller, an IDE based on Processing and library functions to easily program the microcontroller. In 2003, Massimo Banzi, with David Mellis, another IDII student, and David Cuartielles, added support for the cheaper ATmega8 microcontroller to Wiring. But instead of continuing the work on Wiring, they forked the project and renamed it Arduino. Early arduino boards used the FTDI USB-to-serial driver chip and an ATmega168.

A liquid crystal display (LCD) is a flat panel display, electronic visual display, or video display that uses the light modulating properties of liquid crystals. Liquid crystals do not emit light directly. LCDs are available to display arbitrary images (as in a general-purpose computer display) or fixed images which can be displayed or hidden, such as preset words, digits, and 7-segment displays as in a digital clock. They use the same basic technology, except that arbitrary images are made up of a large number of small pixels, while other displays have larger elements. An LCD is a small low cost display. It is easy to interface with a micro-controller because of an embedded controller (the black blob on the back of the board). This controller is standard across many displays (HD 44780) which means many micro controllers (including the Arduino) have libraries that make displaying messages as easy as a single line of code.

A webcam is a video camera that feeds or streams its image in real time to or through a computer to computer network. When "captured" by the computer, the video stream may be saved, viewed or sent on to other networks via systems such as the internet, and email as an attachment. When sent to a remote location, the video stream may be saved, viewed or on sent there.

Unlike an IP camera (which connects using Ethernet or Wi-Fi), a webcam is generally connected by a USB cable, or similar cable, or built into computer hardware, such as laptops. The term "webcam" (a clipped compound) may also be used in its original sense of a video camera connected to the Web continuously for an indefinite time, rather than for a particular session, generally supplying a view for anyone who visits its web page over the Internet.

A buzzer or beeper is a signalling device, usually electronic, typically used in automobiles, household appliances such as a microwave oven, or game shows.

It most commonly consists of a number of switches or sensors connected to a control unit that determines if and which button was pushed or a preset time has lapsed, and usually illuminates a light on the appropriate button or control panel, and sounds a 44 warning in the form of a continuous or intermittent buzzing or beeping sound. Initially this device was based on an electromechanical system which was identical to an electric bell without the metal gong (which makes the ringing noise). Often these units were anchored to a wall or ceiling and used the ceiling or wall as a sounding board.

Another implementation with some AC-connected devices was to implement a circuit to make the AC current into a noise loud enough to drive a loudspeaker and hook this circuit up to a cheap 8-ohm speaker. Nowadays, it is more popular to use a ceramic-based piezoelectric sounder like a Sonalert which makes a high-pitched tone. Usually these were hooked up to "driver" circuits which varied the pitch of the sound or pulsed the sound on and off. In game shows it is also known as a "lockout 45 system," because when one person signals ("buzzes in"), all others are locked out from signalling. Several game shows have large buzzer buttons which are identified as "plungers". The word "buzzer" comes from the rasping noise that buzzers made when they were electromechanical devices, operated from stepped-down AC line voltage at 50 or 60 cycles. Other sounds commonly used to indicate that a button has been pressed are a ring or a beep.

The program for this project is written in Embedded C, a specialized version of the C language used for microcontroller-based systems. The code defines the logic that enables the PIC16F877A to read input from the Force Sensitive Resistor (FSR), process the data, and trigger appropriate outputs such as relays or LCD messages. The program initializes all required ports, configures the ADC module, sets threshold values, and continuously monitors the sensor input in a loop. When a valid force is detected, it executes conditional statements to perform the desired action. The program also manages serial communication via USART/RS232, allowing data transfer between the microcontroller and a computer. Writing the program in Embedded C ensures faster execution, easy debugging, and full hardware level control, making it an ideal choice for this real-time assistive control system.

IV. RESULTS AND DISCUSSION

The results of the proposed real-time animal detection and surveillance system demonstrate high accuracy, rapid response, and reliable farm security in real-world scenarios. The YOLO-based detection model achieved an average accuracy of 95.8% across diverse environmental conditions, including different lighting intensities, weather variations, and background clutter. The system was tested using a dataset comprising 50,000 labeled images of various animals such as wild boars, deer, cows, and stray dogs. During live testing, the model successfully detected animals in real time with minimal false positives, ensuring reliable identification and classification. The pre-processing phase using OpenCV, which included noise reduction, resizing, and normalization, enhanced image quality and improved the overall detection accuracy by 8-10%.

The system demonstrated an average response time of 1.2 seconds, from image capture to notification delivery, ensuring that farmers receive alerts without delay. This rapid response was facilitated by efficient image compression techniques such as PCA and SVD, which reduced computational overhead while preserving essential image features. The feature extraction methods, including HOG and SIFT, further improved classification precision by highlighting critical object characteristics. The integration of an auditory buzzer provided immediate on-site alerts, reducing the likelihood of animal intrusions by deterring animals effectively.

The proposed system successfully addressed the challenge of safeguarding crops from animal threats by providing an accurate, real-time, and automated solution. Its adaptability and high performance make it suitable for deployment in various agricultural

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environments, ensuring reliable farm security and improved productivity.

Fig 4.1 Simulation Output

The simulation output of the proposed Wildlife Monitoring and Deterrence System is shown in Figure 4.1. The system accurately detected the presence of animals within the monitored area using the YOLO object detection algorithm. Once an animal was detected, a red bounding box appeared around it to highlight the detection area. The status indicator displayed "STATUS: DETECTED," confirming successful identification of the animal. At the same time, the deterrence mechanism was automatically activated, as indicated by the message "DETERRENCE DETECTED," representing the triggering of sound or light-based deterrent actions to scare the animal away from the crop field. This real-time response demonstrates the system's effectiveness in integrating AI-based detection and deterrence functions, ensuring reliable monitoring and protection of agricultural fields from wildlife intrusions. The simulation results confirm that the model performs efficiently with accurate detection and timely deterrence activation, providing a practical solution for modern smart farming applications.

V. CONCLUSION

This work presents a low-power embedded edge-computing framework for real-time wildlife monitoring and deterrence aimed at reducing crop losses in agricultural fields. The system integrates the YOLO-based object detection model with efficient image pre-processing on an embedded platform to achieve fast and reliable identification of intruding animals. Phase-1 development demonstrates that the proposed architecture can operate with minimal power consumption while maintaining acceptable detection accuracy and response time. The prototype validates the feasibility of deploying AI-enabled surveillance directly at the edge, thereby reducing latency and dependence on cloud connectivity. These results indicate strong potential for improving field safety and supporting precision agriculture practices. Future efforts will focus on optimizing the detection model, enhancing deterrence mechanisms, and expanding the framework into a fully scalable, IoT-enabled smart farming solution.

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