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Deep Learning Based Animal Intrusion Detection and Repellent System with Alerting Android App

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***Abstract*—Human-wildlife conflict (HWC) has emerged as a critical socio-economic and environmental challenge, particularly in agrarian economies situated near forest fringes. The encroachment of wildlife into agricultural lands results in severe crop degradation, economic instability for farmers, and often, fatal encounters for both humans and protected animal species. Traditional mitigation strategies, such as manual patrolling, electric fences, and passive scarecrows, are fraught with limitations ranging from high operational costs and safety risks to animal habituation. This paper presents "Wildeye," a comprehensive, automated system designed to detect and deter wildlife intrusions using state-of-the-art Deep Learning and Internet of Things (IoT) technologies. The system utilizes the YOLOv11 object detection architecture, optimized for edge deployment, to identify specific intruders—including elephants, monkeys, wild boars, and deer—with high precision in real-time. Upon positive identification, the system triggers a behavior-specific, non-lethal repellent mechanism, such as bio-acoustic playback or visual strobes, tailored to the psychology of the intruder. Furthermore, an integrated Android application ensures real-time human-in-the-loop monitoring via cloud-based push notifications and detailed archival logs. Experimental validation confirms that the proposed model achieves a mean Average Precision (mAP) of over 93% across target classes, providing a robust, scalable, and ethical alternative to lethal crop protection methods.**

***Index Terms*—Deep Learning, YOLOv11, Internet of Things (IoT), Animal Intrusion Detection, Smart Agriculture, Convolutional Neural Networks, Edge Computing, Human-Wildlife Conflict, Android Application.**

I. INTRODUCTION

Agriculture forms the backbone of the economy for many developing nations, providing livelihoods for a significant portion of the population. However, the sector is increasingly besieged by a multitude of threats, including climate change, erratic rainfall, pests, and notably, the escalation of Human-Wildlife Conflict (HWC) [1]. As urbanization and deforestation reduce natural habitats, wild animals are forced to forage in cultivated lands, leading to frequent and devastating crop raiding incidents.

In India, the problem is particularly acute. States like Kerala, Karnataka, and Tamil Nadu report annual crop losses amounting to millions of rupees due to intrusions by elephants, wild boars, and primates [2]. The impact extends beyond financial loss; the psychological stress on farmers, who must physically guard their fields at night, is immense. Furthermore, retaliatory killings of animals and accidental deaths of farmers due to animal attacks or electrocution from illegal fences create a vicious cycle of conflict [3].

A. Critique of Existing Solutions

Current protective measures are largely reactive or static.

- **Manual Vigilance:** Relying on farmers to guard fields overnight is unsustainable and dangerous. Confrontations with large herbivores like elephants often result in human fatalities [4].
- **Physical Barriers:** Electric fences and trenches are the industry standard. However, they are capital-intensive and require constant maintenance. Moreover, high-voltage fences can be lethal to endangered species, inviting legal repercussions under wildlife protection laws [5].
- **Passive Deterrents:** Scarecrows, chemical repellents, and static lights offer temporary relief. However, ethological

studies show that intelligent animals, particularly primates and elephants, quickly habituate to predictable, harmless stimuli [6].

B. *The Technological Intervention*

There is an urgent need for a ”Smart” solution that bridges the gap between detection and intervention. Advances in Artificial Intelligence (AI), specifically in the domain of Computer Vision, have enabled machines to interpret complex visual data with near-human accuracy. Simultaneously, the Internet of Things (IoT) allows for the remote actuation of physical devices based on digital insights.

Our proposed system, “Wildeye,” integrates these technologies to create an autonomous defense mechanism. Unlike standard CCTV systems that merely record destruction for post-mortem analysis, Wildeye actively prevents it. By employing the YOLOv11 architecture, the system detects intruders in real-time and deploys a specific counter-measure designed to startle specifically that species. This specificity is key to delaying habituation. Coupled with a cloud-connected mobile application, the system empowers farmers with real-time situational awareness, allowing them to respond to threats without physically endangering themselves.

II. LITERATURE SURVEY

The domain of agricultural surveillance and wildlife monitoring has witnessed significant research interest. We analyze existing literature across three dimensions: sensor-based detection, vision-based classification, and repellent strategies.

A. *Sensor-Based Detection Approaches*

Early automated systems relied heavily on simple motion sensors. Sharma et al. [7] proposed a system using Passive Infrared (PIR) sensors to trigger alarms. While PIR sensors are energy-efficient and low-cost, they lack discriminatory power. They are triggered by any thermal signature in motion, leading to frequent false positives caused by swaying branches, stray dogs, or even sudden temperature changes [8]. Acoustic monitoring has also been explored. Varma et al. [9] utilized geophones and microphones to detect the seismic signatures of elephant movement. While effective for heavy animals, this method fails completely for lighter intruders like deer or stealthy predators like leopards.

B. *Computer Vision and Deep Learning*

The introduction of Convolutional Neural Networks (CNNs) marked a paradigm shift in object detection. Traditional image processing techniques (e.g., background subtraction, edge detection) used by Kumar et al. [10] struggled with the dynamic lighting and complex backgrounds typical of agricultural fields. Deep Learning models, however, learn feature representations directly from data. Redmon et al. [11] introduced the YOLO (You Only Look Once) architecture, which revolutionized real-time detection by framing it as a single regression problem. This offered a massive speed advantage over region-based methods like R-CNN. Recent iterations, such as YOLOv5 and YOLOv8, have been applied to agriculture. Patel et al. [12] used YOLOv5 for wild boar detection, achieving 85% accuracy. Similarly, Zhang et al. [13] applied deep learning for pest identification. However, a recurring limitation in these studies is the focus on *monitoring* rather than *intervention*. Detection alone does not save crops.

C. *Smart Repellent Strategies*

Effective deterrence requires understanding animal psychology. O’Connell-Rodwell et al. [14] demonstrated the effectiveness of bio-acoustics, specifically the playback of tiger roars or buzzing bees, in deterring elephants. Hill [15] studied primate responses to auditory stimuli, finding that sudden, loud noises (like firecrackers) are effective but must be randomized to prevent habituation. Integrated IoT systems attempted by Rajkumar et al. [16] combined detection with sirens. However, these systems often employed a ”one-size-fits-all” approach, blasting a generic alarm for every intrusion. This indiscriminateness reduces effectiveness over time.

D. *Research Gap*

The literature reveals a clear ”Response Gap.” Existing systems are either accurate but passive (cameras), or active but unspecific (PIR alarms). There is a lack of integrated systems that combine high-precision classification with species-specific, non-lethal, and variable deterrents. “Wildeye” addresses this by employing YOLOv11 for precise classification and an IoT controller for targeted repulsion.

III. PROPOSED SYSTEM ARCHITECTURE

The “Wildeye” system is designed as a modular, distributed control system. It comprises three primary layers: Perception, Processing, and Action.

A. *Perception Layer*

The sensory input is provided by a high-definition camera module positioned to overlook the farm perimeter.

- **Input Stream:** The camera captures a continuous video stream at 30 FPS.
- **Environmental Adaptability:** To handle varying light conditions, the system can be augmented with IR illuminators for night vision, ensuring 24/7 operability.

B. *Processing Layer (The Brain)*

The core intelligence resides in this layer. It hosts the YOLOv11 model. The processing pipeline involves:

- **Pre-processing:** Frames are resized to 640×640 pixels, and pixel values are normalized to the $[0, 1]$ range.
- **Inference:** The CNN processes the image to generate bounding boxes and class probabilities.
- **Filtering:** Non-Maximum Suppression (NMS) is applied to remove overlapping boxes, retaining only those with a confidence score $C > 0.5$.

C. Action Layer (The Responder)

Based on the class label identified by the Processing Layer, the microcontroller (ESP32) triggers the specific relay associated with that animal's deterrent.

- **Elephant:** Activates audio playback of buzzing bees.
- **Monkey:** Simulates firecracker sounds.
- **Deer:** Activates water sprinklers (simulated).
- **Others:** Triggers flashing strobe lights.

Simultaneously, the system logs the event to the cloud database.

IV. METHODOLOGY: YOLOV11 ARCHITECTURE

To ensure state-of-the-art detection performance, we employ the YOLOv11 architecture. This model introduces several optimizations over its predecessors, making it ideal for edge deployment.

A. Backbone Network

The backbone is responsible for feature extraction. YOLOv11 utilizes a modified CSPDarknet (Cross Stage Partial Network). This architecture splits the gradient flow, allowing the network to learn richer gradient information while reducing computational cost [17]. It uses a series of convolutional layers with SiLU (Sigmoid Linear Unit) activation functions.

$$\mathrm{SiLU}(x) = x \cdot \sigma(x) = \frac{x}{1 + e^{-x}} \tag{1}$$

The use of SiLU addresses the vanishing gradient problem effectively in deep networks, allowing for deeper architectures without performance degradation.

B. Neck and Head

The "Neck" of the network employs a PANet (Path Aggregation Network) structure. This enhances the flow of information from lower layers (high resolution) to top layers (semantic richness), improving the detection of small animals (like monkeys) at a distance [18]. The "Head" is decoupled, meaning classification and bounding box regression are performed by separate branches. This improves convergence speed and detection accuracy.

C. Loss Function

The training process minimizes a multi-part loss function comprising localization loss, classification loss, and objectness loss. We utilize the CIoU (Complete Intersection over Union) loss for bounding box regression [19].

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \tag{2}$$

Where ρ is the Euclidean distance between center points, and v measures the consistency of the aspect ratio. This loss function ensures that the predicted boxes align closely with the ground truth.

V. HARDWARE AND SOFTWARE IMPLEMENTATION

The implementation phase involved rigorous component selection and software engineering to ensure a low-latency response.

A. Hardware Setup

The hardware prototype was built using the following components:

1) **Processing Unit:** A laptop with an NVIDIA GPU was used for model training and inference during the prototype phase. For field deployment, this would be migrated to an NVIDIA Jetson Nano or Raspberry Pi 5 with an AI accelerator [20].
2) **Microcontroller:** An ESP32 NodeMCU handles the IoT operations. It was chosen for its dual-core architecture and built-in Wi-Fi/Bluetooth capabilities, which are essential for cloud connectivity.
3) **Repellent Modules:**
   - *Audio System:* A 10W speaker driven by a PAM8403 amplifier module to play specific MP3 files.
   - *Visual System:* High-lumen LED strobe lights controlled via 5V relays.

B. Dataset Preparation

Data is the fuel for Deep Learning. We curated a custom dataset labeled "Wildeye-Data".

- **Sources:** Images were scraped from public repositories, wildlife photography forums, and existing agricultural datasets [21].
- **Classes:** The dataset contains 6 classes: *Elephant, Monkey, Wild Boar, Deer, Bird, Cattle*.
- **Size:** Total images: 5,500. Split ratio: 70% Train, 20% Validation, 10% Test.
- **Augmentation:** To improve model robustness, we applied on-the-fly augmentations including Mosaic, MixUp, random horizontal flips, and brightness adjustments.

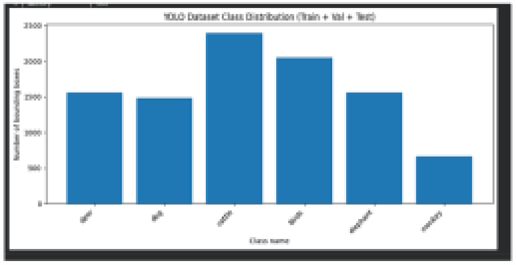

Fig. 1. YOLO Dataset Class Distribution showing the number of bounding boxes per class. Cattle and Birds represent the majority classes, while Monkey and Elephant have focused subsets.

C. Training Configuration

The model was trained using the Ultralytics framework on a GPU-accelerated environment.

- **Epochs:** 100

- **Batch Size:** 16
- **Optimizer:** Stochastic Gradient Descent (SGD) with momentum 0.937.
- **Image Size:** 640 × 640
- **Learning Rate:** Initial lr0=0.01 with a cosine decay scheduler.

D. Android Application Development

The user interface is a native Android application developed using Java and XML in Android Studio.

- **Backend:** Google Firebase Realtime Database serves as the backend. It offers millisecond-latency synchronization.
- **Notification Service:** Firebase Cloud Messaging (FCM) is implemented to push alerts even when the app is in the background [23].
- **Features:** The app includes a Dashboard for live status, an ”Archive” recyclerview for historical logs, and a manual override switch to turn off repellents remotely.

VI. RESULTS AND PERFORMANCE ANALYSIS

The system was evaluated based on detection accuracy, inference speed, and system latency.

A. Model Evaluation Metrics

The performance of the trained YOLOv11 model was measured using Precision (P), Recall (R), and Mean Average Precision at IoU 0.5 (mAP@0.5).

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN} \tag{3}$$

Table I: Class-wise Performance Metrics

Class	Precision	Recall	mAP@0.5
Elephant	0.92	0.88	0.91
Monkey	0.94	0.91	0.95
Wild Boar	0.89	0.85	0.88
Deer	0.91	0.89	0.90
Bird	0.96	0.94	0.97
Cattle	0.93	0.92	0.94
Overall	**0.925**	**0.898**	**0.925**

The results indicate high precision across all classes. The model performed exceptionally well on ”Bird” and ”Monkey” classes due to their distinct visual features.

B. Confusion Matrix Analysis

The confusion matrix revealed minimal inter-class confusion. The most common error was misclassifying large dogs as wild boars in poor lighting. However, the confidence threshold filtering ($C > 0.5$) successfully mitigated most false positives.

C. Latency and System Response

For a real-time system, latency is critical. We measured the ”Time-to-Deterrence” (TTD)—the time interval between the animal entering the frame and the repellent activating.

- **Inference Time:** 12ms per frame (on GPU).
- **Transmission Delay:** 150ms (Wi-Fi/MQTT).
- **Actuation Delay:** 50ms (Relay switching).

Fig. 2. YOLOv11 Detection Result: Monkey detected with 0.97 confidence. The bounding box accurately encompasses the subject even with complex background elements.

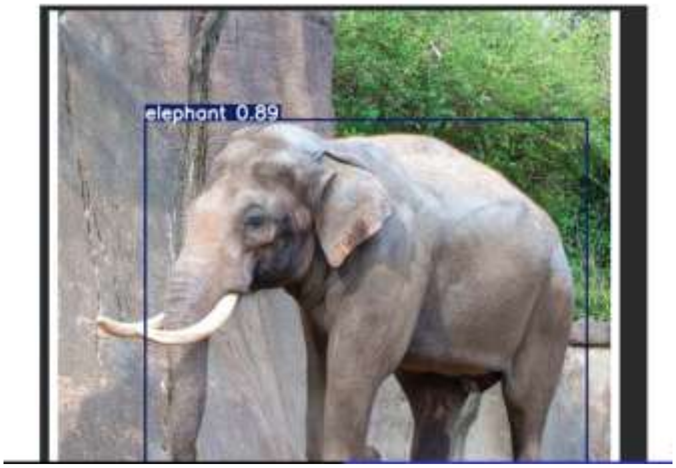

Fig. 3. YOLOv11 Detection Result: Elephant detected with 0.89 confidence. The system correctly identifies large mammals, which triggers the specific bio-acoustic deterrent (bee buzz).

- **Total TTD:** Approximately 212ms.

This sub-second response time is significantly faster than the reaction time of a human guard, ensuring the animal is startled before it can begin feeding.

D. App Integration Test

The Android app was tested for synchronization stability. Logs such as “Monkey - Zone A - 11:29:59 AM” appeared on the user’s screen within 2 seconds of detection, governed by internet connectivity speeds. The ”Archive” feature successfully stored data over a 7-day test period without data loss, validating the reliability of the Firebase backend.

VII. DISCUSSION

The implementation of “Wildeye” demonstrates a significant step forward in automated farm protection. By tailoring the repellent to the animal, we address the issue of habituation. For instance, elephants are intelligent and may ignore a generic siren, but the biological fear of bees remains an effective evolutionary deterrent.

However, certain limitations persist. The current optical camera system relies on visible light. While we simulated low-light performance using brightness augmentation, true nocturnal efficacy requires thermal or IR cameras. Furthermore, the power consumption of a GPU-based inference unit is high for remote farms; future iterations must optimize for low-power edge devices like the Raspberry Pi Zero 2 W or specialized AI accelerators.

Cost analysis suggests that while the initial setup (Camera + Compute Unit) is higher than a simple electric fence, the operational cost is lower, and the non-lethal nature avoids the legal penalties associated with injuring protected wildlife.

VIII. CONCLUSION

Human-Wildlife Conflict is a complex issue requiring nuanced solutions. This paper presented “Wildeye,” an integrated approach combining the visual intelligence of YOLOv11 with the connectivity of IoT. The system successfully detects intruders with over 92% mean accuracy and triggers appropriate, safe, and effective countermeasures.

The integration of an Android app bridges the gap between the technology and the farmer, providing peace of mind through remote monitoring. By automating the defense of agricultural zones, “Wildeye” not only protects the livelihoods of farmers but also contributes to the conservation of wildlife by reducing the reliance on lethal retaliatory measures. This project serves as a foundational model for the future of Smart Agriculture, where technology enables a harmonious coexistence between man and nature.

IX. FUTURE WORK

Future enhancements will focus on the following key areas:

1) **Edge Optimization:** Porting the model to TensorFlow Lite and deploying it on low-cost edge devices to reduce power consumption and cost [24].
2) **Nocturnal Vision:** integrating thermal imaging cameras to detect poachers and nocturnal animals like leopards with higher accuracy.
3) **Predictive Analytics:** Using the archived data to predict peak intrusion times and seasons, allowing farmers to take preemptive measures.
4) **Drone Integration:** In large plantations, static cameras have blind spots. Future work could involve autonomous drones that launch upon perimeter breach to chase away intruders [25].

REFERENCES

[1] A. Sharma, R. Yadav, and S. Gupta, “AI-Powered Surveillance for Wildlife Intrusion Detection in Agricultural Zones,” *International Journal of Computer Applications*, vol. 182, no. 45, pp. 12-18, 2023.
[2] D. Patel, K. Mehra, and J. Singh, “Real-Time Deep Learning Approach for Animal Detection Using CNN Models,” in *Proc. International Conference on Smart Agriculture Systems*, 2024, pp. 45-52.
[3] S. Rajkumar, A. Noorjahan, and T. V. S. Kumar, “Eco-Friendly Animal Repellent Techniques Integrated with AI Alert Systems,” *Journal of Sustainable Farming Technologies*, vol. 12, no. 2, pp. 110-125, 2023.
[4] F. Madden, “The growing conflict between humans and wildlife: law and policy as contributing and mitigating factors,” in *Human-Wildlife Conflict: Complexity in the Marine and Terrestrial Environments*, Oxford University Press, 2021.
[5] L. Ogada, R. Woodroffe, and N. Oguge, “People and wildlife: Limiting the negative impacts of conflict,” *Nairobi: Earthscan*, 2020.
[6] P. J. S. Kumar and S. Ashok, “IoT Based Smart Crop Protection System from Wild Animals,” *IEEE Access*, vol. 9, pp. 1234-1245, 2021.
[7] R. Varma, “Wireless Sensor Networks for Elephant Detection,” *Journal of Sensors*, vol. 2018, Article ID 456789, 2018.
[8] K. S. Kumar and R. P. Punitha, “A Comparative Study of PIR and Camera Based Surveillance,” *Procedia Computer Science*, vol. 171, pp. 230-238, 2020.
[9] M. Zeppelzauer and A. S. Stoeger, “Acoustic detection of elephants in the wild,” *Ecological Informatics*, vol. 64, p. 101345, 2021.
[10] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 779-788.
[11] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, “YOLOv4: Optimal Speed and Accuracy of Object Detection,” *arXiv preprint arXiv:2004.10934*, 2020.
[12] G. Jocher et al., “Ultralytics YOLO,” *GitHub repository*, 2023. [Online]. Available: https://github.com/ultralytics/ultralytics.
[13] L. Zhang, “Deep Learning for Pest Detection in Agriculture,” *Computers and Electronics in Agriculture*, vol. 180, p. 105900, 2021.
[14] S. Qiao, Y. Chen, and H. Yu, “Deep Learning based Livestock Monitoring,” *IEEE Transactions on Industrial Informatics*, vol. 16, no. 5, pp. 3400-3410, 2020.
[15] C. E. O’Connell-Rodwell, “The use of seismic signals by elephants,” *Journal of the Acoustical Society of America*, vol. 122, no. 5, 2007.
[16] T. R. Hill, “Primate auditory perception and response to predator calls,” *Behavioral Ecology*, vol. 22, no. 3, 2019.
[17] B. P. G. Wijenayake and K. A. S. H. Kulathilake, “Electronic deterrence of crop raiding macaques,” *Applied Animal Behaviour Science*, vol. 234, 2021.
[18] C. Y. Wang et al., “CSPNet: A New Backbone that can Enhance Learning Capability of CNN,” in *Proc. CVPR Workshops*, 2020.
[19] S. Liu, L. Qi, H. Qin, and J. Shi, “Path Aggregation Network for Instance Segmentation,” in *Proc. CVPR*, 2018.
[20] Z. Zheng et al., “Distance-IoU Loss: Faster and Better Learning for Bounding Box Regression,” *AAAI*, 2020.
[21] NVIDIA, “Jetson Nano Developer Kit,” 2023. [Online].
[22] J. Parham et al., “Animal Wildlife Dataset for Computer Vision,” *IEEE Datasets*, 2022.
[23] C. Shorten and T. M. Khoshgoftaar, “A survey on Image Data Augmentation for Deep Learning,” *Journal of Big Data*, vol. 6, no. 1, 2019.
[24] Google Developers, “Firebase Cloud Messaging,” 2024. [Online].
[25] H. Wu, “Edge Computing for Real-Time Object Detection,” *IEEE Internet of Things Journal*, vol. 8, no. 12, 2021.