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Agrodefend: AI-Driven Animal Deterrence

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Abstract: Crop damage by animals significantly impacts agricultural productivity, particularly for smallholder farmers. Traditional deterrence methods like scarecrows or manual guarding are often ineffective and costly. AgroDefend, an AI-driven solution, employs a PIR sensor for motion detection, activating a camera module to capture real-time frames analyzed by a deep learning model on Raspberry Pi for animal detection. The system triggers a buzzer to emit non-harmful deterrent sounds while notifying farmers via real-time alerts. This integration of AI and IoT offers a sustainable, efficient, and cost-effective approach to protecting crops, reducing manual intervention, and enhancing agricultural productivity.

***IndexTerms* - IoT, AI, PIR sensor, crop protection, deep learning, Raspberry Pi**

I. INTRODUCTION

Agriculture is a cornerstone of global food security, yet it faces persistent challenges, including crop destruction caused by animal intrusions. These intrusions are particularly detrimental to smallholder farmers, often leading to significant economic losses. Traditional approaches such as scarecrows, physical barriers, or hiring guards are often ineffective, costly, or impractical, especially for large or resource-constrained farms. The lack of a scalable, reliable solution underscores the need for innovative approaches to protect crops from wildlife threats.

To address this issue, we present AgroDefend, an AI-driven system designed to mitigate animal attacks on crops effectively and sustainably. The system integrates advanced technologies, including artificial intelligence, IoT components, and real-time monitoring, to detect and deter animals from entering farm fields. It employs a Passive Infrared (PIR) sensor to detect motion, triggering a camera module that captures real-time frames. These frames are processed on a Raspberry Pi using a deep learning model to identify the presence of animals. Upon detection, the system activates a speaker to emit deterrent sounds and simultaneously sends an alert to the farmer, enabling timely intervention.
The design emphasizes cost-effectiveness, scalability, and adaptability to diverse farm sizes and configurations. By leveraging AI and IoT, AgroDefend reduces reliance on traditional methods and minimizes the need for manual intervention. This system not only enhances agricultural productivity but also supports sustainable farming practices by providing an innovative, humane solution to protect crops from animal intrusions.

1.1 Objectives

1. Develop an Affordable and Automated Crop Protection System:

Design a cost-effective solution to reduce the financial burden on farmers by minimizing the need for manual labor and expensive traditional deterrent methods. The system will provide an economical way to mitigate animal-related crop damage.

2. Create a Scalable and Adaptable Solution:

Build a system that can be easily adopted by farmers with varying field sizes and resource availability. This ensures accessibility for small-scale farms as well as large commercial enterprises, increasing agricultural efficiency and productivity across diverse farming communities.

3. Enhance Crop Protection and Agricultural Sustainability:

Offer a reliable method to prevent crop damage caused by animal intrusions, improving crop yields and reducing food waste. The system aims to enhance farm profitability while promoting sustainable farming practices that support environmental and economic well-being.

1.2 Purpose

1. Enhanced Accuracy: Implement machine learning techniques, including deep learning and image analysis, to improve the precision of animal detection in agricultural fields. This aims to overcome the limitations of traditional motion detection methods.

2. Performance Assessment: Evaluate the effectiveness of various deep learning models in detecting animals under real-world agricultural conditions. Metrics such as precision, recall will be analyzed to measure model accuracy and robustness. These insights will guide system refinement and optimization for broader adoption across diverse farming environments.

1.3 Scope

The system employs advanced deep learning algorithms to ensure high detection accuracy, specifically identifying animals and minimizing false alarms.

Real-time notification features enable farmers to take timely action, enhancing field management. This contributes to increased farm productivity and promotes sustainable agricultural practices.

II. ANIMAL DETECTION USING DEEP LEARNING ALGORITHM

This work focuses on developing an efficient algorithm for detecting and classifying animals in their natural habitats. The diversity and large number of animal species make manual identification challenging and time-intensive. By leveraging deep learning techniques, the proposed system automates animal detection and classification using image data, thereby enabling more efficient monitoring. This solution addresses critical challenges in wildlife conservation, including tracking endangered species and preventing theft or poaching. Additionally, it contributes to public safety by mitigating animal-vehicle collisions through real-time detection and alert mechanisms. The algorithm integrates advanced object detection and classification models, such as YOLO and convolutional neural networks (CNNs), to achieve high accuracy and real-time performance. This system is envisioned as a versatile tool for applications in wildlife monitoring, road safety, and livestock management, supporting conservation efforts and enhancing situational awareness.

III. RELATED WORKS

Several research efforts have been conducted to develop systems for detecting and deterring animal intrusions in agricultural settings using AI, IoT, and embedded systems:

1. YOLO-Based Detection Systems:

A YOLO-based intelligent animal repelling system used YOLOv3 and Tiny-YOLOv3 models for real-time animal detection. While effective for small object detection using Darknet-53, challenges such as Edge-AI deployment complexity and camera reliability issues were noted. Enhancements to YOLOv5s, incorporating GSConv modules and SPP, improved detection speed and accuracy, especially for large animals. However, the system struggled with camouflaged animals and simultaneous multiple detections. An improved YOLOv8n model with Softplus activation and VoV-GSCSP demonstrated better speed and accuracy but required specific training datasets and additional infrastructure for effective integration.

2. IoT and ML Applications in Crop Protection:

An IoT-enabled system integrated Raspberry Pi with R-CNN and SSD algorithms for real-time detection and Firebase cloud-based alerts. Despite its capabilities, delays in alert generation were observed under specific conditions. A lightweight TinyML-based model, EvoNet, achieved 96.7% accuracy by employing pruning and quantization for reduced model size, though sensor integration and advanced ML optimization remain as areas for improvement.

3. Optimization for Embedded Devices:

A YOLOv2-based system incorporated deformable convolutional layers and pass-through layers, achieving a 12% speed improvement. However, GSM network dependency and frequent maintenance limited its practical application in remote areas. WildARe-YOLO, an optimized YOLOv5s model using Mobile Bottleneck Blocks and BiFPN-based necks, improved computational efficiency but faced challenges with lengthy training times (12-15 hours) and limited coverage for specific croplands.

4. IoT-Based Monitoring Systems:

A Raspberry Pi-based IoT system was developed for real-time farm machinery monitoring, integrating multiple sensors. Stable internet connectivity and frequent recalibration were identified as barriers to adoption. An intrusion detection system for home security employed Raspberry Pi and OpenCV, offering methodologies applicable to agricultural monitoring. However, it was hindered by power dependency and delays in image processing.

5. Real-Time Object Detection and Tracking:

A shape-based object identification system used OpenCV for real-time detection and tracking on Raspberry Pi. It was effective in controlled environments but faced reduced accuracy in complex agricultural conditions. These studies emphasize the progress and limitations in leveraging advanced technologies for agricultural applications, providing a foundation for developing scalable and efficient solutions tailored to farmers' needs.

6. Multi-Sensor Fusion for Enhanced Detection

Hybrid AI Model for Wildlife Detection: A system integrating YOLOv4 with LSTMs improved detection accuracy by learning temporal movement patterns of animals. However, it required high computational resources and struggled with unpredictable lighting conditions. Thermal and RGB Camera Fusion: A multi-modal approach combining thermal imaging and RGB cameras enhanced night-time detection, though real-time processing and sensor calibration remained a challenge.

7.Drone-Assisted Monitoring for Animal Intrusion Prevention

UAV-Based Surveillance System: A drone-mounted YOLOv5 model improved monitoring efficiency over large farmland areas. However, the approach faced limitations due to drone battery life and connectivity issues in remote areas. Automated UAV Patrolling with Reinforcement Learning: A reinforcement learning-based UAV path optimization model reduced false positives by 18%, but real-time processing and latency in data transmission were observed.

8. Sound-Based Animal Repellent Systems

Bioacoustic-Based Animal Repulsion: A system utilizing bioacoustic signals and AI-driven sound synthesis successfully deterred wild boars and deer, reducing farm invasions by 23%. However, its effectiveness varied depending on species and environmental noise. Machine Learning for Sound Classification: A convolutional neural network (CNN)-based audio classification model detected animal sounds with 95.3% accuracy. Integration with IoT alert systems was suggested for enhanced real-time response.

9. Edge AI for Low-Power Animal Detection

FPGA-Based Animal Detection: A YOLOv4 FPGA-accelerated system achieved real-time inference with low power consumption. However, the high cost of FPGA hardware limited large-scale adoption. EdgeTPU-Optimized Object Detection: Deployment of Tiny-YOLO with EdgeTPU hardware improved real-time inference, but model retraining was required for different environmental conditions.

10. Smart Fencing and Autonomous Response Mechanisms

AI-Powered Electric Fencing: Integration of YOLOv7 with smart fencing mechanisms allowed selective activation, preventing unnecessary energy consumption. Yet, the system required frequent recalibration based on environmental changes. Autonomous Repellent Sprinklers: A Raspberry Pi-based AI sprinkler system triggered water jets upon detecting animals, effectively preventing small animal intrusions. However, false activations due to wind-induced movement were a concern.

IV. SYSTEM DESIGN

4.1 Proposed System

The major objectives of our initiative are to prevent animal damage to crops and to divert animals safely. The system is designed to integrate IoT hardware and deep learning techniques to detect and deter animals in real-time, ensuring minimal crop damage and logging detected objects on a dashboard.

1. Objectives:

- Real-Time Detection: A system for detecting animals is intended to alert users of their presence by tracking animal movement using a PIR sensor.
- Surveillance and Monitoring: A camera will periodically monitor the entire farm, recording its surroundings throughout the day.
- Deep Learning for Detection: Using a deep learning model, the presence of animals will be detected, and appropriate sounds will be played to deter them safely.

2. System Description:

- Data Collection:

  Collect images of various animal species threatening crops through camera traps or public datasets like COCO or Wild Animal datasets. Capture images under diverse conditions such as day/night, different weather, and varied crop types to ensure robustness.
- Data Preprocessing:

  Apply techniques such as rotation, flipping, and scaling to improve model generalization. Normalize images to standardize inputs and improve training stability. Crop and resize images to a consistent dimension.
- Detection and Deterrence:

  The PIR sensor detects motion and triggers the camera to capture a video stream. The CNN model processes the video stream to detect animals with high accuracy.
- Hardware Functionality:

  USB to UART Converter: Transfers data from the PC to the microcontroller upon detecting an animal using the Yolov8n in an agricultural region. Microcontroller and Deterrence System.

3. Output:

- Alerts: Notify users in real-time when an animal is detected.
- Deterrence: Emit sounds to safely deter animals away from the field.
- Dashboard Logging: Log object details and detection data on a dashboard for monitoring and analysis.

This proposed system effectively combines IoT, deep learning, and real-time mechanisms to protect crops while ensuring animal safety, supporting sustainable and efficient farming practices.

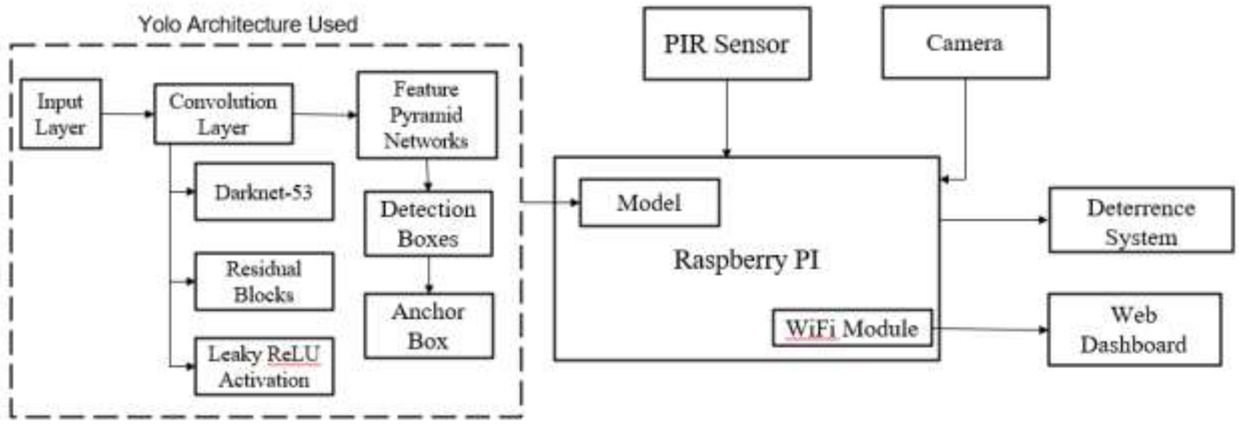


Figure 1: Architecture Diagram

The above figure, Figure 1 represents the Arcitecture Block Diagram of the proposed system containing various parts. The Yolo architecture used explains the inner structure of Yolov8 nano which has been used.

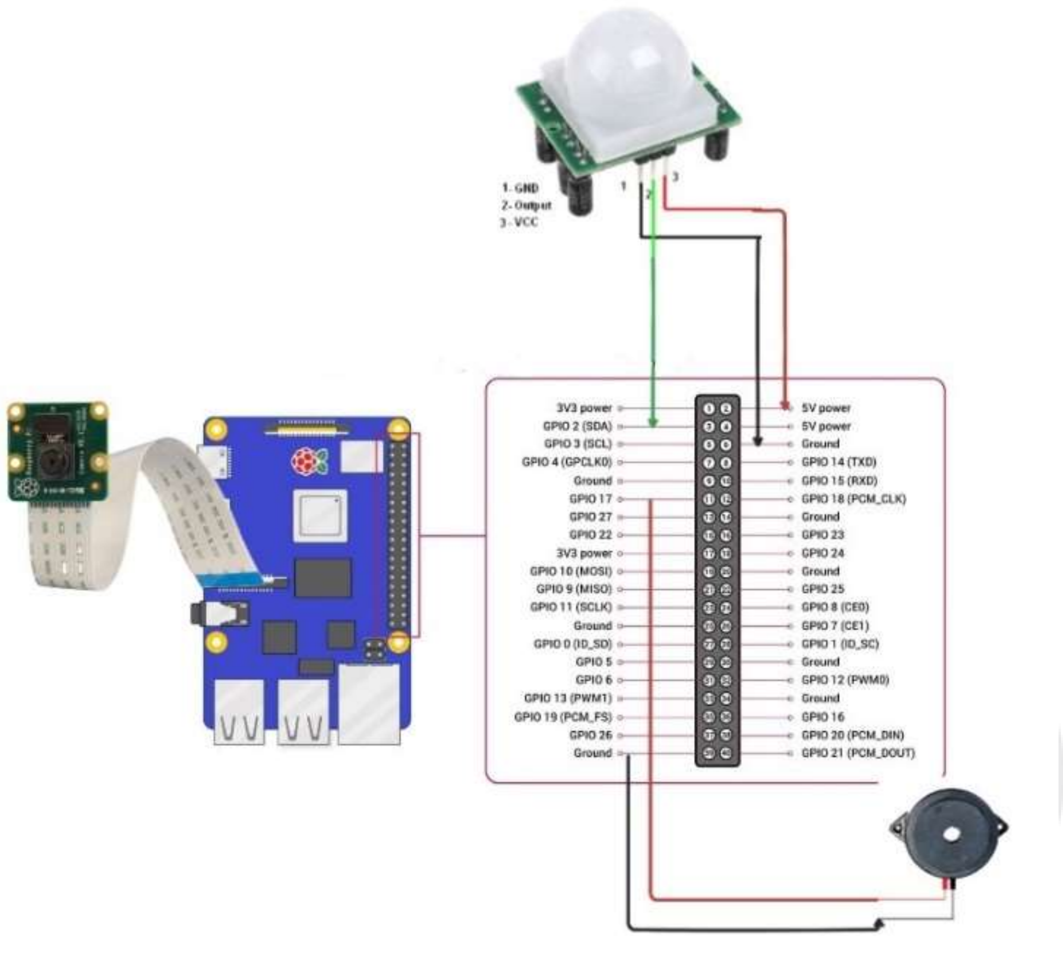


Figure 2: Interface diagram

The above diagram, figure 2 represents the interface diagram representing connection between different parts connected together via different GPIO(General Processing Input Output) Pins.

V. Module Description

1. Model Training and Deployment

The system utilizes the TinyYOLO model for real-time animal detection and classification. The model is trained on TensorFlow using Google Colab to ensure it is lightweight and optimized for deployment on edge devices like the Raspberry Pi. The model is specifically trained to detect various animal species, ensuring high accuracy while maintaining efficiency. After training, both the model and the Raspberry Pi OS are installed on an external SSD for improved performance and faster deployment. This setup enables rapid inference directly on the Raspberry Pi, supporting real-time animal detection and classification in field applications like farm monitoring and wildlife management.

2. Feature Extraction and Optimization

In this module, TinyYOLO is used for feature extraction from images captured by the system's camera. The model isolates key features within the image, which are essential for accurate object detection and classification. These features are optimized using TensorFlow to ensure efficient processing with minimal computational overhead. By enhancing classification accuracy and improving model efficiency, this module enables quick and reliable detection of animals, facilitating real-time responses in applications like farm monitoring and wildlife management.

3. Heat & Motion Detection

The PIR sensor detects motion or the presence of a living organism within its range. Upon detection, it activates the system to trigger further actions, such as turning on the camera and initiating the object detection pipeline. This module plays a crucial role in monitoring farm environments, ensuring that the system is only activated when necessary and reducing unnecessary resource consumption. The PIR sensor enables automated motion-based detection and is a fundamental component for initiating the animal detection process.

4. Camera Activation and Image Capture

When the PIR sensor detects motion or the presence of an organism, this module activates the camera to capture real-time images or video streams. These images are immediately processed by the AI model for animal detection and classification. By using the camera in conjunction with the PIR sensor, the system ensures that only relevant visual data is captured, optimizing resource use while providing accurate input for detection tasks. This module is integral for real-time monitoring and helps identify potential animal intrusions.

5. Animal Detection and Classification

In this module, the TinyYOLO model is used to classify objects detected in real-time images. The model categorizes objects based on a curated dataset that identifies various animal species. The system then triggers specific actions depending on the type of animal detected. For example, if a crop-damaging animal is detected, the system can activate deterrents to drive the animal away. This module plays a vital role in automating decision-making by accurately classifying detected animals and enabling immediate, context-appropriate responses.

6. Sound Activation & User Dashboard

The Sound Activation & User Dashboard module integrates animal deterrence and real-time monitoring to ensure effective field management. Upon detecting an animal, the system activates a buzzer to produce a sound designed to safely deter the animal without causing harm, protecting crops while maintaining environmental balance. Simultaneously, the web-based user dashboard provides real-time monitoring, displaying live images from the detection site, maintaining logs of animal activity, and showing the system's operational status. Users can receive alerts about detections, review detection events, and adjust system settings remotely. This integrated module combines immediate deterrence with interactive monitoring, offering a comprehensive solution for safeguarding agricultural fields.

IV. RESULTS AND CONCLUSION

Agricultural fields located near forests and mountainous regions often face significant crop damage caused by animals such as buffalo, cows, and goats. Research indicates that animal-related damage can account for up to 50% to 60%, and in some cases, nearly 100% of crop losses. This issue is particularly severe for farmers who rely on their crops as a primary source of income. To address this problem, an innovative solution was introduced using acoustic deterrents powered by Arduino technology.
Upon deployment, these deterrent devices effectively reduced the intrusion of animals into the fields, thereby minimizing crop damage. Farmers reported a marked improvement in the protection of their crops, which in turn contributed to better financial stability. Notably, the system not only safeguarded crops but also ensured the safety of both the crops and the workers, with no harm caused to the animals. This solution offered a sustainable and non-invasive means to prevent wildlife interference, making it a valuable addition to agricultural management.

The implementation of the acoustic deterrent system proved successful in significantly reducing crop damage, resulting in enhanced crop yields and higher profitability for the farmers. This solution is highly applicable for regions facing similar challenges and holds the potential for widespread adoption. The use of this technology demonstrates a practical, cost-effective approach to mitigating the impact of animal intrusion on agricultural fields, ensuring long-term sustainability for farmers. Overall, this approach offers a promising solution to protect agricultural lands, increase crop production, and improve the economic stability of farmers.

Figure 3: Login Page

Login page prevents the creation of session for user which acts as a decorator above all other URLs, preventing illegal access to other page, refer Figure 3.

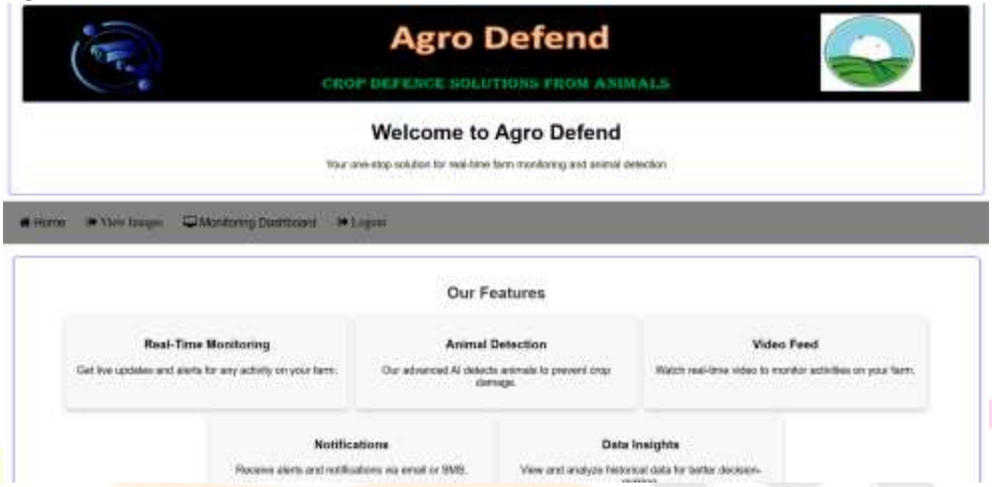
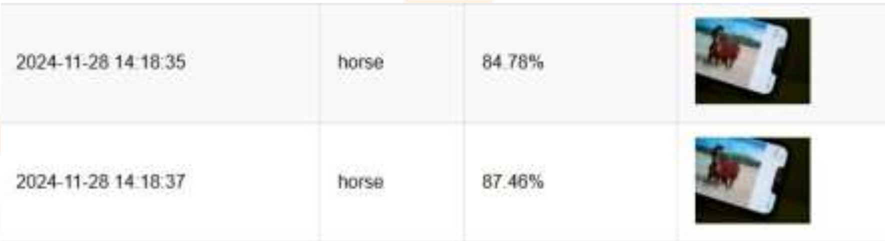


Figure 4: Home Page

The above diagram, figure 3 represents the home page of the web dashboard used for navigation between the Live feed and metadata logs of all the images captures previously.



2024-11-28 14:18:35	horse	84.78%	
2024-11-28 14:18:37	horse	87.46%	

Figure 5: Logs of the metadata

The above diagram, figure 4 shows metadata of image, timestamp, category of classified animal and percentage of matching animal. Percentage of match can be considered as a confidence level.

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References

[1] D. Adami, G. Bardaro, and E. M. Rucci, "Design, development and evaluation of an intelligent animal repelling system for crop protection based on embedded edge-AI," *IEEE Access*, vol. 9, pp. 132125–132139, 2021.

[2] K. Balakrishna, R. K. Sharma, and V. S. Rao, "Application of IoT and machine learning in crop protection against animal intrusion," *Global Transitions Proceedings*, vol. 2, no. 2, pp. 169–174, Nov. 2021, Science Direct.

[3] M. Ibraheam, A. El-Khamisy, and H. Z. Ahmed, "An accurate and fast animal species detection system for embedded devices," *IEEE Access*, vol. 11, pp. 23462–23473, 2023.

[4] K. V. Reddy, P. S. Krishna, and B. T. Mahesh, "Edge AI in sustainable farming: Deep learning-driven IoT framework to safeguard crops from wildlife threats," *IEEE Access*, vol. 12, pp. 77707–77723, 2024.

[5] M. Zhang, L. Sun, and Y. Wang, "Wildlife object detection method applying segmentation gradient flow and feature dimensionality reduction," *Electronics*, vol. 12, no. 2, p. 377, Jan. 2023. Available: https://doi.org/10.3390/electronics12020377

[6] L. Chen, X. Liu, and H. Wu, "YOLO-SAG: An improved wildlife object detection algorithm based on YOLOv8n," *Ecological Informatics*, vol. 83, p. 102791, 2024. [Online]. Available: https://doi.org/10.1016/j.ecoinf.2024.102791

[7] S. R. Bakana, A. Patel, and J. K. Sen, "WildARe-YOLO: A lightweight and efficient wild animal recognition model," *Ecological Informatics*, vol. 80, p. 102541, 2024. [Online]. Available: https://doi.org/10.1016/j.ecoinf.2024.102541

[8] Mahore, P. Tiwari, and R. N. Gupta, "Development and implementation of a Raspberry Pi-based IoT system for real-time performance monitoring of an instrumented tractor," *Automation in Agriculture and Technology*, vol. 9, p. 100530, 2022. [Online]. Available: https://doi.org/10.1016/j.atech.2024.100530

[9] R. A. Nadafa, A. Ghosh, and K. D. Singh, "Home security against human intrusion using Raspberry Pi," *Procedia Computer Science*, vol. 167, pp. 1811–1820, 2021. [Online]. Available: https://doi.org/10.1016/j.procs.2020.03.200

[10] G. Anand, R. Sharma, and M. K. Gupta, "Object detection and position tracking in real time using Raspberry Pi," *Materials Today: Proceedings*, vol. 47, no. 11, pp. 3221–3226, 2021. [Online]. Available: https://doi.org/10.1016/j.matpr.2021.06.437

[11] Prajna P., Soujanya B.S., Divya, "IoT-based Wild Animal Intrusion Detection System," *International Journal of Engineering Research & Technology (IJERT)*, 2018.

[12] Balaji V.S., Mahi A.R., Anirudh Ganapathy P.S., Manju M., "Scarecrow Monitoring System: Employing MobileNet SSD for Enhanced Animal Supervision," *arXiv preprint arXiv:2407.01435*, 2024.

[13] N. Gobalakrishnan, K. Pradeep, C.J. Raman, L. Javid Ali, M.P. Gopinath, "A Systematic Review on Image Processing and Machine Learning Techniques for Detecting Plant Diseases," *International Conference on Communication and Signal Processing (ICCSP)*, 2020.

[14] Mukesh Mahajan, Kiran Patil, Vishesh Geete, Prasad Kondhare, "Developing a Prototype of Smart Crop Protection System from Animals," *International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET)*, 2020.

[15] L. Chen, X. Liu, H. Wu, "YOLO-SAG: An Improved Wildlife Object Detection Algorithm Based on YOLOv8n," *Ecological Informatics*, vol. 83, p. 102791, 2024. [Online]. Available:https://doi.org/10.1016/j.ecoinf.2024.102791

[16] S. R. Bakana, A. Patel, J. K. Sen, "WildARe-YOLO: A Lightweight and Efficient Wild Animal Recognition Model," *Ecological Informatics*, vol. 80, p. 102541, 2024. [Online]. Available: https://doi.org/10.1016/j.ecoinf.2024.102541

[17] Mahore, P. Tiwari, R. N. Gupta, "Development and Implementation of a Raspberry Pi-based IoT System for Real-time Performance Monitoring of an Instrumented Tractor," *Automation in Agriculture and Technology*, vol. 9, p. 100530, 2022. [Online]. Available: https://doi.org/10.1016/j.atech.2024.100530

[18] R. A. Nadafa, A. Ghosh, K. D. Singh, "Home Security Against Human Intrusion Using Raspberry Pi," *Procedia Computer Science*, vol. 167, pp. 1811–1820, 2021. [Online]. Available: https://doi.org/10.1016/j.procs.2020.03.200

[19] G. Anand, R. Sharma, M. K. Gupta, "Object Detection and Position Tracking in Real Time Using Raspberry Pi," *Materials Today: Proceedings*, vol. 47, no. 11, pp. 3221–3226, 2021. [Online]. Available: https://doi.org/10.1016/j.matpr.2021.06.437