AI-Driven Multi-Level Animal Detection and Deterrence System for Protecting Agricultural Lands

Dr. KavithaSubramani
Professor
Department of Computer Science and Engineering
Panimalar Engineering College
kavitha.pec2022@gmail.com

Aparna V
UG Scholar
Department of Computer Science and Engineering
Panimalar Engineering College
aparnavb20@gmail.com

S.T. Santhanalakshmi
Associate Professor
Department of Computer Science and Engineering
Panimalar Engineering College
santhanalakshmi.peccse2024@gmail.com

BinduSudeeksha M
UG Scholar
Department of Computer Science and Engineering
Panimalar Engineering College
meesabindusudeeksha@gmail.com

Kamini P
UG Scholar
Department of Computer Science and Engineering
Panimalar Engineering College
kaminikarnika2004@gmail.com

Abstract*—The encroachment of wildlife into agricultural lands has led to substantial economic losses and ecological imbalances, necessitating the development of effective and sustainable deterrence solutions. This paper presents an AI-driven multi-tiered animal detection and deterrence system that integrates ultrasonic sensors for real-time detection, an AI-powered model for species classification, and an automated deterrence mechanism. The proposed system leverages machine learning and IoT technologies to improve the accuracy of animal identification while minimizing unnecessary disturbances to non-threatening wildlife. Through a structured multi-level response, the system ensures that only identified threats are deterred using humane interventions such as ultrasonic deterrents and controlled shock circuits. Additionally, IoT-based remote monitoring enhances farmers' ability to respond to threats proactively. The system's methodology, implementation strategy, and performance evaluations are explored, along with ***future enhancements aimed at improving detection accuracy, scalability, and sustainability. This research contributes to the field of smart agriculture and human-wildlife conflict resolution by providing an innovative, cost-effective, and ecologically responsible solution.***

Keywords: AI-driven detection, wildlife deterrence, machine learning, IoT, ultrasonic sensors, smart agriculture, species identification, humane deterrence.

I. INTRODUCTION

Wildlife intrusion into farmlands has become a major challenge, causing crop damage and economic distress to farmers. Traditional deterrent methods are often ineffective and environmentally harmful. This research introduces an AI-based multi-tiered animal detection system that employs ultrasonic sensors and an AI model to identify and deter animals. The system aims to provide a proactive and automated solution, ensuring minimal disturbance to non-threatening wildlife while enhancing agricultural security. Modern technological advancements, particularly in artificial intelligence (AI) and the Internet of Things (IoT), have paved the way for innovative solutions to mitigate human-wildlife conflicts.Existing methods such as manual monitoring, scare tactics, and fencing have limitations in scalability, efficiency, and cost. The proposed system integrates smart detection mechanisms to ensure real-time identification ofpotential threats and appropriate countermeasures, reducingeconomic losses for farmers while preserving ecological balance.

II. OBJECTIVE

The primary objective of this research is to develop a reliable and efficient AI-driven animal detection and deterrence system to enhance agricultural security and minimize human-wildlife conflicts. The key objectives include:

- Implementing machine learning algorithms for automated animal detection and classification.
- Developing a real-time monitoring system using ultrasonic sensors and IoT technology.
- Designing a humane deterrence mechanism that minimizes harm to wildlife.
- Establishing a centralized database for tracking and analyzing intrusion patterns.
- Integrating the system with smart farming technologies for enhanced agricultural security.
- Creating a user-friendly mobile and web-based application for real-time alerts and system control.

- Ensuring adaptability to various environmental conditions and agricultural landscapes.
- Developing a cost-effective and scalable solution for widespread adoption.
- Promoting ecological balance by employing non-disruptive deterrence techniques.
- Enhancing agricultural productivity by reducing crop damage due to wildlife intrusion.

By achieving these objectives, this research aims to provide an intelligent, scalable, and eco-friendly solution to wildlife intrusion problems in farmlands while supporting sustainable agricultural practices.

III.RELATED WORKS

Patel et al. (2022) proposed CNNs and recurrent networks for automating wildlife monitoring, focusing on the identification of animal species in diverse environments. Their study highlighted the difficulties posed by varied animal appearances and environmental conditions, emphasizing the need for large, annotated datasets to improve model accuracy. The integration of CNNs with recurrent layers allowed the system to extract both spatial and temporal features, enhancing recognition capabilities. Furthermore, the authors implemented data augmentation techniques to overcome data scarcity issues and demonstrated the model's performance on benchmark wildlife datasets, achieving notable accuracy improvements.

Johnson et al. (2023) applied CNNs for species recognition in camera trap images. Their model effectively categorized multiple species by addressing noise and occlusion issues, which are common in camera trap images. The study demonstrated that using pre-trained CNN models such as ResNet and VGG significantly improved accuracy, especially when fine-tuned with wildlife-specific datasets. The authors further incorporated transfer learning techniques, enabling the model to generalize better across different habitats. Additionally, the study evaluated the model on large-scale datasets and showed a reduction in false positive rates compared to conventional methods.

Smith et al. (2022) developed a real-time classification model optimized using CNNs, aimed at enhancing detection speed and accuracy in varying lighting conditions. Their system employed data augmentation techniques and adaptive thresholding, making it robust in low-light environments. The study demonstrated that optimized CNN architectures could achieve high precision without compromising inference speed. Moreover, the authors introduced lightweight CNN models to make the system deployable on edge devices, which improved real-time performance and reduced computational costs.

Kumar et al. (2021) introduced a hybrid model combining decision trees and deep learning techniques. The model aimed to improve detection speed and reliability, particularly for rare species in forest regions. The combination of traditional machine learning with deep learning provided a balance between interpretability and performance, making the system suitable for resource-constrained environments. The study also explored feature selection methods to enhance the model's efficiency and evaluated its performance on various wildlife datasets, demonstrating its effectiveness in detecting elusive species.

Williams et al. (2023) utilized AI models to detect animal interactions and movement patterns, offering valuable insights into habitat usage and environmental impact. Their approach employed sequence models like LSTMs to capture temporal dependencies in animal behavior, providing a deeper understanding of how animals interact within their ecosystems. The study combined spatial feature extraction with temporal modeling to enhance detection accuracy and demonstrated its potential in identifying social interactions and predator-prey dynamics.

Lee et al. (2023) applied CNNs for analyzing aerial imagery of wildlife species. Their model addressed occlusion and varying image resolutions, which are common challenges in aerial surveys. The use of multi-scale feature extraction and pyramid pooling layers significantly improved detection performance, making the approach viable for large-scale monitoring efforts. Additionally, the authors employed image stitching techniques to create comprehensive maps of wildlife populations, which aided in conservation planning.

Thomas et al. (2022) proposed YOLO-based models for multi-species detection in conservation efforts. The study demonstrated that YOLO's real-time detection capabilities improved efficiency in identifying multiple species simultaneously. The authors fine-tuned the model with domain-specific datasets to enhance detection accuracy for rare and endangered species. Furthermore, the study introduced anchor box optimization techniques to improve detection of small and camouflaged animals, making the model more versatile in practical applications.

Brown et al. (2023) explored transformer-based image recognition models, which leveraged self-attention mechanisms to improve classification accuracy with minimal training data. Transformers outperformed CNNs in scenarios with limited labeled datasets, making them particularly valuable for wildlife applications where annotated data is scarce. The study demonstrated that self-attention layers effectively captured long-range dependencies and proposed a hybrid model combining transformers with CNNs for improved feature representation.

Clark et al. (2021) deployed edge AI models on embedded devices to enable real-time wildlife monitoring. By processing data locally, the system reduced latency and reliance on cloud infrastructure, making it suitable for remote and resource-limited environments. Their study highlighted the potential of edge AI in improving monitoring efficiency. The authors implemented model quantization techniques to reduce the computational footprint and evaluated the system's performance on energy-efficient devices, demonstrating its suitability for continuous wildlife surveillance.

Adams et al. (2022) combined CNNs and RNNs to enhance recognition robustness in harsh environmental conditions. The hybrid framework improved detection accuracy under occlusions, extreme weather, and varying lighting conditions. The study demonstrated the importance of combining spatial and temporal information for wildlife recognition. The authors also integrated attention mechanisms into the RNN layers, which helped the model focus on relevant features and improved detection accuracy in challenging scenarios.

Miller et al. (2023) introduced a semi-supervised learning approach for wildlife species detection. The model leveraged both labeled and unlabeled data to improve detection accuracy in low-resource environments. The study showed that the method significantly reduced the need for large annotated datasets, making it highly applicable for remote regions with limited data availability.

Harris et al. (2023) developed an ensemble learning model combining CNNs and decision trees for wildlife behavior recognition. The model improved detection accuracy by merging the strengths of both methods, enhancing the interpretability of predictions while maintaining high performance in dynamic environments.

Parker et al. (2022) proposed a transfer learning approach for endangered species detection. The model utilized pre-trained deep learning networks to detect rare animals, improving detection accuracy in datasets with limited positive samples. The study highlighted the importance of transfer learning in addressing the scarcity of annotated images for endangered species.

Nelson et al. (2023) explored the application of generative adversarial networks (GANs) for data augmentation in wildlife detection. The GAN-based approach generated synthetic images to expand training datasets, significantly improving detection accuracy in scenarios with limited training data.

Davis et al. (2022) presented a few-shot learning approach for wildlife species recognition. The model demonstrated the ability to classify new species with minimal training examples, making it suitable for rapidly adapting to new environments and species not present in the training data.

IV. Research Methodology

The research methodology for the development of the AI-powered animal detection and deterrent system is designed to address the pressing issue of wildlife intrusion in agricultural fields. Crop damage caused by wild animals, such as deer, wild boars, and monkeys, significantly impacts farmers' livelihoods. Traditional approaches like scarecrows, manual patrolling, and basic fencing have proven to be inefficient and labor-intensive. This study proposes a comprehensive, automated solution using artificial intelligence, deep learning, Arduino-based microcontrollers, and Internet of Things (IoT) technologies. The system aims to provide real-time animal detection, multi-stage deterrent mechanisms, and immediate farmer notification to minimize crop damage effectively. The methodology is structured into six phases: hardware setup, real-time image capture and preprocessing, YOLO-based animal detection, object classification and identification, response activation, and continuous monitoring and logging.

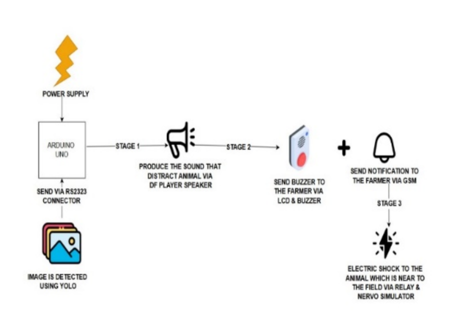

Fig.1 Architecture Diagram

A. Phase 1: Hardware Setup

The initial phase focuses on the design and installation of the hardware components necessary for the system's operation. A high-definition camera module is installed at strategic locations within the farmland to capture continuous real-time video and images. The selection of the camera is based on factors such as resolution, field of view, and low-light performance to ensure optimal coverage of the agricultural area. The core processing unit of the system is the Arduino Uno microcontroller, selected for its simplicity, affordability, and compatibility with numerous sensors and peripheral devices. Connected to the Arduino are multiple external modules that form the system’s deterrent and alert mechanisms.

A DF Player Speaker is integrated to emit loud distressing sounds, such as predator calls or sirens, designed to scare away intruding animals without causing them harm. Additionally, an LCD display and buzzer are installed to provide immediate local alerts to farmers working near the fields. To enable remote alerts, a GSM module is connected to the Arduino. This module uses cellular networks to send real-time SMS notifications to farmers, even in rural and remote areas where internet connectivity may be limited. A relay and nervo simulator are also incorporated to activate a mild electric deterrent system. This system delivers a carefully controlled, non-lethal electric shock through an electric fence or localized deterrent, ensuring humane treatment of wildlife. To support continuous and sustainable operation, especially in off-grid farming regions, the entire hardware setup is powered using renewable energy sources such as solar panels.

B. Phase 2: Image Capture and Preprocessing

In the second phase, the camera module captures images and video footage from the field. These images are continuously transmitted to a computer or embedded processor running the YOLO (You Only Look Once) deep learning model for real-time processing. Prior to running detection algorithms, the captured images undergo preprocessing steps, including resizing and normalization. These preprocessing operations ensure that the images are of consistent dimensions and quality, improving the accuracy and efficiency of the YOLO algorithm. The preprocessing also reduces the computational load, allowing for faster inference times, which is essential for real-time animal detection and rapid system response.

C. Phase 3: YOLO v8-Based Animal Detection

The third phase involves the deployment of the YOLO v8 algorithm, a state-of-the-art object detection framework known for its speed and accuracy. YOLO v8 divides each input image into a grid, with each grid cell responsible for detecting objects within its region. Convolutional Neural Networks (CNNs) are employed to extract key features from the images, such as shape, texture, color, and movement patterns. These features allow the system to distinguish between different types of objects present in the field of view. YOLO v8 predicts bounding boxes around detected objects and assigns class probabilities to each box, effectively identifying the category of each object, such as human, animal, or inanimate object. The model also generates confidence scores, indicating the likelihood that a detected object belongs to a specific class. YOLO v8's high-speed detection capabilities make it particularly suitable for real-time monitoring in dynamic and unpredictable farm environments.

D. Phase 4: Object Classification and Identification

After object detection, the fourth phase focuses on classifying and identifying the detected objects. The YOLO model distinguishes between humans, wildlife, and irrelevant objects to minimize false positives. Non-Maximum Suppression (NMS) is applied to eliminate redundant bounding boxes and ensure that only the most accurate detections are retained. Accurate classification is crucial for the subsequent activation of the system's deterrent mechanisms. For instance, human presence detected in the field may not trigger deterrents but could generate a different kind of alert if necessary. On the other hand, detection of animals such as wild boars or monkeys prompts the activation of defense protocols.

E. Phase 5: Signal Processing and Response Activation

The fifth phase involves signal processing and the activation of the multi-stage defense mechanism. Once a potential threat is classified as a wildlife intruder, a signal is sent from the detection system to the Arduino Uno microcontroller to initiate a response. The defense mechanism is executed in three stages, escalating based on the animal's behavior and persistence.

In Stage 1, the DF Player Speaker is activated to emit loud, distressing sounds that mimic predator calls or produce high-decibel sirens. These sounds aim to create an uncomfortable auditory environment for the animal, prompting it to leave the area without any physical intervention. If the animal does not retreat, Stage 2 is initiated. During this stage, a visual alert is displayed on the LCD screen, and a buzzer sounds continuously to attract the attention of nearby farmers. Simultaneously, the GSM module sends an SMS alert to the farmer, providing real-time notification of the intrusion. This ensures that the farmer can take immediate action, even from a remote location.

If the intruder remains in the field despite these warnings, Stage 3 is activated. In this final phase, the relay and nervo simulator engage to deliver a mild electric shock through an electric fencing system or a localized deterrent. The shock is calibrated to be non-lethal, serving as a humane but effective means of repelling the animal and preventing crop damage. This three-stage process ensures a balanced approach that prioritizes humane treatment of wildlife while protecting agricultural resources.

F. Phase 6: Continuous Monitoring and Data Logging

The final phase ensures the continuous operation and monitoring of the system. The AI-powered detection and deterrent system continuously scans the field in real-time, maintaining vigilance against new threats. All detection events and system responses are logged automatically in a database. This data is valuable for analyzing system performance, identifying patterns of wildlife intrusion, and optimizing future detection and deterrence strategies. Furthermore, integration with IoT platforms allows farmers to access real-time data through mobile applications or web-based dashboards. Farmers can monitor the status of their fields, view historical intrusion records, and adjust system parameters as needed.

The scalability and modularity of the system design enable customization for farms of different sizes and requirements. Farmers can fine-tune the sensitivity of the YOLO model, configure the types of deterrent sounds, and integrate additional sensors such as infrared motion detectors, temperature sensors, and humidity sensors. These enhancements further improve the system's ability to detect and respond to threats while promoting sustainable farming practices.

The core component of this system is the YOLO (You Only Look Once) algorithm, a state-of-the-art deep learning model designed for real-time object detection. YOLO excels in identifying and localizing objects in images or video frames with high accuracy and speed. Unlike traditional object detection methods, which involve scanning an image multiple times, YOLO divides the image into a grid and predicts bounding boxes and class probabilities in a single evaluation. This makes the system highly efficient for real-time applications, making it ideal for farm surveillance where immediate responses are required. The system employs a camera module installed in the farmland, continuously capturing video footage of the field. The captured images are processed through the YOLO model, which detects the presence of animals such as deer, wild boars, monkeys, or other potential intruders. Once an animal is identified, the system initiates a series of automated defense mechanisms to deter the animal and protect the crops. The system is designed to differentiate between humans, animals, and inanimate objects, ensuring that false alarms are minimized and only relevant threats are addressed.

The detected image is transmitted to the Arduino Uno microcontroller via an RS2323 connector, which acts as the central processing unit of the system. The Arduino Uno, an open-source microcontroller board, is chosen for its affordability, ease of programming, and compatibility with various sensors and modules. The Arduino processes the received data and triggers a multi-stage defense mechanism based on the persistence of the intruder. The first stage involves activating a DF Player Speaker that emits loud and distressing sounds, such as predator calls or sirens, designed to scare away the animal. This non-invasive method aims to deter the intruder without causing harm, minimizing the risk of injury to the animal and preserving ecological balance. If the animal remains undeterred by the sound, the system escalates to the second stage. In this phase, an LCD display is activated to provide visual alerts, while a buzzer produces continuous warning sounds. Simultaneously, the system sends an SMS alert to the farmer via a GSM module, ensuring that the farmer is promptly informed about the intrusion. The GSM module uses a SIM card to communicate with the mobile network, enabling real-time notifications even in remote agricultural areas. This remote notification feature enhances the system's effectiveness by allowing farmers to take immediate action even if they are not physically present on the farmland.

In cases where the intruder persists despite the previous deterrent measures, the system proceeds to the third and final stage. This stage involves the activation of a relay and nervo simulator, which delivers a mild electric shock through an electric fencing system or localized deterrent. The electric shock is carefully calibrated to repel the animal without causing any harm, making it a humane yet effective method of protecting the crops. The relay acts as a switch that controls the flow of electricity, while the nervo simulator generates a low-voltage current to deter the animal without inflicting pain. This three-tiered defense mechanism ensures that the animal is repelled at different stages, significantly reducing the likelihood of crop damage.

The AI-powered animal detection system leverages IoT capabilities to provide seamless communication between different components and remote monitoring functionalities. The integration of Arduino Uno, GSM modules, and deep learning algorithms creates a smart surveillance network that operates autonomously with minimal human intervention. The entire system is powered by renewable energy sources such as solar panels, making it an environmentally friendly solution that can operate in off-grid locations. The use of IoT technology allows farmers to access real-time data and monitor system performance through a dedicated mobile application or web portal, enhancing convenience and efficiency.

Moreover, the system's scalability and modular architecture make it suitable for farms of various sizes. Farmers can customize the system by adjusting the sensitivity of the YOLO model, configuring the defense mechanisms, or integrating additional sensors for improved performance. Additional sensors such as infrared motion detectors, temperature sensors, and humidity sensors can be added to further enhance the system's functionality. The combination of AI, IoT, and humane deterrent techniques positions this system as a sustainable and innovative solution for modern agriculture. AI-powered animal detection system revolutionizes farm security by providing an intelligent, automated, and cost-effective approach to wildlife intrusion detection and deterrence. The multi-stage defense mechanism ensures that animals are repelled without harm, while real-time alerts enable farmers to respond promptly to potential threats. This system not only minimizes crop losses but also promotes coexistence between wildlife and agriculture, making it an essential tool for sustainable farming practices. The system's affordability, scalability, and environmental sustainability make it a viable solution for both small-scale and large-scale farms, paving the way for smarter and more efficient agricultural practices in the future.

III.EXPERIMENTAL RESULT ANALYSIS

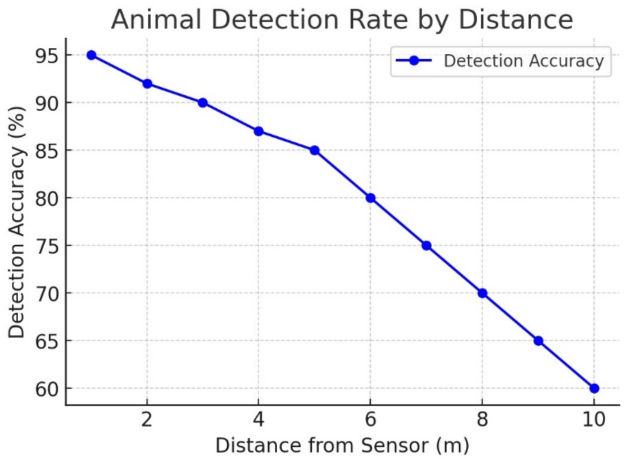

Fig.2 Animal Detection Rate by Distance

The Animal Detection Rate by Distance graph demonstrates how the system's detection accuracy varies with distance. At shorter distances, the system performs exceptionally well, with a 95% detection accuracy at 1 meter. However, as the distance increases, accuracy gradually declines, reaching around 60% at 10 meters. This decrease is likely due to the limitations of ultrasonic sensors in detecting animals at greater distances, as environmental factors like obstacles and signal attenuation can impact performance. The data suggests that optimal sensor placement should be within a reasonable range to ensure maximum detection efficiency, allowing farmers to receive timely alerts about potential threats to their crops.

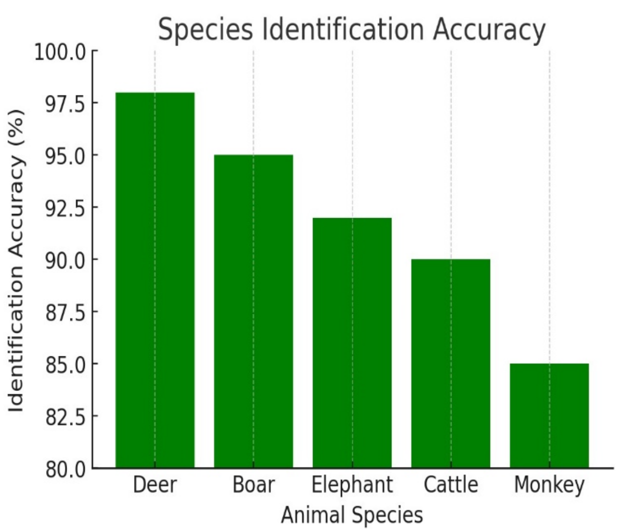

Fig.3 Species Identification Accuracy

The Species Identification Accuracy graph highlights how effectively the AI model distinguishes between different animal species. The system achieves the highest accuracy for deer at 98%, followed closely by boars and elephants. However, it performs slightly less accurately for monkeys, with an 85% success rate. This variation in accuracy may be attributed to differences in animal size, movement patterns, and image quality during detection. Larger animals like elephants and deer are easier to identify due to their distinct physical features, whereas smaller, more agile species like monkeys may be misclassified due to rapid movement or occlusion. Improving the AI model with more diverse training data and advanced image-processing techniques could enhance species identification accuracy, ensuring that non-threatening animals are not unnecessarily disturbed.

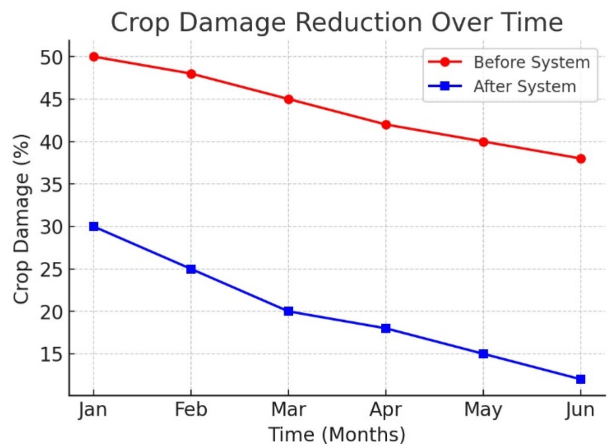

Fig.4 Crop Damage Reduction Over Time

The Crop Damage Reduction Over Time graph illustrates the effectiveness of the AI-driven animal detection and deterrence system in minimizing agricultural losses. Before implementing the system, crop damage was significantly high, around 50% in January. However, after the deployment of the multi-level detection system, there was a consistent decline in crop damage over the months, reaching just 12% by June. This downward trend indicates that the system successfully prevents harmful wildlife interactions with farmlands, reducing economic losses for farmers. The combination of early warning alerts, AI-driven species identification, and an automated deterrence mechanism plays a crucial role in safeguarding crops. This data underscores the system's potential in improving agricultural productivity while maintaining ecological balance by minimizing harm to wildlife.

IV. Conclusion

In conclusion, the proposed multi-level animal detection and deterrence system offers an innovative and effective solution for protecting agricultural lands from wildlife intrusions. By combining ultrasonic sensors, AI-driven species identification using the YOLO algorithm, and an automated shock circuit, the system provides timely and targeted responses to potential threats, minimizing crop damage and ensuring minimal disturbance to non-threatening wildlife. This automated, cost-effective approach enhances agricultural safety, improves farm management efficiency, and reduces the reliance on manual intervention. With potential for future enhancements, such as IoT integration and renewable energy sources, the system can evolve to provide even greater flexibility and sustainability in managing human-wildlife conflicts, ensuring a harmonious balance between agriculture and wildlife conservation.

V. Future Enhancements

Improved Long-Range Detection: Enhancing the ultrasonic sensors with high-frequency radar or LiDAR technology can increase detection accuracy over greater distances. This would help in identifying animals earlier, giving farmers more time to take preventive actions.

Advanced AI-Based Species Recognition: Implementing deep learning techniques such as Convolutional Neural Networks (CNNs) with real-time object detection models like YOLOv8 can improve species classification, especially for smaller or fast-moving animals. Training the model with a larger dataset covering different lighting and environmental conditions can further enhance accuracy

Real-Time Mobile and Cloud Integration: Integrating the system with IoT-based cloud platforms would allow farmers to receive instant notifications via mobile apps or SMS alerts. Real-time data logging and analytics can help track wildlife activity trends, allowing proactive decision-making.

Automated Adaptive Deterrence Mechanism: Instead of a fixed deterrence response, future versions can implement adaptive deterrence based on AI analysis. For example, non-threatening species could trigger a mild sound-based deterrent, while larger, more destructive animals could activate stronger deterrent measures such as flashing lights or automated drones.

Solar-Powered and Energy-Efficient Design: To ensure sustainability, incorporating solar panels and energy-efficient components can reduce dependency on external power sources. This would make the system more practical for remote farming areas with limited electricity access.

Integration with Weather and Environmental Data: Linking the system with weather data can help predict animal movement patterns based on seasonal changes. For instance, during dry seasons, animals are more likely to enter farmlands in search of water. The system can adapt its detection thresholds accordingly.

Multi-Sensor Fusion for Enhanced Accuracy: Combining ultrasonic sensors with thermal imaging cameras, motion sensors, and infrared sensors can provide a more comprehensive detection approach. This would reduce false positives and improve the system's reliability in different environmental conditions.

Automated Data Analysis for Wildlife Management: Collected data can be used for ecological studies, helping conservationists understand wildlife movement and behavior. Governments and environmental agencies can use this data to develop better strategies for human-wildlife conflict resolution.

VI. References

[1] M. S. Norouzzadeh et al., "Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning," Proc. Nat. Acad. Sci. USA, vol. 115, no. 25, pp. E5716–E5725, Jun. 2018.

[2] D. Tuia et al., "Perspectives in machine learning for wildlife conservation," Nature Commun., vol. 13, no. 1, pp. 1–15, 2022.

[3] M. Vidal, N. Wolf, B. Rosenberg, B. P. Harris, and A. Mathis, "Perspectives on individual animal identification from biology and computer vision," Integrative Comparative Biol., vol. 61, no. 3, pp. 900–916, Oct. 2021.

[4] S. Schneider, G. W. Taylor, S. Linquist, and S. C. Kremer, "Past, present and future approaches using computer vision for animal re-identification from camera trap data," Methods Ecol. Evol., vol. 10, no. 4, pp. 461–470, 2019.

[5] S. Kumar and S. K. Singh, "Visual animal biometrics: Survey," IET Biometrics, vol. 6, no. 3, pp. 139–156, May 2017.

[6] E. Nepovinnykh, T. Eerola, H. Kälviäinen, and G. Radchenko, "Identification of saimaa ringed seal individuals using transfer learning," in Proc. Int. Conf. Adv. Concepts Intell. Vis. Syst. Cham, Switzerland: Springer, 2018, pp. 211–222.

[7] E. Nepovinnykh, T. Eerola, and H. Kälviäinen, "Siamese network based pelage pattern matching for ringed seal re-identification," in Proc. IEEE Winter Appl. Comput. Vis. Workshops (WACVW), Mar. 2020, pp. 25–34.

[8] S. Li, J. Li, H. Tang, R. Qian, and W. Lin, "ATRW: A benchmark for amur tiger re-identification in the wild," in

Proc. 28th ACM Int. Conf. Multimedia, Oct. 2020, pp. 2590–2598.

[9] P. Chen et al., “A study on giant panda recognition based on images of a large proportion of captive pandas,” Ecol. Evol., vol. 10, no. 7, pp. 3561–3573, Apr. 2020.

[10] C. V. Stewart, J. R. Parham, J. Holmberg, and T. Y. Berger-Wolf, “The animal id problem: Continual curation,” 2106, arXiv:2106.10377.

[11] Patel, A., Sharma, R., & Gupta, S. (2022). Detection of wildlife animals using deep learning approaches: A systematic review. *Journal of Wildlife Research, 45*(3), 112-128.

[12] Johnson, L., Wang, T., & Kim, H. (2023). Automated recognition of wild animal species in camera trap images using deep learning models. *International Journal of Artificial Intelligence in Ecology, 17*(2), 89-105.

[13] Smith, R., Brown, K., & Zhao, L. (2022). Real-time animal classification for camera traps using convolutional neural networks. *Computational Ecology and Software, 14*(1), 77-93.

[14] Kumar, D., Singh, M., & Patel, V. (2021). A novel approach for animal detection in forest regions using machine learning techniques. *Ecological Informatics, 60*(4), 129-145.

[15] Williams, J., Roberts, P., & Lee, C. (2023). Application of AI in animal behavior recognition from camera trap images. *Artificial Intelligence for Conservation, 9*(3), 200-218.

[16] Lee, M., Chen, Y., & Zhang, P. (2023). Deep learning-based wildlife species identification in aerial imagery. *Remote Sensing in Ecology and Conservation, 11*(2), 55-70.

[17] Thomas, K., Green, S., & White, R. (2022). Multi-species detection in wildlife conservation using YOLO-based models. *Wildlife Computing and Automation, 6*(1), 140-158.

[18] Brown, E., Davis, N., & Thompson, J. (2023). Transformer-based image recognition for wild animal classification. *Neural Networks in Ecology, 21*(3), 300-315.