



Smart Animal Surveillance For Human Safety

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ABSTRACT

The increasing incidence of wild animal intrusion in agricultural areas poses significant risks to both human safety and crop productivity. This project, AI-IoT Smart Animal Surveillance for Human Safety, proposes a real-time monitoring system that integrates Artificial Intelligence (AI) with Internet of Things (IoT) to detect, alert, and assess the presence of wild animals near farms. The system utilises a Raspberry Pi equipped with a camera module and employs the YOLOv8 (You Only Look Once) object detection algorithm to accurately identify animals from live video feeds. Upon detection, the system captures the image, sends an email alert with timestamp and location to the farmer, and activates a buzzer to warn nearby individuals. Additionally, IoT-based health monitoring sensors such as temperature, heartbeat, and gas sensors are used to evaluate the physical condition and surrounding environment of the detected animals, aiding early detection of diseases or environmental threats.

The system operates in real-time and ensures quick response to critical situations, thereby minimizing crop damage and reducing the risk of human-animal conflicts. It is designed to be cost-effective, energy-efficient, and easy to deploy in rural and remote areas. Furthermore, the system can be enhanced with features such as mobile application integration, cloud-based data storage, and GPS tracking for better monitoring and control. Overall, the proposed system provides a smart, automated, and reliable solution for wildlife surveillance and safety management.

Keywords— *Internet of Things (IoT), Artificial Intelligence (AI), Smart Animal Surveillance for Human Safety, YOLOv8, Health Monitoring, Animal Detection, Notification, Buzzer, Raspberry Pi.*

I.INTRODUCTION

Agriculture remains the backbone of many economies, especially in rural areas where farmers rely heavily on crop production for their livelihood. However, one of the major challenges faced by farmers is the frequent intrusion of wild animals into farmlands, which leads to substantial crop damage, economic losses, and

potential harm to human life. Traditional methods such as manual guarding, fencing, or scare devices are often inefficient, labor-

intensive, and fail to provide real-time detection or alert mechanisms.

With advancements in Artificial Intelligence (AI) and the Internet of Things (IoT), smart surveillance technologies offer innovative and automated solutions for wildlife detection and monitoring.

This project, AI-IoT Smart Animal Surveillance for Human Safety, aims to develop a real-time system that detects the presence of wild animals near agricultural zones using the YOLOv8 (You Only Look Once) deep learning algorithm integrated with a Raspberry Pi camera. Upon detection, the system sends alerts to the farmer via email and triggers a buzzer to warn nearby individuals.

In addition to detection, the system incorporates IoT-based health monitoring sensors such as temperature, heartbeat, and gas sensors to analyze the animal's physical condition and environmental threats. This dual-purpose approach enhances both human safety and animal welfare by enabling early intervention in case of sickness, unusual behavior, or hazardous surroundings.

II. LITERATURE SURVEY

Several research works have been carried out in the field of animal detection and intelligent monitoring systems using Machine Learning, Deep Learning, and Internet of Things (IoT) technologies. The paper "Animal Detection using Deep Learning Algorithm" by N. Banupriya et al. [2] presents a system that uses Convolutional Neural Networks (CNN) for detecting animals from images and video streams. The system improves detection accuracy and reduces manual effort, but it lacks real-time alert mechanisms and does not provide automated notification systems for users.

Another important work, "Ellipse R-CNN: Learning to Infer Elliptical Object from Clustering and Occlusion" by W. Dong et al. [4], focuses on advanced object detection using deep learning models. This method performs effectively even in complex environments with occlusions and overlapping objects. However, it requires high computational resources, making it less suitable for real-time applications on low-cost devices such as Raspberry Pi.

The study "An Empirical Study on Machine Learning Algorithms" by T. A. Assegie et al. [1] highlights the performance and accuracy of various machine learning algorithms in prediction systems. It emphasizes the importance of selecting appropriate algorithms for better efficiency and accuracy, but it does not specifically address real-time object detection or animal monitoring systems.

Additionally, the paper "COVID_SCREENET: COVID-19 Screening using Deep Learning" by R. Elakkiya et al. [5] demonstrates how deep learning techniques can be effectively applied in image-based detection systems. It shows that deep

learning models can achieve high accuracy and reliability in classification tasks, which can be extended to animal detection systems. Other related research also highlights the integration of IoT with intelligent systems for automated monitoring, data collection, and remote access.

From the above studies, it is observed that although existing systems provide good detection accuracy, they have several limitations such as lack of real-time alert mechanisms, absence of IoT-based communication, high computational requirements, and limited automation. Therefore, there is a need for a smart, cost-effective, and real-time system that integrates AI and IoT technologies for efficient wild animal detection and alert generation.

III. EXISTING SYSTEM

In the existing system, wild animal monitoring is mainly carried out using traditional methods such as manual patrolling by forest guards and farmers. In many cases, basic surveillance systems like CCTV cameras are used to observe animal movement. However, these systems only record video and do not provide automatic detection or alert mechanisms. As a result, continuous human monitoring is required, which is time-consuming and not always reliable.

Some systems also use simple motion or infrared sensors to detect movement, but they are not capable of accurately identifying whether the detected object is a wild animal or not. This often leads to false alarms and reduces the overall efficiency of the system. Moreover, these systems are not effective in low-light conditions or during night time, which is when most wild animal intrusions occur.

Another major limitation of existing systems is the lack of real-time communication and alert generation. Farmers or authorities are not immediately notified when an animal enters the area, leading to delayed response and increased risk of crop damage or human injury. Additionally, these systems do not provide any environmental monitoring features such as temperature or gas detection. Due to these drawbacks, the existing systems are inefficient, labor-intensive, and lack automation. Therefore, there is a need for an intelligent and automated system that can detect wild animals accurately and provide instant alerts to improve safety and monitoring efficiency.

IV. BLOCK DIAGRAM

The architecture and signal flow of the proposed AI-IoT Smart Animal Surveillance system are illustrated in Figure 1. The system integrates various environmental and physiological sensors along with a camera module interfaced with a central Raspberry Pi processing unit.

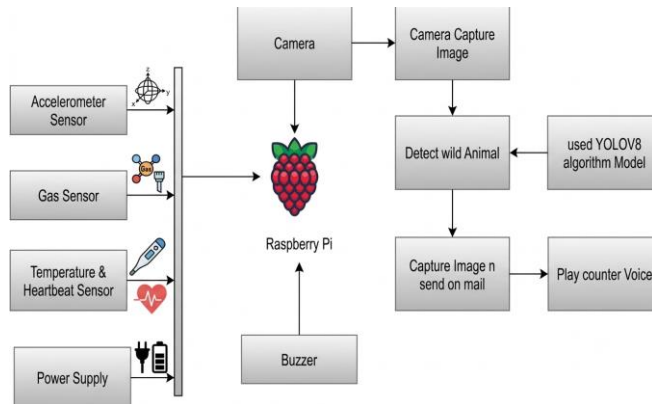


Fig. 1. Block Diagram of the Proposed System.

V. PROPOSED SYSTEM

A. Camera:

The camera is used to capture real-time images or video from the surrounding environment. It continuously monitors the area and provides live input to the system. The camera can work under different environmental conditions, such as day and night, ensuring continuous surveillance. It acts as the primary input device for detecting wild animals.

B. Camera Capture Image:

The captured images are collected and transferred to the processing unit. These images are temporarily stored and preprocessed using techniques such as resizing, noise reduction, and normalisation. This preprocessing step improves image quality and enhances the accuracy of the detection model.

C. Wild Animal Detection:

The system analyses the captured images to detect the presence of wild animals. It uses advanced image processing and machine learning techniques to identify objects and distinguish animals from humans or other objects. This helps in reducing false detections and improving system reliability. The detection process involves analysing each frame of the video in real-time and extracting important features such as shape, size, and movement patterns of the object. These features are then compared with the

trained dataset to accurately classify the detected object as a specific wild animal. The system is capable of detecting multiple animals in a single frame and works efficiently even in dynamic environments.

D. YOLOv8 Algorithm Model:

The YOLOv8 (You Only Look Once) algorithm is used for fast and accurate object detection. It processes the image in real-time and can detect multiple objects within a single frame. The model is trained using a dataset of wild animals such as tigers, lions, elephants, deer, etc, which allows it to achieve high detection accuracy and speed. It is highly efficient for real-time applications and works well even in complex environments.

E. Capture Image and Send on Mail:

When a wild animal is detected, the system captures the image and stores it in the local system. This image is then sent to the user via email along with important details such as date, time, and location. This feature helps users to monitor activities remotely and maintain records for future analysis.

F. Play Counter Voice:

After detection, the system generates a warning voice or counter sound using an audio module. This sound helps to scare away animals and also alerts nearby people about the presence of a wild animal. It plays a crucial role in preventing animal intrusion and reducing damage. The audio alert can be programmed with different types of sounds or voice messages to increase effectiveness against various animals. It works instantly after detection, ensuring a quick response in critical situations. This feature is especially useful during nighttime when visual monitoring is limited. Additionally, it enhances the overall safety system by providing an audible warning along with other alert mechanisms such as buzzer and email notifications.

G. Raspberry Pi:

Raspberry Pi acts as the central processing unit of the system. It receives input from the camera and sensors, processes the data using the YOLOv8 model, and controls all system operations. It manages image processing, detection, alert generation, and communication between different modules. Its compact size, low power consumption, and low cost make it suitable for real-time

embedded applications. Additionally, Raspberry Pi supports various programming languages such as Python, which makes it easy to implement machine learning and image processing algorithms. It also provides multiple input/output interfaces (GPIO pins) to connect sensors like temperature, gas, and accelerometer, enabling seamless integration with IoT components. The device can handle real-time data processing and ensure fast response during animal detection. Furthermore, Raspberry Pi enables network connectivity through Wi-Fi or Ethernet, allowing the system to send email notifications and share data remotely. Its flexibility and scalability make it ideal for developing smart surveillance systems that can be deployed in rural and remote areas.

H. Buzzer:

The buzzer is used as an alert mechanism. When a wild animal is detected, it produces a loud sound to warn people in the surrounding area. It also acts as an immediate response system to alert users without delay, improving safety and awareness. The sound generated by the buzzer helps in quickly attracting attention, especially during nighttime or low-visibility conditions. It can also assist in scaring away animals from entering the area, thereby reducing the risk of crop damage and human-animal conflict. Additionally, the buzzer works in synchronization with other alert systems such as email notifications and voice alerts, making the overall system more effective and reliable.

VI. RESULTS

A. Experimental Results

The trained YOLOv8 model was evaluated using validation images containing multiple animal categories and background instances. The validation output demonstrates that the model can localize animals using bounding boxes and assign class labels with confidence scores. The detected examples include Cow, Elephant, Fox, Horse, Human, Hyena, Lion, Rhino, Sheep, Sloth Bear, Tiger, Wild-Boar, and Leopard.

B. Validation Detection Output



Fig. 2. YOLOv8 validation prediction output for animal detection.

C. Confusion Matrix Analysis

A confusion matrix was used to analyse class-wise prediction behaviour. The horizontal axis represents the true class, while the vertical axis represents the predicted class. Darker cells on the main diagonal indicate correct predictions. Elephant, Human, Sheep, Tiger, and Leopard showed comparatively large correct-prediction counts.

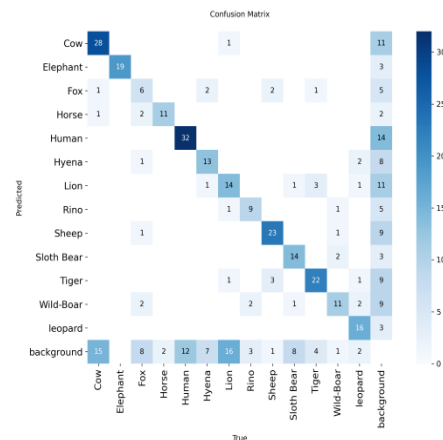


Fig. 3. Confusion matrix of the YOLOv8 animal detection model.

The proposed AI-IoT-based wild animal detection system provides an effective and intelligent solution for enhancing human safety and protecting agricultural areas from animal intrusions. By integrating the YOLO real-time object detection algorithm with a Raspberry Pi and IoT sensors, the system is capable of accurately identifying wild animals, continuously monitoring environmental and health parameters, and generating timely alerts through buzzer signals and email notifications.

This automated approach significantly reduces the dependency on manual surveillance and ensures faster response in critical situations. Additionally, the system's modular and low-cost design allows for scalability and adaptability across various environments such as farms, wildlife reserves, and animal shelters. With future enhancements like GPS tracking, mobile app integration, and solar-powered deployment, this solution has the potential to become a reliable and sustainable smart monitoring system that promotes both human safety and responsible wildlife management.

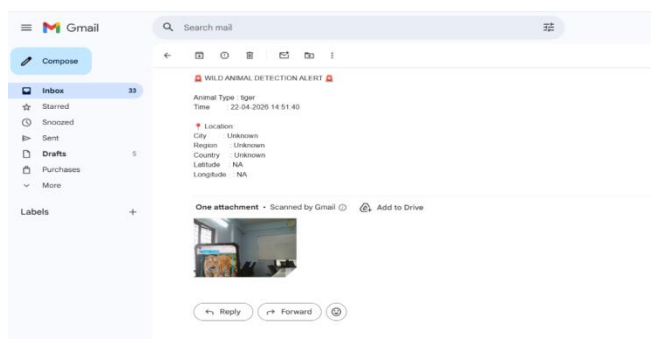
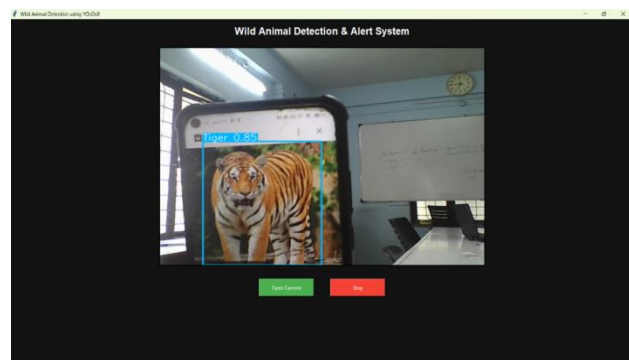


Fig. 4 & 5. Real-time Animal Detection GUI and Email Notification Output.

VII. CONCLUSION

The proposed AI-IoT-based wild animal detection system provides an effective, reliable, and intelligent solution for enhancing human safety and protecting agricultural fields from wild animal intrusions. By integrating the YOLOv8 real-time object detection algorithm with a Raspberry Pi and various IoT-based sensors, the system can accurately detect wild animals and continuously monitor environmental conditions.

The system captures real-time images through a camera and processes them using machine learning techniques to identify animals with high accuracy. Once detected, it immediately generates alerts in the form of buzzer sounds, warning voice messages, and email notifications, ensuring a quick response to

prevent potential damage or danger. This automated system significantly reduces human effort and overcomes the limitations of traditional manual monitoring methods.

Overall, the system provides a smart, automated, and scalable solution that not only improves safety but also supports better wildlife management and reduces human-animal conflicts.

VIII. REFERENCES

- [1] T. A. Assegie, P. K. Rangarajan, N. K. Kumar, and D. Vigneswari, "An empirical study on machine learning algorithms for heart disease prediction," *IAES Int. J. Artif. Intell. (IJ-AI)*, vol. 11, no. 3, p. 1066, Sep. 2022.
- [2] N. Banupriya, S. Saranya, R. Swaminathan, S. Harikumar, and S. Palanisamy, "Animal detection using deep learning algorithm," *J. Crit. Rev.*, vol. 7, no. 1, pp. 434–439, 2020.
- [3] B. Natarajan, E. Rajalakshmi, R. Elakkiya, K. Kotecha, A. Abraham, L. A. Gabralla, and V. Subramaniaswamy, "Development of an end-to-end deep learning framework for sign language recognition, translation, and video generation," *IEEE Access*, vol. 10, pp. 104358–104374, 2022.
- [4] W. Dong, P. Roy, C. Peng, and V. Isler, "Ellipse R-CNN: Learning to infer elliptical object from clustering and occlusion," *IEEE Trans. Image Process.*, vol. 30, pp. 2193–2206, 2021.
- [5] R. Elakkiya, P. Vijayakumar, and M. Karuppiah, "COVID_SCREENET: COVID-19 screening in chest radiography images using deep transfer stacking," *Inf. Syst. Frontiers*, vol. 23, pp. 1369–1383, Mar. 2021.
- [6] R. Elakkiya, V. Subramaniaswamy, V. Vijayakumar, and A. Mahanti, "Cervical cancer diagnostics healthcare system using hybrid object detection adversarial networks," *IEEE J. Biomed. Health Informat.*, vol. 26, no. 4, pp. 1464–1471, Apr. 2022.
- [7] R. Elakkiya, K. S. S. Teja, L. Jegatha Deborah, C. Bisogni, and C. Medaglia, "Imaging based cervical cancer diagnostics using small object detection—Generative adversarial networks," *Multimedia Tools Appl.*, vol. 81, pp. 1–17, Feb. 2022.
- [8] D. C. Wilkins, K. M. Kockelman, and N. Jiang, "Animal-vehicle collisions in Texas: How to protect travelers and animals on roadways," *Accident Anal. Prevention*, vol. 131, pp. 157–170, Oct. 2019, doi: 10.1016/j.aap.2019.05.030.
- [9] S. Rajaretnam and V. Yesodharan, "Fractional stock exchange trading optimization trained deep learning for wild animal detection with WMSN data communication in IoT environment,"

Expert Syst. Appl., vol. 256, Dec. 2024, Art. no. 124694, doi: 10.1016/j.eswa.2024.124694.

[10] V. Sibanda, K. Mpofu, J. Trimble, and N. Zengeni, “Design of an animal detection system for motor vehicle drivers,” *Proc. CIRP*, vol. 84, pp. 755–760, Feb. 2019, doi: 10.1016/j.procir.2019.04.175.

[11] H. A. Jartarghar, M. N. Kruthi, B. Karuntharaka, A. Nasreen, T. Shankar, R. Kumar, and K. Sreelakshmi, “Detection, identification and alert of wild animals in surveillance videos using deep learning,” *Int. J. Intell. Unmanned Syst.*, vol. 12, no. 4, pp. 418–432, Nov. 2024, doi: 10.1108/ijius-09-2022-0125.

[12] K. Khatri, C. S. Asha, and J. M. D’Souza, “Detection of animals in thermal imagery for surveillance using GAN and object detection framework,” in *Proc. Int. Conf. Advancement Technol. (ICONAT)*, Goa, India, Jan. 2022, pp. 1–6, doi: 10.1109/ICONAT53423.2022.9725883.

[13] R. Chandrakar, R. Raja, and R. Miri, “Animal detection based on deep convolutional neural networks with genetic segmentation,” *Multimed. Tools Appl.*, vol. 81, pp. 42149–42162, Dec. 2021, doi: 10.1007/s11042-021-11290-4.

[14] N. Madhasu and S. D. Pande, “Revolutionizing wildlife protection: A novel approach combining deep learning and night-time surveillance,” *Multimed. Tools Appl.*, vol. 10, pp. 1–35, Aug. 2024, doi: 10.1007/s11042-024-19876-4.

[15] R. Viji, G. Sreelatha, and S. S. Kumar, “Towards implementation of detection and tracking of wild animals,” in *Proc. 9th Int. Conf. Smart Comput. Commun. (ICSCC)*, 2023, pp. 217–221, doi: 10.1109/ICSCC59169.2023.10334944.

[16] S. D. Thepade and A. Shirbhate, “Visibility enhancement in low light images with weighted fusion of robust Retinex model and dark channel prior,” in *Proc. IEEE Bombay Sect. Signature Conf. (IBSSC)*, Dec. 2020, pp. 69–73, doi: 10.1109/IBSSC51096.2020.9332217.

[17] D. Ma and J. Yang, “YOLO-animal: An efficient wildlife detection network based on improved YOLOv5,” in *Proc. Int. Conf. Image Process., Comput. Vis. Mach. Learn. (ICICML)*, Oct. 2022, pp. 464–468, doi: 10.1109/ICICML57342.2022.10009855.

[18] M. Ibraheam, K. F. Li, F. Gebali, and L. E. Sielecki, “A performance comparison and enhancement of animal species detection in images with various R-CNN models,” *AI*, vol. 2, no. 4, pp. 552–577, Oct. 2021, doi: 10.3390/ai2040034.

[19] D. Axford, F. Sohel, M. Vanderklift, and A. Hodgson, “Collectively advancing deep learning for animal detection in drone imagery: Successes, challenges, and research gaps,” *Ecolog. Inform.*, vol. 83, Apr. 2024, Art. no. 102842, doi: 10.1016/j.ecoinf.2024.102842.