Wild Watch Sentry

Manna Mariam Abraham
Computer Science and Engineering
Amal Jyothi College of Engineering.
Kanjirappally, Kerala, India.
mannabraham0098@gmail.com

Naveen Moncy Mathew
Computer Science and Engineering
Amal Jyothi College of Engineering.
Kanjirappally, Kerala, India.
naveenmoncy05@gmail.com

Richu Sakeer Hussain
Computer Science and Engineering
Amal Jyothi College of Engineering.
Kanjirappally, Kerala, India.
richusakeerhussain@gmail.com

Tima Jose Thachara
Computer Science and Engineering
Amal Jyothi College of Engineering.
Kanjirappally, Kerala, India.
timajose9402@gmail.com

Bibin Varghese
Computer Science and Engineering
Amal Jyothi College of Engineering.
Kanjirappally, Kerala, India.
bibinvarghese@amaljyothi.ac.in

Abstract—**The aim of every farmer is to yield potential crop production every year. So, it is the responsibility of the farmerto protect the crop fields from wild animals' attack. Mostof the wild animals often come into contact with agricultural crops in search of food especially at night-time. Some of these animals attack those crops which results in an increase in human-wildlife conflicts. As a result, WildWatch Sentry (WWS) represents a revolutionary leap in crop protection by employing state of the art technologies. Prioritizing non-harmful deterrents, WWS minimizes losses for farmers while promoting sustainable agricultural practices and reducing conflicts between humans and wildlife. Its real-time monitoring capabilities not only enhance farm security and efficiency but also contribute to maintaining biodiversity and ecosystem balance. This is achieved by the YOLOv8 detection system and the production of a repelling audio. When a wild animal is detected, it recognises the species of the same accurately, produces a repelling sound that makesit go away from the crop field and parallelly, sends an email to the field owner as an alert message.**

I. Introduction

Agriculture is very important to the economy. It is the primary source of nourishment for all living things. As a result, it is well understood that agriculture provides numerous benefits for living beings. As a result, it is the responsibility of each farmer to safeguard such valuable crops. The successful farmer will employ the most effective crop protection techniques.With the goal of assisting farmers in protecting their crops from animals, our project will develop a real time monitoring-animal alarm system prior to their arrival in the farming area.In the last three years, wild animal invasions have increased dramatically in Kerala. Farmers suffer significant financial losses as a result of this. As a result, our study intends to design a crop monitoring system to provide a solution. Farmers will benefit greatly from this technology, particularly at night. Because farmers will not be around to defend their cropsduring the night. The system we suggest will be inexpensive due to readily available components and will be simple to use.As a result, the goal of our study is to create a crop protection system that is safe for both animals and humans. The YOLO Version 8 algorithm processes the captured images, enabling rapid and accurate identification of animals in real-time. Upondetection, the system activates intelligent deterrents to repel intruders, thereby minimizing crop losses.

II. Related Work

Maciej et al. has published an article based on Activity Detection and Recognition with Passive Electric Field Sensors. This article presents the development of an electric field sensor used to detect motion and identify animals and humans. There is another work related to the animal detection system proposed by Davide Adami, Mike O Ojo, and Stefano Giordano in an article called "Evaluation of an Intelligent Animal Repelling System for Crop Protection System." They aim to develop a smart agriculture application to protect crops from ungulate attacks. This system greatly reduces production losses through the development of an innovative device designed using computer vision and ultrasound emission. Recently, deep learning has emerged as a key technology in major fields. It is a technique that teaches computers to perform tasks that come naturally to humans. Zhang et al. describe a camera trap photo-based approach to animal segmentation. The method generates ideas for object regions and accurately identifies regions of interest by using a multi-level iterative graph cut. This is especially useful when it's hard to distinguish an animal from the background. In the second step, these regions were classified as the foregroundor background. Fisher vectors are generated by combining the histogram of oriented gradients (HOG) with feature vectors extracted from each image using the AlexNet architecture. The system's accuracy rate for detecting animals and species was 82.1 percent. A multi-stage pipeline for animal detection and recognition is proposed by Parham et al. Animal classification, animal localization, and animal property forecasting, including direction, are the three fundamental stages. Animal locationsare determined using the YOLO object detection model. The proposed method achieves an overall detection accuracy of 76.58% acros 6 species.

III. Proposed System

This research paper introduces a camera system designed to monitor wildlife activity near small villages by capturing images of animals exclusively when motion is detected. Subsequently, these images undergo comprehensive analysis, leading to species identification, and upon detection, residents receive timely alerts.

The real time monitoring camera system uses the Yolov8 model for detection. Upon detecting an animal, it further classifies the accurate species of the animal. Accuracy in detection is what is given the most importance to. After detection, a repelling sound for the detected sound is produced so that the animal will no longer remain in the field area and can run back to where it came from. The repelling sound will be different for each species thus making the system more effective. Apart from these features, we will be sending an email to the field owner and to the nearby authorities in case of detecting any harmful wild animals through the system. This helps us solve the problem of wild animal intrusion in farm lands during day and night without human interactionas well as without harming the animal thus maintaining an ecological balance. The repellent sound production helps to prevent the entry of animals to agricultural land. The email helps the owner to be notified about the intrusion of an animalin real time. In case of dangerous animals, the authorities can also take precautionary measures on receiving such a messageand can pass relevant messages to nearby residents about the same. The usage of Yolov8 leads to the most accurate detectionof animals in the field and further dataset training is made to obtain an increase in accuracy of the same.

A flowchart of the proposed system is shown in fig 1.Here, the input is obtained from the field area and is analysed by Yolov8 for animal detection. If any animal is detected,it clearly classifies the exact species of the animal preciselyto produce the exact same repellent sound for that particular animal. Along with this, an alert message is sent to the field owner as an email. If the animal detected is a dangerous wild animal, alert messages will be sent to forest authorities and nearby residents as instructed before. The system can generally classify anything but can be trained for a particular region where it is setup with the most common animal which is a threat to farm land. In Kerala, wild boars and elephants arethe two animals which mainly cause a threat to agricultural fields and humans. By the proposed system we can produce bee sound which repels wild boars and the sound of dogs barking to scare elephants that come across farm land. This ensures the safety of farmland and human life 24 x 7 in a less expensive method.

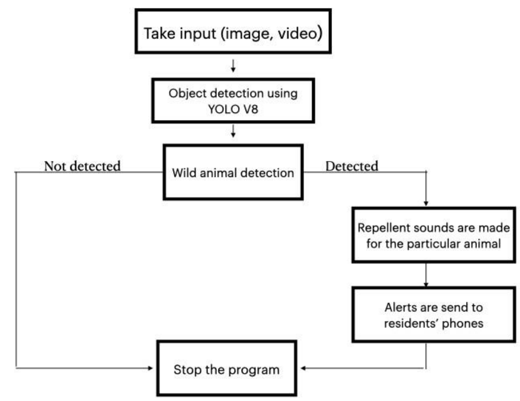

Fig. 1. Block diagram of the proposed system

IV. Methodology

A. YOLO

YOLO (You Only Look Once) is an object detection algorithm that identifies objects within images or video frames in real-time. Unlike traditional methods that perform region proposals and classification separately, YOLO divides the image into a grid and predicts bounding boxes and class probabilities for each grid cell simultaneously. This approach enables YOLO to achieve impressive speed and accuracy, making it suitable for applications like surveillance, autonomous vehicles, and image analysis. With a single neural network, YOLO v8, the latest version, enhances detection accuracy, reduces false positives, and optimizes speed for efficient real-time object detection tasks.

B. YOLOv8

We have employed the regression-based YOLO V8 method. YOLO V8 represents the latest iteration of this model, aiming to improve upon its predecessors by enhancing detection accuracy, reducing false positives, and optimizing speed. It employs a single neural network to predict bounding boxes and class probabilities directly from full images in a single pass, enabling real-time inference. YOLO v8 likely incorporates advancements in deep learning architectures, optimization techniques, and dataset augmentation to achieve its objectives. This version of YOLO continues to be widely used in various applications, including surveillance, autonomous vehicles, and image analysis, due to its balance of speed and accuracy in object detection tasks.

C. Simple Mail Transfer Protocol

SMTP is integral to projects requiring email functionality. In web applications, it sends automated emails for verification, password resets, and notifications. Automated systems rely on SMTP for alerts and reports to users or administrators. Feedback forms on websites use SMTP to deliver user-submitted messages. Email marketing platforms utilize SMTP for mass campaigns and newsletters. Transactional email services send real-time notifications via SMTP. Additionally, SMTP facilitates internal communication within organizations. Overall, SMTP is vital for ensuring reliable email delivery in projects, enabling seamless communication between systems and users.

V. Implementation

A. Requirements

Python and the Jupyter Notebook or Visual Studio Code or Google Collab are required pieces of software. Installing the Jupyter Notebook App on a remote server and using the internet to access it is one option; another is to use it locally on a PC without an internet connection. Numerous programming languages, including Python, C, and C++, are supported. Python is the language of choice for machine learning and artificial intelligence (AI) applications because it is more intuitive, takes less time to debug, and is easier to understand. We repeatedly train and test the model to make sure it comprehends real-time input and that it is accurate. The accuracy of the model is increased overall when more data is used for testing and training. OpenCV, NumPy, Pytorch, PyQt, and Twillio are among the necessary libraries. A camera is the main tool that is employed. The field area is photographed by the camera seven days a week, and the data it collects is utilized to feed into the model that helps it identify animals.

B. Data Collection

Without data, any Al model would be insufficient. Data is essential to machine learning. It's the most important component that makes algorithm training possible. It is an organized process for gathering data, such as observations or measurements. It is the initial stage of any project including machine learning.

The dataset that we have utilized here is an assortment of picture data that includes pictures of different animals, including tigers. Elephants, cheetahs, rhinoceroses, bears, etc. The Kaggle database provides the dataset. It includes around 2000 photos and roughly 20 distinct categories of wild creatures. For each class, a few pictures from the dataset are displayed.

C. Data Pre-processing

Following data gathering, data processing is required. It involves cleaning up and preparing the data so that it may be used for various model building, testing, and training purposes. Making labels and bounding boxes is a crucial stage in the YOLO process.

Labeling and bounding boxes: The YOLO method divides the image into many cells, in contrast to other conventional machine learning or deep learning techniques. Depending on how many items are covered in that image, each cell predicts a multiple bounding box. The likelihood that an object is within the bounding box is called confidence. This method may result in the appearance of bounding boxes with no objectsor intersecting bounding boxes with the same image spaces. The bounding box for the rhinoceros class is depicted in the figure of bounding.

An image series is used as input. The bounding boxes are marked with class labels. A crucial component in the construction of bounding boxes is standardization. To calculate the number of pixels, divide it by the total number of pixels in the image.

D. Object Detection

Among the many essential elements of computer vision, object detection is particularly noteworthy. A supervised machine learning model is utilized in object recognition to identify and locate different items in photos. When object identification is involved, it is necessary to provide the algorithm with a training dataset that consists of photos together with labels so that the model may be trained to identify the desired items. YOLO V8, a well-known and efficient object identification model, is one of the most popular ones available today. YOLO V8 is unique since it is a deep neural network that performs exceptionally well in situations involving object detection in real time. When it comes to retraining, this model's user-friendliness is one noteworthy benefit.

This model's ease of use in terms of retraining on unique datasets is one of its main advantages. One of YOLO v8's most notable features is how easy it is to retrain, which makes it a flexible and approachable option for adding object detection capabilities to a variety of applications.The working of the detection system and its accuracy is shown in fig 2.

E. Alerts

A machine learning (ML) model that is intended to identify the existence of wild animals and produce corresponding repelling sounds is the first step in the procedure in this system. Notifying the local residents of the potential risk is the next step once the model has identified an animal. In order toprotect local residents and avoid any confrontations with wild animals, this is essential.

To ensure resident safety, an automated notification system leverages email alerts. When the machine learning model detects a wild animal venturing beyond the forest boundaries, an email is promptly sent to all registered residents. This email effectively communicates the specific type of wild animal identified, keeping residents informed about potential dangers.

F. Repellent Sounds

We utilize our ML model to categorize animals after the camera takes pictures. If an animal enters a community, warning sounds are produced first, then the animals are terrified. Signals are transmitted to an ultrasonic frequency generator based on the animal anticipated by the machine learning algorithm. Given that various animals have differing sensitivity to sound frequencies, the sound repellent we would deploy would produce frequencies between 16 and 60 kHz. Amplification can be employed to extend the range or improve efficacy if necessary. When an animal's identity is predicted, a directive to generate a specific frequency range associated with that animal is delivered since the categorized animal is known. Because they are easily agitated by certain frequencies, wild animals might be sensitive to. We generate the necessary frequency to frighten and force the animal back to its natural environment. Creating loud noises could scare off wild boars,

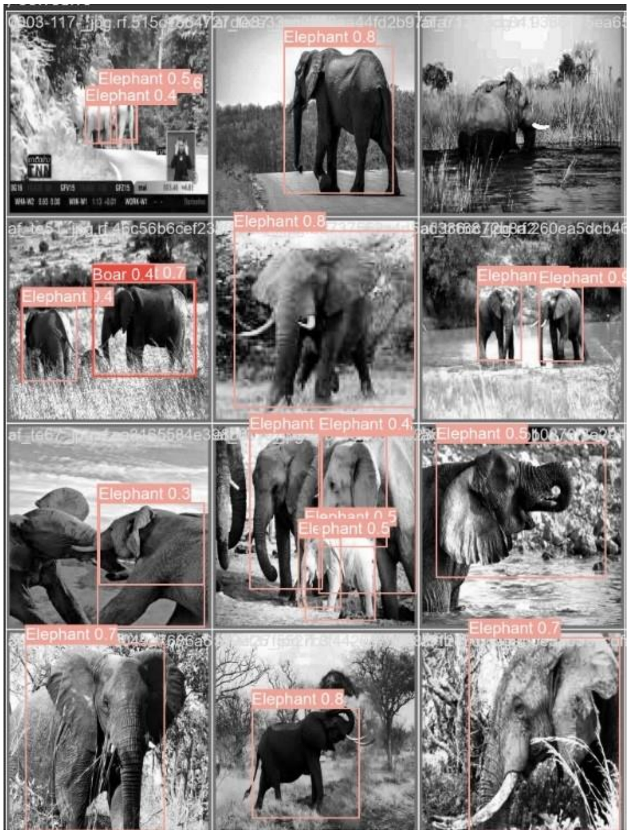

Fig. 2. Detection of animals

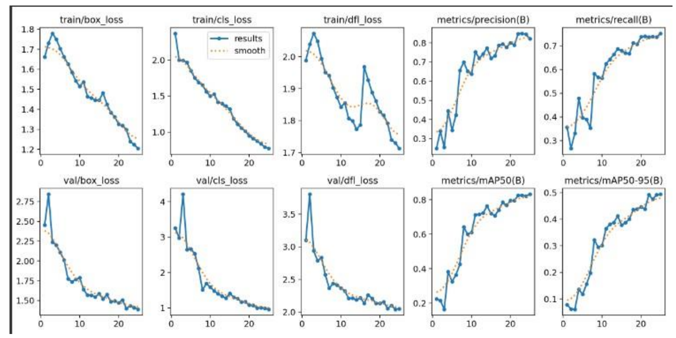

Fig. 3. Training results

but it might also set off an elephant's rage. Playing the appropriate sound or frequency that irritates the identified animal is therefore crucial to preventing false-positive situations.

VI. Training and Observations

In our research, we utilize Google Colab for training our model, visualizing key metrics through graphs. These include box and diff losses, demonstrating how our model's error decreases over time, and precision and recall metrics, illustrating the balance between accuracy and the model's ability to detect relevant instances as shown in figure 3. When training models in environments like Google Colab, these metrics and losses are typically visualized using plots to help developers understand how the model is performing across different aspects. These visualizations usually show: How the loss values (e.g., train/box loss, train/diff loss) decrease over epochs, indicating how well the model is learning to predict the training data.

The changes in precision and recall metrics over epochs or validation steps, which help in understanding the trade-offs between detecting as many positives as possible and minimizing incorrect positive predictions. Train/box loss and train/diff loss: Box loss: This typically refers to a component of the loss function associated with the bounding boxes in object detection tasks. In models like YOLO, Faster R-CNN, or SSD, box loss calculates how well the model predicts the location and size of the bounding box around each object relative to the ground truth boxes. Diff loss: This could be a less common or specific type of loss, and it may relate to the difference in prediction from a certain baseline or target, perhaps focusing on changes or differences in successive frames or predictions. However, without more specific context, "diff loss" isn't a standard term widely recognized in thefield. Metrics/Precision and Metrics/Recall: Precision (alsoknown as Positive Predictive Value): This metric evaluates theaccuracy of the positive predictions made by the model. It is the ratio of true positive results to all positive results, includingthose that are actually negative (false positives). Precision = True Positives / (True Positives + False Positives). Recall (also known as Sensitivity or True Positive Rate): This measures the model's ability to detect positive samples. It is the ratio of true positives detected by the model to the total actual positives in the data. Recall = True Positives / (True Positives + False Negatives).

VII. Future Work

One promising avenue for future development lies in integrating the system with drones. Imagine a scenario where the real-time monitoring system detects a dangerous animal. The system could then automatically dispatch a drone equipped with targeted repelling sounds and visual deterrents like flashing lights. This drone would then autonomously follow the animal, guiding it back towards the forest boundary using a carefully calibrated combination of sound and visual cues.This approach would prevent the animal from making sud- den, impulsive movements towards residential areas. However, careful consideration needs to be given to factors like weather conditions, battery life limitations of drones, and potential regulatory hurdles for autonomous drone operation.

The current real-time monitoring system could be further developed to offer a user-friendly interface similar to conventional CCTV systems. This would allow authorized personnel to monitor animal activity in real-time and intervene manually if necessary. For instance, if a specific animal appears hesitant to follow the drone's guidance, a human operator could adjust the approach or even remotely trigger additional deterrents if the situation demands it.

While the current system utilizes email for notifications, future iterations could explore a multi-channel alerting strategy. Platforms like Twilio could be integrated to send text messages and phone calls to pre-registered residents. This would significantly improve the system's reach and ensure residents receive timely alerts regardless of their preferred communication method. Additionally, developing a mobile application would provide residents with real-time updateson animal activity near their area. This app could also offer interactive features like allowing residents to report animal sightings directly to wildlife authorities or request further assistance if they feel threatened.

REFERENCES

[1] S. P. M.Gogoi, "Protection of Crops From Animals Using Intelligent Surveillance System," Jafs, vol. 2, pp. 200–206, 2015.

[2] P. A. V Deshpande, "Design and Implementation of an Intelligent Security System for Farm Protection from Wild Animals," Int. J. Sci. Res., vol. 5, no. 2, pp. 956–959, 2016. .

[3] Abel, D. T. Gowtham, S. B. Kaliraj, and M. Y. Khanna, "Real Time Animal Repellent System using Image Processing," vol. 4, no. 02, pp. 2094–2097, 2016. .

[4] G.Abbas,"Prospects and challenges of adopting and implementing smart technologies in poultry production," *Pakistan J. Sci.*, vol. 74, no. 2, p. 108, 2022.

[5] Rashmi Jayakumar. Rashmi Swaminathan. Sanchitaa Harikumar. N. Banupriya and S. Saranya, "Animal Detection Using Deep Learning Algorithm". July 2019

[6] B. Liu, "Temperature management of cage broilers during brooding period," (in Chinese), *Animals Breeding Feed*, vol. 20, no. 3, pp. 46–47, 2021.

[7] S. S. Niu and F. Liu, "Research on summer ventilation technology of 5- row, 4-layer layer cages for laying hens," (in Chinese), *Shandong J. Animal Sci. Veterinary Med.*, vol. 43, no. 3, pp. 11–14, 2022.

[8] Ruilong Chen. Ruth Little, Lyudmila Mihaylova. Richard Delahay and Ruth Cox. "Wildlife surveillance using deep learning methods". August 2019.

[9] C. Lamping, M. Derks, P. G. Koerkamp, and G. Kootstra,"Chicken Net—An end-to-end approach for plumage condition assessment of laying hens in commercial farms using computer vision," *Comput. Electron. Agricult.*, vol. 194, Mar. 2022.

[10] D. Wu, D. Cui, M. Zhou, and Y. Ying, "Information perception in modern poultry farming: A review," *Comput. Electron. Agricult.*, vol. 199, Aug. 2022.

[11] T. Leroy, E. Vranken, E. Struelens, B. Sonck, and D. Berckmans, "Computer vision based recognition of behavior phenotypes of laying hens," in *Proc. ASAE Annu. Meeting*, 2005.

[12] M. Sozzi, G. Pillan, C. Ciarelli, F. Marinello, F. Pirrone, F. Bordignon, A.Bordignon, G. Xiccato, and A. Trocino, "Measuring comfort behaviours in laying hens using deep-learning tools," *Animals*, vol. 13, no. 1, p. 33, Dec. 2022.

[13] W.Zhao,M.Syafrudin,andN.L.Fitriyani,"CRAS-YOLO:Anovelmulti-category vessel detection and classification model based on YOLOv8s algorithm," *IEEE Access*, vol. 11, 2023.

[14] H. Wang, Y. Xu, Y. He, Y. Cai, L. Chen, Y. Li, M. A. Sotelo, and Z. Li, "YOLOv8-fog: A multiobjective visual detection algorithm for fog driving scenes based on improved YOLOv8," *IEEE Trans. Instrum. Meas.*, vol. 71, 2022.

[15] G. Dai, L. Hu, J. Fan, S. Yan, and R. Li, "A deep learning-based object detection scheme by improving YOLOv8 for sprouted potatoes datasets," *IEEE Access*, vol. 10, 2022.

[16] Dr. R. S. Sabeenian, N. Deivanan and B. Mythili, "Wild Animals Intrusion Detection using Deep Learning Techniques". September 2020 .

[17] Z. Liu, Y. Gao, Q. Du, M. Chen, and W. Lv, "YOLO-extract: Improved YOLOv8 for aircraft object detection in remote sensing images," *IEEE Access*, vol. 11, pp. 1742–1751, 2023. .

[18] J. Zhao, X. Zhang, J. Yan, X. Qiu, X. Yao, Y. Tian, Y. Zhu, and W. Cao, "A wheat spike detection method in UAV images based on improved YOLOv8," *Remote Sens.*, vol. 13, no. 16, p. 3095, Aug. 2021.

[19] L. Wang, Y. Cao, S. Wang, X. Song, S. Zhang, J. Zhang, and J. Niu, "Investigation into recognition algorithm of helmet violation based on YOLOv8-CBAM-DCN," *IEEE Access*, vol. 10, pp. 60622–60632, 2022.

[20] Vaidehi Fulzele, Yash Kulkarni and Supriya Aras. "Conservation of Wildlife from Poaching by using Sound Detection and Machine Learning". ICSITS 2020.

[21] Ashwini V Sayagavi. Sudarshan TSB and Prashanth C Ravoor. "Deep Learning methods for Animal Recognition and Tracking to Detect Intrusions. ICTIS 2020.

[22] S. Li, Y. Li, Y. Li, M. Li, and X. Xu, "YOLO-FIRI: Improved YOLOv8 for infrared image object detection," *IEEE Access*, vol. 9, pp. 141861–141875, 2021.

[23] S. Gao, M. Cheng, K. Zhao, X. Zhang, M. Yang, and P. Torr, "Res2Net: A new multi-scale backbone architecture," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 43, no. 2, pp. 652–662, Feb. 2021.

[24] W.Zhou,Y.Chen,C.Liu,andL.Yu,"GFNet:Gatefusionnetworkwith Res2Net for detecting salient objects in RGB-D images," *IEEE Signal Process. Lett.*, vol. 27, pp. 800–804, 2020.

[25] A.Vaswani,N.Shazeer,N.Parmar,J.Uszkoreit,L.Jones,A.N.Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 30, 2017.

[26] Y. Sun, W. Liu, Y. Gao, X. Hou, and F. Bi, "A dense feature pyramid network for remote sensing object detection," *Appl. Sci.*, vol. 12, no. 10, p. 4997, May 2022.

[27] Z. Xue, H. Lin, and F. Wang, "A small target forest fire detection model based on YOLOv8 improvement," *Forests*, vol. 13, no. 8, p. 1332, Aug. 2022.

[28] Jason Parham. Charles Stewart, Jonathan Crall, Daniel Rubenstein. Jason Holmberg and Tanya Berger-Wolf. "An Animal Detection Pipeline for Identification 2018.