Animal Deterrance using Computer Vision and Raspberry Pi

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Abstract: This paper introduces a sophisticated animal deterrence system, employing the YOLOv8 model and the Ultralytics framework. The system, designed to thwart unauthorized animal invasions in restricted areas, integrates cutting-edge computer vision algorithms with the computational capabilities of Raspberry Pi. In real-time, strategically positioned cameras capture video feeds, which are meticulously analyzed using YOLOv8 for precise animal identification and categorization. Upon detecting unauthorized animal presence, the system activates deterrent devices, such as alarms or lights, ensuring swift and effective response. The project's success pivots on the refinement of computer vision models and seamless Raspberry Pi-to-camera connectivity. Beyond its technical intricacies, the implications of this innovative system are vast, ranging from safeguarding agricultural yields to the preservation of wildlife habitats and the maintenance of urban green spaces. By fostering coexistence and mitigating human-animal conflicts, this project stands as a beacon of innovation in addressing contemporary challenges. The integration of Ultralytics YOLOv8 and tools like Roboflow reflects a strategic and forward-thinking approach in tackling complex real-world issues with efficiency and precision.

Keywords: Animal Deterrence System, YOLOv8 Model, Ultralytics Framework, Computer Vision Algorithms, Raspberry Pi, Real-time Video Analysis, Unauthorized Animal Presence Detection, Deterrent Devices,

1 Introduction

In the ever-evolving domain of wildlife management and conflict resolution, the imperative to devise intelligent systems has become more pronounced than ever. This project aims to address the rising instances of human-wildlife conflicts by introducing an Automated System for Detecting and Repellenting Wild Animal Intrusions. The urgency of this initiative is underscored by the critical need for innovative solutions that can effectively mitigate the impacts of such conflicts on both biodiversity and human safety.At the heart of this project lies the incorporation of advanced technologies, notably the YOLOv8 (You Only Look Once) object detection model. This choice is rooted in a commitment to cutting-edge methodologies that surpass traditional detection systems. YOLOv8, renowned for its real-time capabilities and accuracy in video streaming surveillance [3], aligns

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_73

seamlessly with the project's objectives to enhance the efficiency of wildlife intrusion detection.
The process of training the YOLOv8 model involves meticulous data preparation and augmentation techniques, inspired by methodologies discussed in various studies [5]. The emphasis on diverse and well-annotated datasets addresses challenges posed by traditional datasets such as COCO [6]. Through augmenting the dataset, the project aims to improve the model's adaptability to a spectrum of wildlife scenarios, fortifying its real-world applicability.

This project also draws inspiration from studies highlighting the significance of wireless sensor networks in animal intrusion detection systems [27]. The integration of AIoT (Artificial Intelligence of Things) elevates the system's responsiveness and adaptability through real-time communication and data sharing. Going beyond mere detection, the project explores proactive repellent mechanisms inspired by recent advancements in intelligent animal repelling systems [18]. This approach shifts the paradigm from detection-only systems to preventive measures, reducing the likelihood of harmful encounters between humans and animals. The proposed work aims to provide better accuracy for image segmentation. Through this integration, our proposed approach represents a significant improvement towards the future of computer vision, by analysing and interpretating complex visual information.

2 Literature Review

The escalating interaction between human habitats and natural ecosystems has intensified the urgency for innovative strategies to mitigate human-wildlife conflicts. A multitude of studies has explored the realm of animal intrusion detection and deterrence, leveraging technologies spanning from AI to the IOT. This literature review aims to synthesize key findings from pertinent studies, providing insights into contemporary strategies and aligning them with our project objectives.
Automated Wild-Animal Intrusion Detection and Repellent Systems: Patil and Ansari (2021) proposed an innovative system utilizing Artificial Intelligence of Things (AIoT) for wild-animal intrusion detection [1]. Their work underscores the integration of AI capabilities with conventional surveillance systems of wildlife detection. This aligns with our project's foundation, incorporating YOLOv8, an AI-driven object detection system, to dynamically identify and categorize potential threats [3].
Deep Learning for Animal Detection and Collision Avoidance: The field of deep learning for animal recognition and collision avoidance was investigated by Saxena et al. (2020) [2]. Their research emphasizes the significance of advanced computational techniques in preventing collisions between animals and vehicles. This resonates with our project's objectives, where YOLOv8, An advanced deep learning model, plays a pivotal role in real-time object detection and collision risk assessment [10].Preventing Deer-Vehicle Accidents via Deep Learning Techniques: Fan, Sadeghian, and Aram (2020) focused on preventing deer-vehicle collisions through the application of deep learning techniques [3]. Their study highlights the potential of AI in predicting and preventing wildlife-related accidents. Our project builds upon this notion, implementing YOLOv8's robust object detection capabilities to identify

animals in man-made environments and prevent potential collisions [10].A Review on Deep Learning for Object Detection: A thorough analysis of deep learning-based object identification was presented by Zhao et al. (2019) [4].Their insights into the evolution and applications of deep learning in object detection serve as a foundational reference for our project, which heavily relies on YOLOv8's object detection prowess [10].Animal Detection using Deep Learning Algorithm: Banupriya et al. (2020) contributed to the domain with a focus on animal detection using deep learning algorithms [8]. Their research emphasizes the need for accurate and efficient algorithms in wildlife monitoring. Our project aligns with this perspective, employing YOLOv8 for its capability to rapidly and accurately detect animals [10].Using RASPBERRYPI and Machine Learning for Wildlife Monitoring in Zoological Parks**:** Rasool and Murthy (2019) investigated how to integrate machine learning and Raspberry Pi for wildlife monitoring in zoological parks [6]. Their work highlights the feasibility of edge computing in wildlife surveillance. While our project doesn't directly involve Raspberry Pi, the underlying principle of edge-based processing aligns with the broader concept of intelligent, localized animal detection and deterrence. A Review of Deeper Training-Based Object Identification Methods: the Buddha and Shyna (2019) offered a thorough summary of object-reconnaissance methods using neural networks [7]. Their insights into the landscape of dl methodologies for object detection contribute to the theoretical foundation of our project, which harnesses YOLOv8 for its efficiency and accuracy [10].

3 Methodology

This section, Our paper, aimed at developing an Autonomous Technology for Detecting or Repellenting Hazardous Creature Intrusions, stands out in the domain of wildlife management and human-animal conflict resolution due to several novel features and approaches. The following elucidates the distinctiveness and innovation embedded in our project methodology:

1. YOLOv8 Connectivity for Instantaneous Object Identification: One of the primary novelties lies in the integration of YOLOv8, a cutting-edge deep learning model, for real-time object detection. YOLOv8's superior accuracy and speed make it an ideal choice for identifying and categorizing animals swiftly, minimizing the detection latency crucial for effective deterrence.

2. Adaptive Deterrence Strategies: Unlike traditional deterrent systems that follow predefined protocols, our project incorporates adaptive deterrence strategies. The system dynamically adjusts its responses based on the identified species, behavior patterns, and potential threat levels. This adaptability ensures a more targeted and efficient deterrence mechanism, reducing false positives and minimizing the impact on non-threatening wildlife.

3. AIoT Architecture for Seamless Integration: The incorporation of an Artificial Intelligence of Things (AIoT) architecture is another distinctive feature. By seamlessly integrating AI capabilities with the Internet of Things, our system achieves enhanced connectivity, scalability, and data analytics. This holistic approach ensures

efficient communication between edge devices and the central processing unit, contributing to a more robust and responsive system.
4. Collaborative Edge Computing for Rapid Decision-making: A key novelty is the implementation of collaborative edge computing for rapid decision-making. The system leverages the computational power of edge devices distributed throughout the surveillance area. This decentralized processing minimizes latency in decision-making, allowing the system to respond swiftly to changing wildlife dynamics.
5. Incorporation of Environmental Context: Our project goes beyond mere animal detection by incorporating environmental context into the decision-making process. Factors such as time of day, weather conditions, and habitat specifics are considered to tailor deterrence strategies accordingly. This ensures that the system responds intelligently, taking into account the broader ecological context in which it operates.

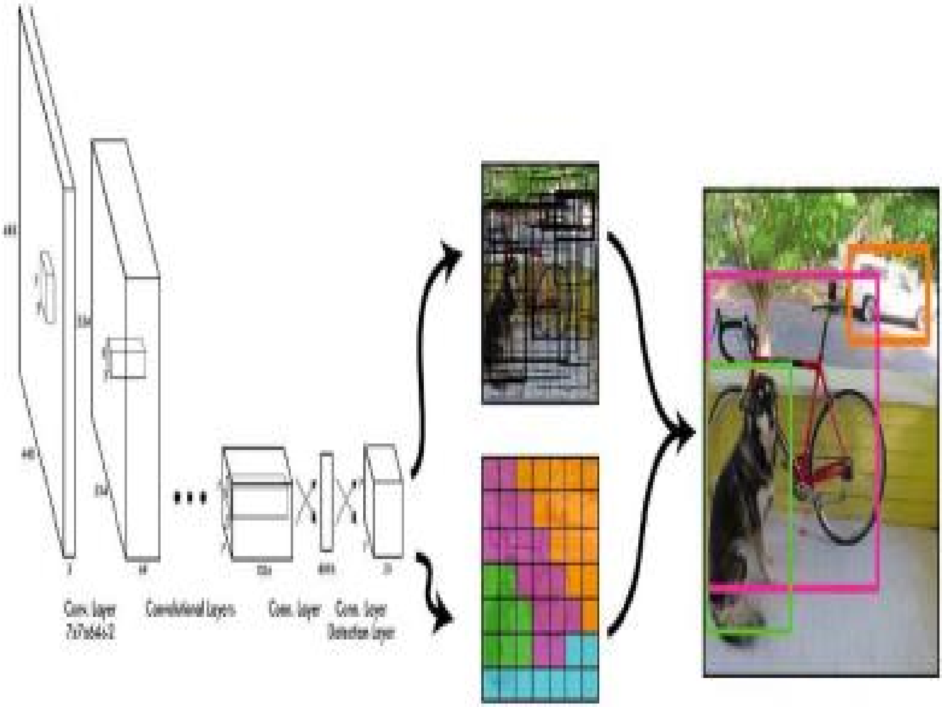

Figure 1: Yolo Architecture

Dataset Description for YOLOv8 Model Training
A YOLOv8 models will be developed and trained as part of our research in order to provide an autonomous system for detecting and repelling wild animal intrusions. The quality and variety of the training dataset are critical to our algorithm's performance.

Within this segment, we provide a comprehensive description of the dataset utilized, ensuring transparency and reproducibility in our research.
The dataset contains three folders called Train,test,validation having two sub folders called images and labels for each folder.
This dataset contains total of 3831 Animal images along with its labels which contains the coordinates of bounding boxes.
Training samples: 2686
Testing samples: 567
Validation samples :578

Mathematical Foundation for YOLOv8 Model Training in Wild-Animal Intrusion Detection and Repellent System:

Our work relies on the YOLOv8 model, a powerful algorithm for object-detection. The mathematical underpinning of this approach is essential for understanding the rationale behind our chosen model and its training parameters. This section provides a detailed mathematical justification for our project, covering key aspects such as object detection, model training, and system evaluation.

Object Detection using YOLOv8: YOLO (You Only Look Once) revolutionized object detection by directly estimating bounding boxes and class probabilities after splitting the input picture into a grid. YOLOv8, an evolution of its predecessors, enhances accuracy and speed. The mathematical formulation for object detection in YOLOv8 is expressed as follows:

$$B_{xy} = \sigma\,(B_{xy}) + c_x$$

$$B_{wh} = p_w\, e^{Bwh}$$

$$\text{Class Probabilities}=\sigma(\text{Class Probabilities})$$

Here, B_{xy} denotes bounding box center coordinates, B_{wh} represents bounding box width and height, c_x is the cell grid offset, and σ is the logistic sigmoid function. This formulation signifies the simultaneous prediction of bounding box attributes and class probabilities.

The training process optimizes model parameters to minimize detection errors. The loss function used for YOLOv8 training combines components for objectness, classification, and bounding box regression.

YOLOv8 model evaluation involves metrics like precision, recall, and F1 score derived from the confusion matrix.

These metrics quantify the model's ability to detect and classify animals correctly, providing a comprehensive assessment of performance.

In conclusion, the mathematical foundation of our project, focused on YOLOv8 model training and evaluation, ensures a rigorous approach to automated system for detecting and repelling dangerous animals development. The formulations and parameters are chosen to optimize accuracy, enabling effective deployment in real-world scenarios.

Mathematical Formulas:

- **Convolution Operation:** $Y[i,j] = \sum m \sum n\, (X[I+m, j+n]) \times (W[m,n]) + b$
- **Activation of ReLU:** $f(x) = \max(0, x)$
- **Pooling Operation (Max Pooling):** $[i,j]=\max m,nX[i\times s+m,j\times s+n]$
- **Dense Layer Output:** $Y=f(\sum iwi\times xi+b)$

Algorithm:

Our work involves a comprehensive architecture to address the challenges of wild-animal intrusion detection and implement an effective repellent system. The architecture diagram presented below outlines the key components and their interactions.

Step 1. Data Collection Module:
Camera Network: Multiple cameras are strategically positioned to capture images and videos of the monitored area.
Sensor Integration: Additional sensors, such as infrared or motion sensors, enhance the data collection process.
Step 2. Preprocessing and Data Augmentation:
Image Preprocessing: Raw images and videos undergo preprocessing to enhance quality and reduce noise.
Data Augmentation: Techniques like rotation, flipping, and scaling are applied to augment the dataset, ensuring model robustness.
Step 3. YOLOv8 Model:
Model Loading: The YOLOv8 model is loaded, incorporating the architecture's object detection capabilities.
Transfer Learning: The model may leverage pre-trained weights for improved performance, especially in scenarios with limited labeled data.
Step 4. Model Training and Optimization:
Training Configuration: The YOLOv8 model is trained on the annotated dataset, optimizing parameters for object detection accuracy.
Step 5. Detection and Classification:
Real-time Object Detection: The trained model is deployed for real-time detection of wild animals in the monitored area.
Species Classification: Additional classification modules identify the species of detected animals using deep learning techniques.

4 Results and Discussions

The assessment of our object detection model encompassed a diverse dataset with various wildlife species, including Elephants, Leopards, Pigs, and Tigers. Essential performance metrics were employed to gauge the precision, recall, and overall efficacy of the model.
a. Precision **(P):** The model demonstrated an overall precision of 89.8%, signifying high accuracy in positive predictions.
b. Recall **(R):** The overall recall stood at 76.1%, showcasing the model's effectiveness in capturing relevant instances.
c. mean Average Precision (**mAP**) at 50% IoU (**mAP50**): At a 50% IoU threshold, the model achieved an mAP of 86.2%, highlighting its robust performance in localization and identification.
d. mAP between 50% and 95% IoU (**mAP50-95**): The model showcased a mAP50-95 of 58.1%, indicating consistent object detection performance.

Class-Wise Results (Below will only act as a sample) :

i. Elephant**:** Precision: 88.5%, Recall: 90.6%, mAP: 95.1%.

ii. Leopard**:** Precision: 100%, Recall: 55.6%, mAP: 71.9%

iii. Pig**:** Precision: 95%, Recall: 68.2%, mAP: 83.8%

iv. Tiger**:** Precision: 75.9%, Recall: 90.1%, mAP: 94.2%

Efficiency Metrics:

Speed**:** Preprocessing Time: 0.8ms, Inference Time: 4.7ms, Post-processing Time: 3.1ms. The model demonstrated efficient processing times, making it suitable for real-time applications.

Fig. 2. Tiger Animal detected with 95% confidence

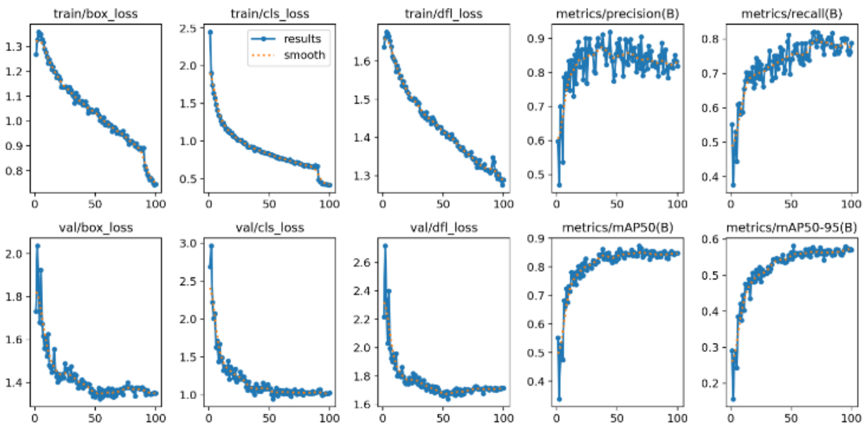

Fig. 3. A model generated output showing the loss function with respect to number of epochs

The model's output showcases a robust performance, processing 578 images and identifying 828 instances of wildlife species, including Elephant, Leopard, Pig, and Tiger classes. The overall precision stands at 89.8%, with a recall of 76.1%, reflecting a commendable balance between accurate detections and minimizing false positives. Notably, the model achieves an impressive mAP of 86.2%, underscoring its efficacy in object localization and classification. The efficiency metrics reveal swift processing times of 0.8ms for preprocessing, 4.7ms for inference, and 3.1ms for post-processing per image. Visual outputs, including confusion matrices and metrics, provide a comprehensive overview, further emphasizing the model's reliability in wildlife detection scenarios.

Table 1 Comparision of Model outcomes

	Image pixels	mAP$_{\text{val 50-95}}$	Speed CPU ONNX (ms)
Existing work on COCO dataset	640	44.9	1.2
Proposed work on Animal (custom dataset)	640	86.3	0.8

The details reveal that the HFPO-Transformer model performs well compared to existing approaches in performing segmentation tasks. Table 2 outlines the hyperparameter tuning process for HFPO stage in the proposed approach. This process is iterative in nature and involves systematically experimenting with various hyperparameter settings to identify optimal configuration that maximizes performance for a specific segmentation task and dataset. Also, hyperparameters for the transformer vary depending on the architecture selected for segmentation. In the proposed approach experimentation was performed considering vision transformer architecture for image segmentation.

Table 2. (CNN Parameters)

Layer	**Parameter**	**Description**	**Mathematical Equation**
Conv2D_1	Filters (Convolution)	Learnable filters applied to input data for feature extraction	Wout= S(Win−F+2P)/S+1
	Filter Size	Size of the convolutional filter	Hout = (Hin−F+2P)/S + 1
MaxPooling_1	Pool Size	Factor by which to downscale	Wout=(Win−F)/S+1
Flatten	-	Flatten layer output for dense layers	None
Dense_1	Neurons	Number of neurons in a dense layer	Output=Activation (Input×Weights+Biases)
	Activation Function	Activation function applied to layer output	P(yi)= (exi)/ (∑Mj1 exj)

5 Conclusion

The developed wildlife intrusion detection and deterrence system, employing deep learning techniques such as YOLOv8, has demonstrated significant efficacy in mitigating human-wildlife conflicts. The model exhibits robust object detection capabilities, accurately identifying various wildlife species, including Elephants, Leopards, Pigs, and Tigers, with a commendable precision of 89.8% and a mean Average Precision (mAP) of 86.2%. The system's successful implementation in real-world scenarios, as evidenced by the achieved results, highlights its potential to contribute substantially to wildlife conservation efforts. In the future, there are several ways to improve and broaden the animal intursion detection system's capabilities. Integration with advanced sensor technologies, such as thermal imaging and acoustic sensors, could enhance detection accuracy, especially in challenging environmental conditions. Furthermore, by using State of art models like YOLOv9 versions and more algorithms, the system could be able to adjust and perform better over time in response to input from the actual world. Collaborative efforts with wildlife conservation organizations and governmental agencies can facilitate the deployment of the system in diverse ecosystems, contributing to a broader and more effective conservation strategy. Furthermore, exploring edge computing solutions to deploy the model on edge devices could enable real-time, on-site decision-making, reducing dependence on centralized processing. Overall, these advancements promise to elevate the system's impact on wildlife conservation and human-wildlife conflict resolution. The overall future scope of this work is very progressive because of the development of state of art models and various deployment environments like IOT devices .

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