IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 1, November 2023

Guardians of Wild: Artificial Intelligence for Wildlife Conservation

Shubham Shrihari Gade, Rushikesh Machhindra Dhole and Prof. D. S. Sisodiya

Department of Artificial Intelligence & Data Science

ISBM College of Engineering, Nande, Pune, India

shubhamgade0802@gmail.com,rushikeshdhole220@gmail.com,

rushikeshdhole220@gmail.com , dharamveersisodiya4@gmail.com

Abstract*: A growing number of animal species are in danger of being extinct or becoming endangered, making wildlife conservation an essential global responsibility. Cutting edge methods in computer vision, such as deep learning models for object detection, provide exciting new possibilities for wildlife preservation and monitoring. The most recent research on using cutting-edge object identification algorithms, particularly YOLOv8, for animal conservation initiatives is reviewed in this review paper. We review important works that use deep learning to identify poaching and classify animal species. We analyse deep learning systems designed for wildlife conservation, including their performance benchmarks, operational deployments, training approaches, and algorithm design. The review outlines the key takeaways from the body of research and suggests future research avenues to address the challenging issue of scaling AI to stop the loss of biodiversity and protect threatened species around the world.*

Keywords: Object Detection, Poaching Detection, Deep Learning, Convolutional Neural Network, YOLOv8, Bounding Box Detection

I. INTRODUCTION

The need to conserve wildlife has grown in importance in recent years as poaching, habitat degradation, and conflicts between humans and wildlife have become greater threats to animal populations worldwide. Because they allow for automatic monitoring and analysis of animal species populations and activities, intelligent computer vision techniques have the potential to completely transform conservation efforts. Deep learning has become a game-changing tool for tasks involving object recognition, such as identifying wildlife. Specifically, the object detectors in the YOLO (You Only Look Once) family have shown to be quite successful in real-time visual data analysis. This paper summarizes important scientific contributions that tackle important issues in animal conservation, like species classification and poacher detection, using YOLO models and other deep learning methods.

We carefully review significant research that have created artificial intelligence (AI) systems with the newest deep neural networks to save threatened species and stop the loss of biodiversity. The entire pipeline including data collection, model training, deployment topologies, and real-world performance is covered by our analysis. We showcase innovative initiatives that effectively showcase the use of deep learning techniques in field conservation applications. The evaluation also covers important deployment obstacles, such as restricted data availability. In conclusion, we provide a summary of the most important findings from the analysis of the literature and suggest future lines of inquiry for this fascinating field at the nexus of artificial intelligence and conservation biology.

II. LITERATURE SURVEY

Research on artificial intelligence (AI) methods for automated wildlife monitoring and protection has been spurred by the dangers to world biodiversity. The papers review recent efforts that use deep learning for tracking, counting, and classifying animals in order to accomplish conservation goals.

[1]Wildlife Identification using Object Detection using Computer Vision and YOLO: Mehta et al. evaluate YOLO for real-time detection in camera traps, pointing out that it is faster and has a lower mean area percentage than classifiers. They talk about how to handle complicated scenarios using improved models that use contextual reasoning

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 1, November 2023

and multi-scale processing. An overview of training methods, restrictions such as small object detection, and performance indicators such as IOU and mAP are provided by the work.

[2] Wild Animal Intrusion Detection System Using Yolov8: For the purpose of animal intrusion detection, Mrs. R. Gayathri et al. compare YOLOv8 with earlier iterations. They state that YOLOv8 performs noticeably better than previous models, achieving over 70% accuracy for important species. The study suggests employing Internet of Things sensors and notifications to notify authorities and avoid conflicts between wildlife and humans. Wenzhao Feng et al. create an ideal image transmission protocol for wireless networks with limited bandwidth so that static cameras can monitor wildlife. They select regions of interest and send only relevant data by using saliency detection and segmentation. The method maintains detection accuracy while increasing transmission efficiency.

[3]Conservation AI: Live Stream Analysis for the Detection of Endangered Species Using Convolutional Neural Networks and Drone Technology: Chalmers et al. provide a pipeline that achieves 83% mAP in real-time rhino and automobile detection utilizing drone-captured video, the Faster R-CNN model, and cloud inferencing. To strike a compromise between speed and accuracy, they suggest adaptive frame sampling. According to the study, R-CNNs can resolve issues with lightweight models such as YOLO when dealing with small, far-off, or obscured objects.

[4]Poacher Detection using YOLO Algorithm: YOLO and aerial drones are used to detect poachers, as demonstrated by Shreya Shivaji Gaikwad et al. They contend that for this use case, YOLO's speed and accuracy outperform methods like Faster R-CNN. To enable real-time monitoring, the article suggests using on-drone inferencing and optimizing training.

[5]Evaluating YOLO-based Object Detectors for Detecting Road-Killed Endangered Brazilian Animals: For the purpose of identifying frequently poached species, Gabriel Ferrante et al. benchmark YOLO models against a dataset of Brazilian wildlife. Recall is highest for Scaled-YOLOv4, and speed is optimized for YOLOv5-Nano. Transfer learning and data augmentation make up for a lack of training data. Image variability causes differences in performance between species.

[6]Poaching Detection Technologies—A Survey: Sensor technologies for poacher detection systems, such as radar, infrared, acoustic, seismic, etc., are surveyed by Jacob Kamminga et al. Using a combination of machine learning and multiple sensors, they suggest "cognitive sensor networks" to improve detection. The challenge of detecting intrusions quickly, accurately, and with few false alarms is still open.

[7]Deep Learning for Wildlife Conservation and Restoration Efforts: The Tidzam AI system, which uses deep learning for wildlife conservation and monitoring at the Tidmarsh wildlife sanctuary, which is undergoing ecological restoration, is described in the paper. To detect and identify animal species based on sounds gathered from microphones placed throughout the sanctuary, it uses a convolutional neural network classifier trained on wildlife vocalizations. To increase the size of the training dataset and improve the models, professionals are hired by Tidplay, a crowdsourcing platform, to annotate recordings. Additionally, computer vision methods such as YOLO are used to analyze thermal camera feeds in order to detect animals.

After three years of operation, the system has helped Tidmarsh's conservation efforts by offering insights into species presence and activities. Compared to manual surveys or conventional signal processing, deep learning considerably improves large-scale automated biodiversity monitoring.

Rare species detection, model generalization across habitats, real-time optimized performance, and realistic deployment constraints are still areas of difficulty, Work in progress centers on low-power deployments in remote environments such as the Amazon, multimodal data fusion, and high-resolution processing using NAS networks.

III. PROPOSED MODEL

In order to identify potential threats in wildlife areas, object detection, image recognition, and real-time monitoring are combined to create a robust model for poaching detection using YOLOv8. This is a suggested example of an architecture:

Architecture Model:

1. Gathering and preprocessing data:

Collecting Datasets: Compile a varied dataset of pictures and videos showing wildlife, both with and without signs of poaching. To differentiate between legitimate operations and possible poaching incidents, label these data.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 1, November 2023

Data Augmentation: To improve model generalization, apply transformations to the dataset, such as rotation, scaling, flipping, and adding noise.

2. Integration of YOLOv8:

YOLOv8 Object Detection: Use the real-time object detection system, YOLOv8 architecture, as the foundation for object identification in pictures and videos. This one-stage detector is well-known for its quickness.

3. Optimizing to Find and Stop Poaching:

The process of anomaly detection involves teaching the model to identify unusual actions or items, like guns, traps, or human presence in areas designated for the protection of wildlife.

4. Mechanism for Alarm and Alert:

Create alerts by setting up the system to send out notifications or alerts in the event that any possible poaching incidents or questionable activity are discovered. One possible use for this would be to notify authorities or wildlife rangers.

5. Feedback Loop for Continuous Improvement:

Establish a feedback mechanism so that the model updates itself to increase accuracy and decrease false positives by learning from new incidents.

Frequent Model Assessment: Make sure the model is accurate and efficient at identifying poaching activity by conducting regular evaluations.

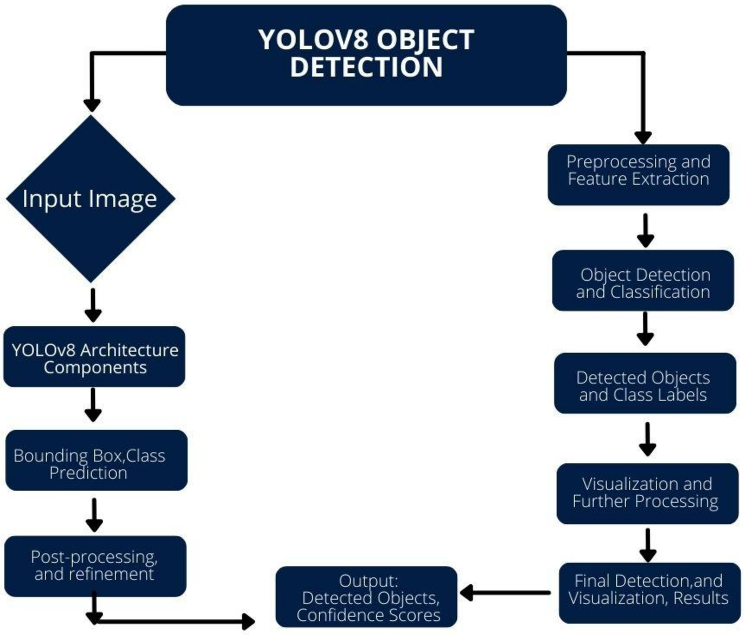

FIGURE 1: SYSTEM ARCHITECTURE FOR THE PROPOSED MODEL

IV. CONCLUSION

A promising technological frontier for wildlife conservation is the application of Deep Learning, specifically Convolutional Neural Networks (CNNs) and YOLOv8, in poaching detection and animal species identification. The study shows how well CNNs work to automatically extract features from pictures and video frames, which can help distinguish between different animal species and possible threats in protected areas. Furthermore, YOLOv8's quick object detection features provide real-time monitoring and identification of items or people connected to poaching incidents.

These technologies have a lot of promise, but there are obstacles in the way of their successful implementation. Important challenges that require more investigation and resolution include those pertaining to data quality, model robustness, real-time detection, ethical considerations, and the requirement for constant adaptation.

Multi-sensor data integration, continuous learning techniques, moral AI policies, and enhanced cooperation between law enforcement and conservation groups are critical to the field's future. For these technologies to be deployed responsibly and effectively in remote wildlife areas, advances in sustainability, scalability, and privacy-preserving techniques are imperative.

In conclusion, even though YOLOv8 and deep learning CNNs show great promise for wildlife conservation, resolving issues and considering new avenues are essential to realizing the full potential of these technologies and, eventually, safeguarding and conserving the variety of wildlife on our planet.The development of intelligent surveillance systems that can simultaneously identify and track animals in their natural habitats and detect poachers is made easier by the integration of YOLOv8 with CNNs. In addition to helping to stop poaching, these systems support population monitoring, research on wildlife, and general conservation tactics. By giving wildlife organizations, conservationists, and authorities the tools they need to effectively monitor and protect endangered species, the application of this technology offers real-time insights and data that can greatly enhance conservation efforts. In the battle against poaching, the conservation community gains a potent ally by utilizing YOLOv8 and deep learning CNNs for animal species detection. This approach offers a proactive and cutting edge way to protect our planet's diverse and vulnerable wildlife.

REFERENCES

[1]. Prasham Mehta, Keval Shah, Rohit Raval, Manan Shah (2023). “Wildlife Identification using Object Detection using Computer Vision and YOLO”. *International Research Journal of Engineering and Technology* , e-ISSN: 2395-0056, p-ISSN: 2395-0072.

[2]. Mrs. R. Gayathri , P. Hannah Princy, P. Krishandhini (2023). “WILD ANIMAL INTRUSION DETECTION SYSTEM USING YOLOV8”. *International Research Journal of Modernization in Engineering Technology and Science,* e-ISSN: 2582-5208.

[3]. C. Chalmers, P.Fergus, Serge Wich and Aday Curbelo Montanez (2019). “Conservation AI: Live Stream Analysis for the Detection of Endangered Species Using Convolutional Neural Networks and Drone Technology”. arXiv:1910.07360, https://doi.org/10.48550/arXiv.1910.07360 .

[4]. Shreya Shivaji Gaikwad, Pranit Mohan Mhatre, Cyril Silvester Dabre, Ms. Nazneen Ansari (2021). “Poacher Detection using YOLO Algorithm”, ISSN: 2278-0181.

[5]. Gabriel SoutoFerrante, Luis Hideo Vasconcelos Nakamura , Sandra Sampaio, Geraldo Pereira Rocha Filho, and Rodolfo IpolitoMeneguette. “Evaluating YOLO-based Object Detectors for Detecting Road-Killed Endangered Brazilian Animals” https://doi.org/10.21203/rs.3.rs-3225864/v1

[6]. Jacob KammingaID ,EyuelAyele ID , Nirvana Meratnia and Paul Havinga * (8 May 2018). “Poaching Detection Technologies—A Survey “. Sensors (Basel). 2018 May; 18(5): 1474.,Published online 2018 May 8,PMCID: PMC5982520, PMID: 29738501. doi: 10.3390/s18051474

[7]. Clement Duhart , Gershon Dublon , Brian Mayton , Glorianna Davenport , Joseph A. Paradiso(2019/6). “Deep Learning for Wildlife Conservation and Restoration Efforts”. 36th International conference on machine learning, Long Beach., PMLR. https://www.climatechange.ai/papers/icml2019/31/paper.pdf