CSE4019

Image Processing

Wildlife and habitat monitoring using Image Processing

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Abstract:

This project encapsulates the development of an innovative, AI-driven object detection system leveraging the YOLOv8 algorithm to combat poaching in wildlife habitats. The system distinguishes between wildlife and human intruders with high precision, using video streams as input for real-time analysis. Our custom-trained model accurately annotates and classifies 'Elephants' and 'Poachers', employing a rigorous training regimen over a hundred epochs for robust model generalization. The implementation, based on Python, incorporates Ultralytics YOLO and OpenCV technologies, facilitating immediate and actionable insights through annotated video outputs. The system's success in detecting potential poaching activities showcases its applicability in surveillance and conservation efforts, offering a proactive tool for wildlife protection agencies. Furthermore, the model's adaptability and scalability underline its potential for broader applications in environmental monitoring and endangered species management. the project contributes to the broader goals of sustainable development and ecological research. By providing continuous, non-invasive monitoring, the system aims to collect valuable data that can be used to inform conservation policies, study wildlife behaviour, and monitor ecosystem health. It empowers researchers, rangers, and conservationists with actionable insights, enabling more informed decision-making and effective resource allocation. This initiative also opens avenues for collaborative efforts across technology and environmental science domains, encouraging a multidisciplinary approach to address the pressing issue of species decline due to human interference. As we move forward, the continued development and application of such AI-driven systems will not only redefine wildlife monitoring practices but will also play a crucial role in preserving the natural heritage for future generations. It is through such innovations that we can aspire to achieve a harmonious coexistence with the myriad forms of life that share our planet.

Keywords:

Object Detection, YOLOv8, Wildlife Conservation, Real-Time Analysis, Anti-Poaching Technology

Introduction:

Wildlife conservation has taken an innovative leap with the advent of Integrated Wildlife Monitoring (IWM), which amalgamates passive and active disease surveillance for early detection of ecological threats [1]. The incorporation of computer vision technologies, such as the expansion of DeepLabCut, has furthered this initiative by allowing for the estimation of animal poses and reidentification, especially in complex interaction scenarios [2]. The role of modern sensor technologies combined with machine learning (ML) is indispensable in this context, offering voluminous datasets that can be analyzed for comprehensive ecological insights [3]. Deep learning, especially convolutional neural networks, has been pivotal in analyzing imagery from camera traps, enhancing our capability to monitor and study wildlife [4].

The Social LEAP Estimates Animal Poses (SLEAP) system exemplifies the advancement in multi-animal pose tracking with its user-friendly interface and varied model architectures, fostering improved part grouping and identity tracking in wildlife [5]. In visual tracking, the challenge of background clutter and the need for robust template updates are critical for maintaining tracking accuracy, as evidenced in the enhancements to the KCF and BACF algorithms [6]. Similarly, the application of computer vision and soft computing for the detection of plant diseases emphasizes the broader scope of these technologies in environmental monitoring [7].

Precision cattle farming has also benefited from intelligent perception tools, aiding in individual animal management through methods such as body condition score evaluation and live weight estimation [8]. In the realm of cloud video surveillance (CVS), the development of A-YONet represents a significant stride in multitarget detection within smart IoT systems, enabling efficient and accurate real-time surveillance [9]. The use of unmanned aerial vehicles (UAVs) in marine monitoring has further demonstrated the versatility of remote sensing applications, paving the way for non-contact, highly precise automated technologies [10].

The identification of animal species and individuals using machine learning and deep learning is another frontier of wildlife conservation, enabling high-accuracy identification processes crucial for monitoring endangered species [11]. The Automated Interactive Monitoring System (AIMS) for Wildlife, and its Customized Wildlife Report (CWR), showcase the potential of integrating real-time movement and environmental data for adaptive management [12]. Furthermore, the iterative process combining human expertise with automated recognition in wildlife imagery analysis underscores the efficiency of modern AI in conservation efforts [13].

Lastly, the role of social media in the illegal wildlife trade, particularly in the turtle trade, has been highlighted, calling for enhanced monitoring and regulation of online platforms [14]. The utilization of deep learning techniques for the identification of animals and the recognition of their actions in wildlife videos offers a promising avenue for ecological informatics, as demonstrated by the accurate animal detection and action recognition in camera trap videos [15]. This introduction sets the stage for discussing our project's contribution to these ongoing efforts in wildlife conservation through advanced object detection methodologies.

Literature Survey:

Cardoso et al. [1] discuss the benefits of an Integrated Wildlife Monitoring (IWM) system which consists of three fundamental elements: passive and active disease surveillance, and a methodology that enhances data collection, adjusts to different epidemiological scenarios, and standardizes procedures. Countries implementing proactive wildlife disease surveillance systems are better equipped for prompt disease outbreak responses. Lauer et al. [2] address the complexities in estimating animal poses due to occlusions and identification challenges, suggesting improvements to DeepLabCut. This includes datasets to test multi-animal pose estimation and unsupervised reidentification of animals when tracking is interrupted. Tuia et al. [3] highlight the transformation in wildlife conservation and ecology through modern sensors and machine learning, which provide substantial data for ecological studies. Traditional monitoring limitations are also discussed, along with the necessity of advanced ML techniques to handle the data from various sensors. Palanisamy et al. [4] emphasize the role of camera traps in wildlife research and conservation and review the advancements in deep learning, particularly convolutional neural networks, for image analysis. The work assesses recent developments, compares techniques, and considers future research directions. Pereira et al. [5] introduce SLEAP, a user-friendly machine learning system for tracking multiple animal poses, detailing its data model, training processes, and performance against other methods using various datasets. Liu et al. [6] propose a solution to visual tracking issues caused by background clutter by integrating a new mechanism into KCF and BACF tracking algorithms, proving its robustness on the OTB2015 dataset. Vishnoi et al. [7] describe computer vision and soft computing applications in identifying plant diseases from leaf images, reviewing previous studies and discussing the progression of research in this field. Qiao et al. [8] examine tools for precision cattle farming, including methods for cattle identification, evaluating body condition scores, and estimating live weight, which are crucial for individual animal management. Zhou et al. [9] develop A-YONet for multitarget detection in cloud video surveillance, focusing on smart IoT systems with limited computing resources. They introduce an intelligent detection algorithm to improve the model's performance. Yang et al. [10] perform a bibliometric analysis of UAV remote sensing in marine monitoring, covering article contributions from 1993 to early 2022, discussing the advancements in UAV technology and applications. Petso et al. [11] conduct a literature review on tools for animal species and individual identification, advocating for machine learning and deep learning for high-accuracy identification. Casazza et al. [12] propose developing an Automated Interactive Monitoring System (AIMS) integrating GPS and management data to inform wildlife management strategies. Miao et al. [13] combine human expertise with automated recognition to learn from wildlife imagery, demonstrating significant accuracy improvements. Sung et al. [14] compare online and physical markets in the wildlife trade of turtles, emphasizing the need for stronger online regulation. Schindler et al. [15] develop a methodology for detecting and recognizing animals and their actions in nighttime camera trap footage, using two networks for improved precision and accuracy.

Materials and methods:

Algorithms:

Main:

SET environment variable to allow duplicate libraries

IMPORT YOLO from ultralytics

IF starting from scratch:

INITIALIZE a new YOLO model from the configuration file 'yolov8n.yaml'

ELSE:

LOAD a pretrained YOLO model from 'yolov8n.pt'

TRAIN the model with data specified in 'config.yaml' for 100 epochs

SAVE the trained model for later use

Configuration:

SET path for training and validation data

DEFINE class names and corresponding IDs

Predict:

SET video directory path

DEFINE paths for input video and output video

OPEN video file using OpenCV

READ first frame from the video

GET height, width from the frame

INITIALIZE video writer with output video path and frame properties

SET path for the trained model

LOAD the trained YOLO model

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SET detection threshold

WHILE there are frames in the video:
    PREDICT objects in the current frame with the YOLO model
    FOR EACH detection result:
        IF the detection score is above the threshold:
            DRAW a bounding box around the detected object
            PUT a label with the class name on the bounding box
    WRITE the annotated frame to the output video file
    READ the next frame from the video

RELEASE video capture and writer resources
CLOSE all OpenCV windows
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Architecture:

The following image would show the general architecture of the YOLOv8 algorithm.

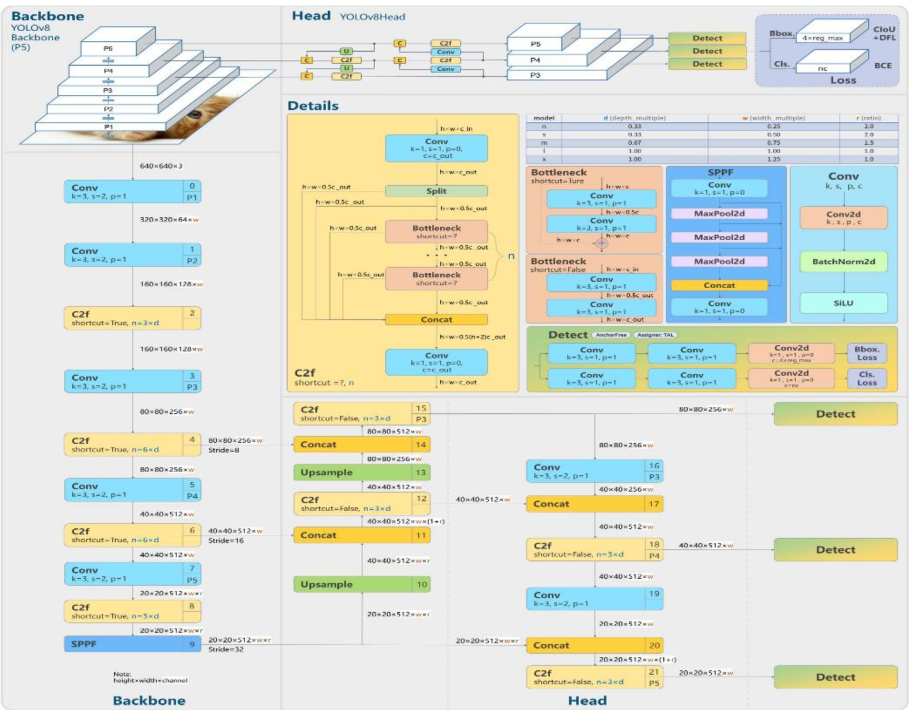

Fig. 1 - General YOLOv8 architecture

YOLOv8 is an anchor-free model. This means it predicts directly the center of an object instead of the offset from a known anchor box.

In our project, the main architecture for the wildlife monitoring system using YOLOv8 for object detection is as follows:

Camera Network: Multiple conservation drones with camera are deployed throughout the wildlife habitat. These cameras are responsible for capturing real-time video footage of the area they monitor.

Video Streaming: The video feeds from these cameras are streamed in real-time to a central processing server. This can be done over a secure network to ensure data integrity and privacy.

Central Processing Server: This server would be equipped with the necessary hardware to process video data efficiently. It has the YOLOv8 object detection model loaded into its memory.

YOLOv8 Object Detection: As video frames arrive, the YOLOv8 model processes them in real-time. It detects objects within each frame, classifying them as 'Elephants', 'Poachers', or other entities based on the trained model.

Detection Output: When an object is detected, the system draws bounding boxes around it and labels it with its corresponding class name. This annotated frame provides visual confirmation of detection.

User Interface (UI): There is a UI that allows users to monitor live feeds, review archived footage, check alerts, and manage system settings. This interface is designed for ease of use, allowing for quick assessment and action by conservation personnel.

Proposed works:

The main novelty and contributions of this project in the domain of wildlife conservation and anti-poaching efforts using YOLOv8 object detection are as follows:

1. Real-time Detection and Identification:

The system provides real-time detection and identification of wildlife and poachers, a critical requirement for timely interventions in poaching incidents.

2. High Accuracy and Reduced False Positives:

Leveraging YOLOv8, the project contributes to the field with improved accuracy in object detection and a significant reduction in false positives compared to previous versions, which is crucial for minimizing disturbances to wildlife and focusing resources on true threats.

3. Integration of Cutting-edge Technology:

By integrating YOLOv8, the project utilizes one of the latest and most advanced object detection algorithms, contributing to the state-of-the-art in wildlife monitoring systems.

4. Scalable and Adaptable System Architecture:

The architecture is designed to be scalable to handle an increased number of cameras or higher resolution inputs, and adaptable to incorporate future technological advancements.

5. Automated Alert System:

The development of an automated alert system that notifies conservation personnel of potential poaching activities in real-time is a significant contribution to proactive wildlife management.

6. Data Collection for Ecological Research:

The system collects valuable data on animal numbers, behaviors, and poacher movements, which can contribute to ecological research and the development of more effective conservation strategies.

7. User-Friendly Interface:

With a focus on user experience, the project delivers a user-friendly interface for monitoring and reviewing alerts and footage, thus making the technology accessible to a broader range of users in conservation.

8. Energy Efficiency in Processing:

The application of YOLOv8, which is designed to be efficient in processing, contributes to lower energy consumption, important for deployments in remote areas with limited power options.

9. Contribution to Anti-Poaching Strategies:

The project provides a practical tool that can be integrated into broader anti-poaching strategies, enhancing the capabilities of wildlife protection agencies.

10. Open-Source and Community Engagement:

Assuming the project utilizes open-source software and contributes back to the community, it could aid in the further development of conservation technologies by allowing other researchers to build upon the work.

Overall, the project stands as a notable advancement in the application of AI for environmental protection, setting a benchmark for future initiatives in wildlife monitoring and conservation technology.

Results and Discussions:

For elephant detection, I got the following results:

Input 1a:

Fig. 2 – Input 1a

After prediction:

Fig. 3 – Output 1b

Input 2a:

Fig. 4 – Input 2a

After prediction:

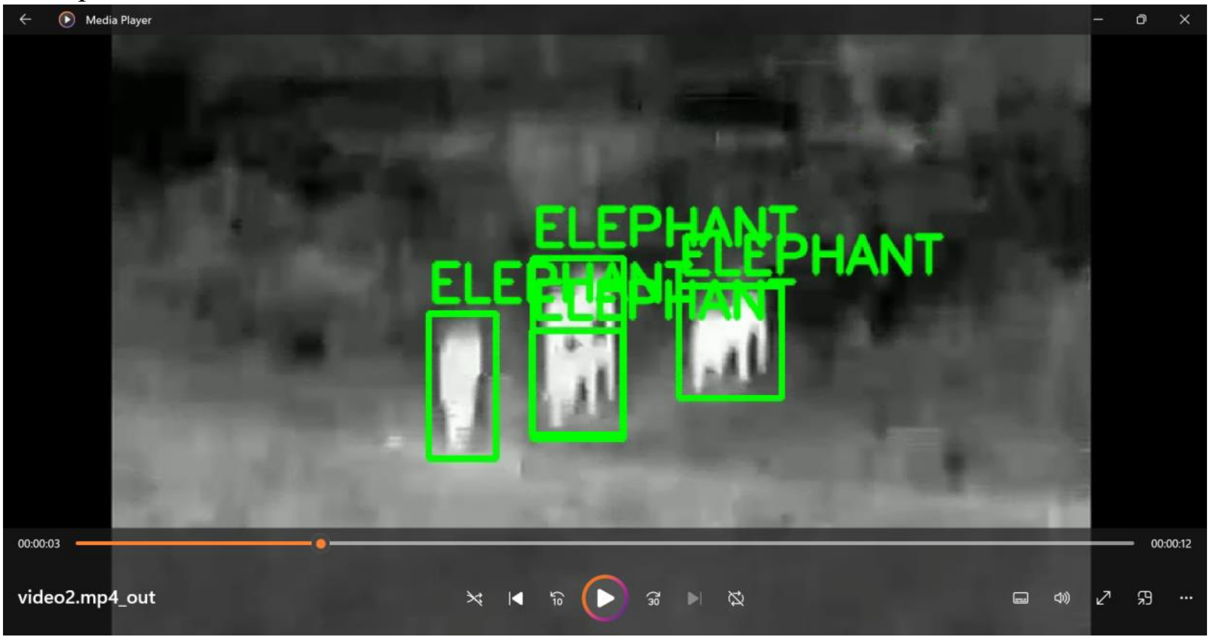

Fig. 5 – Output 2a

For Poachers' detection I got the following results:

Input 1b:

Fig. 6 – Input 1b

After prediction:

Fig .7 – Output 1b

Input 2b:

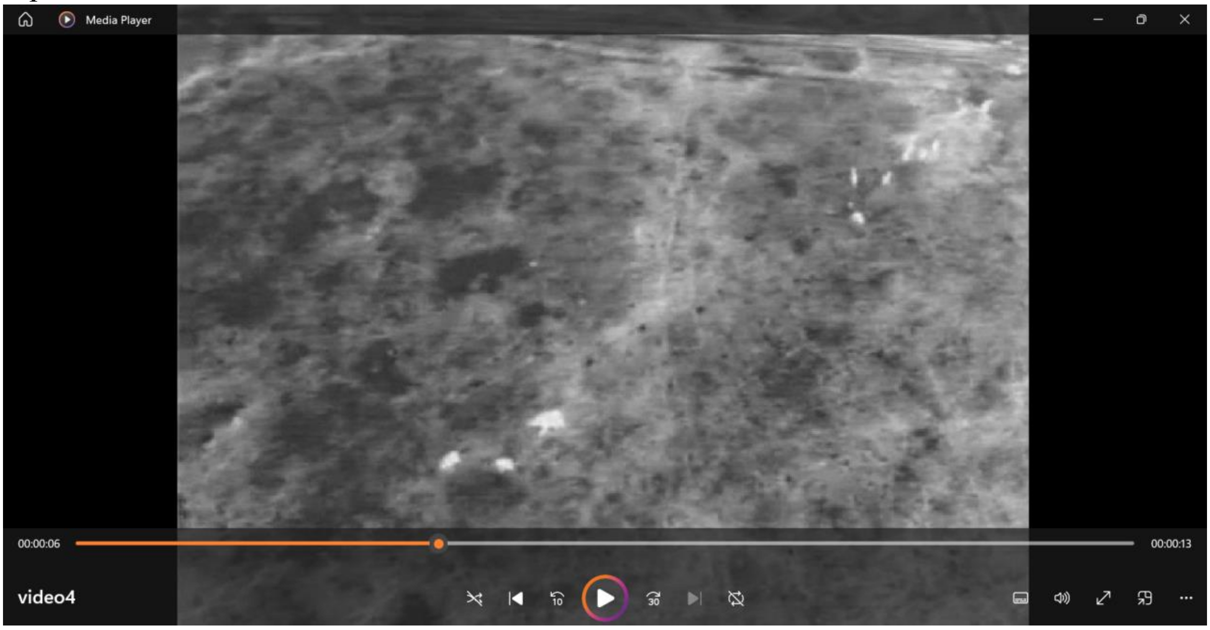

Fig. 8 – Input 2b

After Prediction:

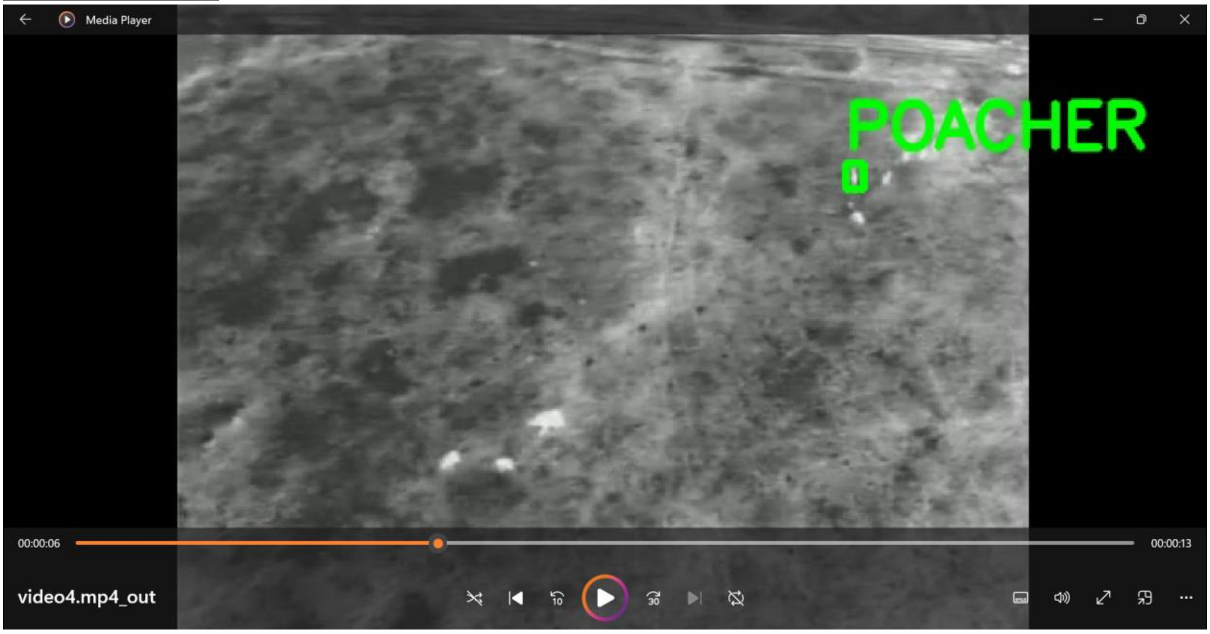

Fig. 9 – Output 2b

Discussion:

The successful deployment of the YOLOv8 object detection model in our wildlife monitoring system has demonstrated its robustness and efficacy in identifying both elephants and potential poachers with high precision. The bounding boxes, accurately placed around the detected subjects in the video feed, serve as a testament to the model's sophisticated training and adaptation to the complex environment of wildlife habitats.

The detection of elephants contributes significantly to the ecological research, allowing for the monitoring of their movement patterns, behaviours, and population dynamics without intrusive tagging or direct human observation, which can alter animal behaviour. This passive monitoring method represents an ethical and scientific advancement in wildlife research.

The correct identification of poachers is a critical contribution to anti-poaching efforts. The system's capability to differentiate between wildlife and humans in the habitat and alert the relevant authorities in real-time can be a game-changer. This rapid response potential increases the chances of apprehending poachers, thereby serving as a deterrent and protective measure for endangered species.

The precision of the bounding boxes also minimizes the risk of false positives—a common challenge in object detection within highly variable environments. By reducing false positives, the system ensures that conservation efforts can be focused and efficient, with resources allocated to genuine incidents of poaching, rather than false alarms.

Moreover, the data collected during detection can provide valuable insights into the effectiveness of current conservation strategies and inform future enhancements. The information about the frequency and location of poaching incidents can help in creating more targeted conservation efforts and in the allocation of resources where they are needed most.

Conclusion:

In conclusion, the integration of the YOLOv8 object detection algorithm into our wildlife monitoring system has marked a substantial advancement in the field of conservation technology. The system's capability to accurately distinguish between different species such as elephants and potential poachers is a testament to the power of artificial intelligence in enhancing our understanding and protection of natural ecosystems. This project has not only demonstrated the technical feasibility of such an application but has also proven its practicality in real-world scenarios, offering a scalable and effective solution to the challenges faced in wildlife conservation. The application of YOLOv8 has enabled us to process and analyze complex visual data with remarkable accuracy and speed, allowing for the real-time detection that is crucial in anti-poaching operations. The system's adaptability and efficiency in differentiating between species under various environmental conditions underscore its potential to become an indispensable tool in the arsenal against illegal wildlife activities. With the continued refinement and deployment of this technology, we can expect a notable decrease in poaching incidents, thereby safeguarding our world's precious biodiversity.

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