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Wild Animal Detection and Alert System Using YOLOv8

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Abstract : This study endeavors to autonomously identify crucial characteristics in wild animal detection without human intervention. Utilizing a wealth of wildlife images, the system autonomously learns distinctive features for various animal species, harnessing the computational efficiency of YOLOv8. In this article, we propose a novel implementation of a wild animal detection and alert system employing YOLOv8. Deep learning models like YOLOv8 have demonstrated remarkable efficacy in identifying animals in diverse habitats. By integrating with Telegram, the system disseminates real-time alerts to a designated group, accommodating an unlimited number of participants. This integration holds promise for enhancing wildlife conservation efforts, providing timely notifications to stakeholders and facilitating swift responses to wildlife sightings, thereby bolstering conservation initiatives and minimizing human-wildlife conflicts.

Keywords - Detection of wildlife, identification of objects, employing YOLOv8, and continuous real-time surveillance.

I. INTRODUCTION

The tiger, a magnificent apex predator, stands as a symbol of Asia's diverse and rich wildlife. Unfortunately, their numbers have seen a drastic decline over the years, plummeting from over 100,000 in the early 20th century to a mere 4,000 today. This decline is largely attributed to factors such as habitat destruction, illegal trade, poaching, and the impact of excessive tourism.

The approach outlined in this study presents a comprehensive strategy aimed at seamlessly blending advanced technologies into wildlife monitoring and conservation efforts.

Fig1 shows the methodology and implementation of weapons detection using deep learning.

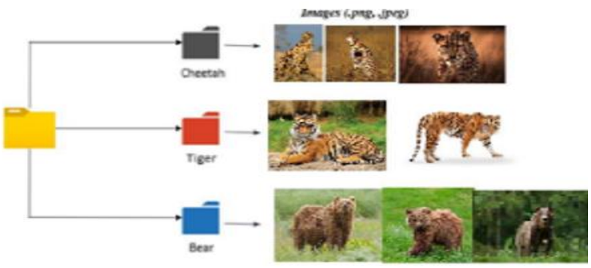

Fig:1 Methodology

It incorporates various essential elements, such as leveraging YOLOv8 for real-time identification of wildlife activities, establishing edge computing systems for efficient data processing, and integrating instant messaging platforms for swift dissemination of notifications. This methodology is grounded in the goal of enhancing the efficacy and efficiency of surveillance techniques, bridging the traditional methods with state-of-the-art technology. Through the implementation of these innovative tools and methods, the project seeks to empower conservationists with timely, data-driven insights to inform decision-making processes and contribute significantly to the safeguarding of our natural ecosystems.

SYSTEM ARCHITECTURE

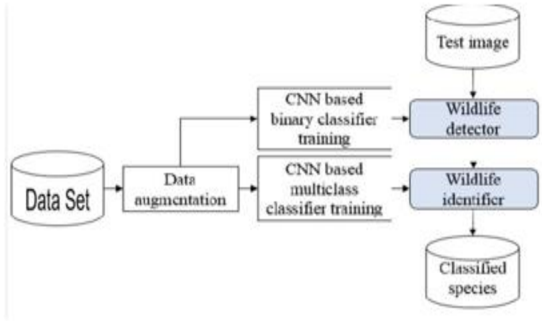

Fig:2 System architecture

II. SYSTEM ANALYSIS AND EXISTING SYSTEM

Current wildlife monitoring systems face various limitations, including the restricted coverage of manual patrols by park rangers, the frequent maintenance required for motion-triggered camera traps, the high costs and short ranges of radio collars, the expense and infrequency of aerial surveys conducted by aircraft, and the delayed data access and expense associated with satellite tracking. Emerging AI wildlife cameras show promise with their integration of artificial intelligence, but they are hindered by their limited field of view. Thus, there is a pressing need for automated, wide-area, and real-time monitoring solutions to overcome these challenges and enhance the wild life conservation efforts.

III. PROPOSED SYSTEM

The proposed system is an integrated solution that combines deep learning and instant messaging technologies to revolutionize wildlife surveillance and conservation efforts in natural habitats. By leveraging advanced deep learning algorithms, the system can recognize and track wildlife activity in real-time, triggering immediate notifications to forest officers and relevant stakeholders through readily available messaging platforms. This seamless integration, along with the utilization of edge computing, enables continuous, cost-effective, and efficient surveillance, bridging the gap between traditional methods and modern technology. The primary goal is to empower conservationists with timely and actionable information, enhancing data-driven decision- making to mitigate habitat degradation and illegal activities, ultimately contributing significantly to the preservation of ecosystems and wildlife.

IV. IMPLEMENTATION MODULE DESCRIPTION

CNN: A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data.

When it comes to Machine Learning, Artificial Neural Network performs really well. Neural Networks are used in various datasets like images, audio and texts.

YOLOv8: YOLOv8, an abbreviation for You Only Look Once version 8, is a cutting-edge convolutional neural network (CNN) architecture widely utilized in computer vision applications. Renowned for its real-time object detection capabilities, YOLOv8 enables rapid and precise identification and classification of objects within visual data.

In the realm of machine learning, YOLOv8 is highly regarded for its versatility across diverse datasets, including images, audio, and text. Its advanced neural network design empowers it to excel in various tasks, from image classification to scene understanding and semantic segmentation.

Implementation Steps:

1. Model Architecture: The system will utilize an advanced object detection model known as YOLOv8 for the purpose of detecting and categorizing different animal species.
2. Training Data Split: The labeled dataset will undergo a randomized division into training, validation, and testing subsets. The training subset will serve the purpose of training the YOLOv8 model, while the validation subset will facilitate hyperparameter tuning and monitor model performance during training. Lastly, the testing subset will be employed to gauge the final efficacy of the model on unseen data.
3. Hyperparameter Optimization Techniques like grid search or Bayesian optimization will be utilized to fine-tune the hyperparameters of the YOLOv8 model, aiming to achieve optimal performance.
4. Model Training: The training phase will entail the utilization of suitable optimization algorithms and learning rate schedules to train the YOLOv8 model on the training subset. Continuous Monitoring of the training process will be carried out, with the possibility of implementing early stopping mechanism to mitigate overfitting risks.

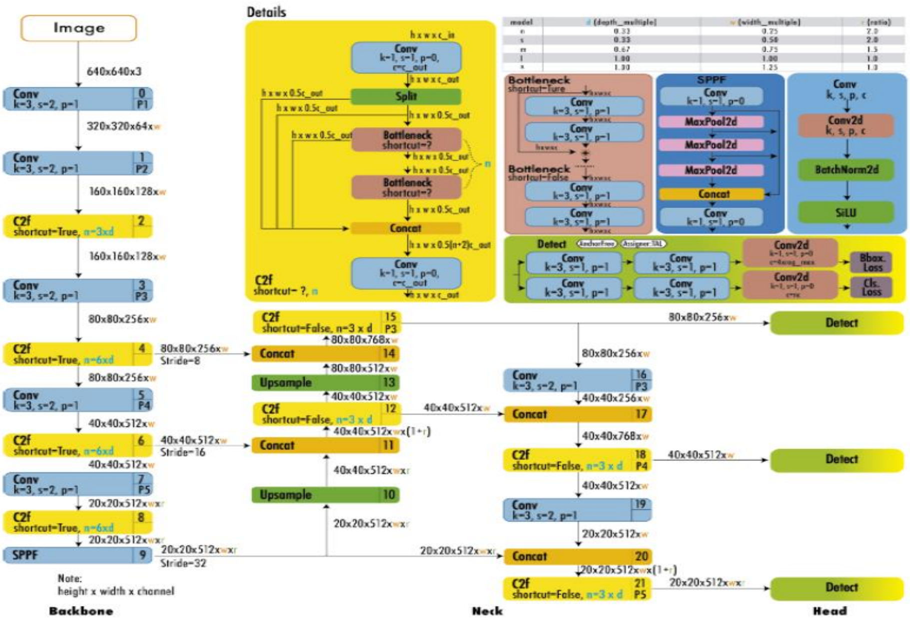

Fig:3 Deep Learning Model Training

Inference and Alert Generation:

1. Utilizing Real-Time Video Analysis: Following its training phase, the YOLOv8 model will play a crucial role in processing live video feeds obtained from various cameras.
2. Object Detection and Classification with YOLOv8: Each frame of the video stream will undergo thorough examination through the YOLOv8 model for the purpose of detecting and categorizing objects. YOLOv8's capabilities will enable precise identification and positioning of animals within the frame, along with assigning corresponding labels for species recognition.
3. Evaluating Risks and Issuing Alerts: A specialized module will be employed to conduct risk assessments based on the identified animal species' proximity to human presence and the potential threat it poses. Upon determining a significant risk level, the system will promptly initiate alert notifications through Telegram, leveraging the Twilio API for seamless integration. These notifications will furnish recipients with pertinent information concerning the species, its location, and any other relevant details.
4. Seamless Integration with Twilio API: The system will seamlessly incorporate the Twilio API, facilitating the transmission of alert messages either via SMS to designated phone numbers or through chat messages to a specific Telegram group. This integration ensures the swift and efficient dissemination of alerts to relevant stakeholders.

V. RESULTS AND DISCUSSION

The effectiveness of the suggested system will be assessed utilizing various metrics, including:

1. Accuracy of detection: This measures the proportion of accurately recognized animal species. Dataset folder to load the dataset.
2. False positive rate: This indicates the frequency of incorrect identifications of animals.
3. ‘Extract texture and GLCM features’ to extract features.
4. False negative rate: This evaluates the frequency of missed detections of animals.
5. Accuracy of alerting: This assesses the percentage of accurately activated alerts for potentially hazardous situations.
6. Success rate of delivery: This measures the percentage of alerts successfully sent via the Twilio API to Telegram.

Fig:4 Recall-Confidence Curve

Fig:5 Precision-Recall Curve

Fig:6 Precision-Confidence Curve

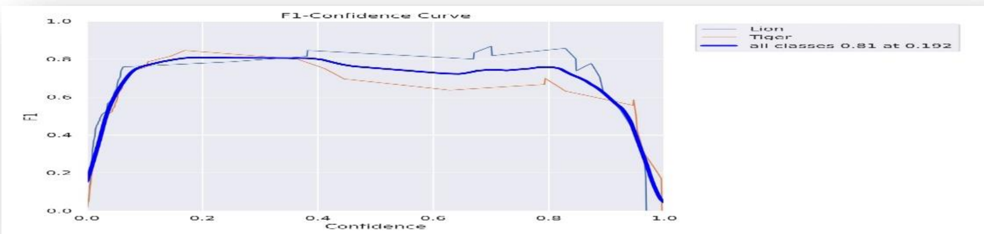

Fig:7 F1-Confidence Curve

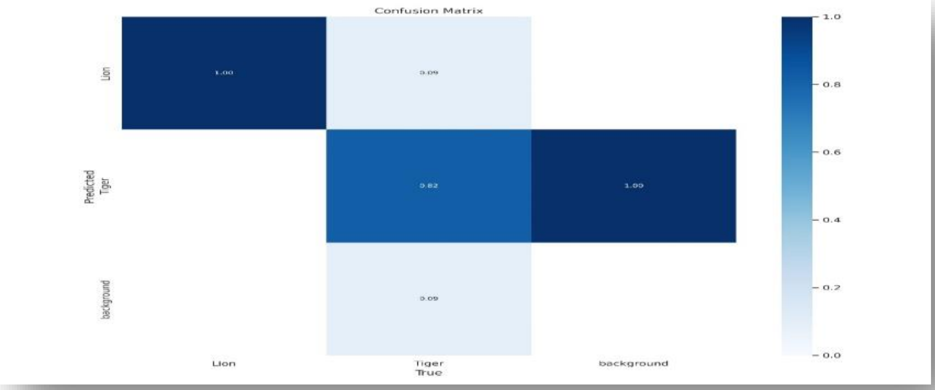

Fig:7 Confusion Matrix

OUTPUT:

Fig:8 Client-Side Alert Message in Telegram Group

VI. CONCLUSION

In recent times, the automation of wildlife surveillance has surged, driven by advancements in computer vision techniques. A primary challenge faced in this endeavor is the variability in illumination conditions, which impedes effective object detection during surveillance. In response, this paper proposes an innovative framework utilizing YOLOv8 to address illumination variations and enhance tiger detection capabilities, offering potential solutions to mitigate human-wildlife conflicts and reduce the impact of human activities on the environment.

The integration of deep learning systems presents significant promise in bolstering wildlife monitoring efforts. By accurately identifying instances of interference, such systems enable proactive measures to combat threats like habitat destruction, poaching, and conflicts between humans and wildlife. Through timely detection and classification of intrusion events, wildlife intrusion detection systems empower authorities and conservation groups to respond swiftly, thereby fortifying protection and conservation endeavors for natural habitats and their inhabitants. Continued advancements in deep learning for wildlife intrusion detection hold the key to mitigating human-induced pressures on wildlife populations and preserving our natural ecosystems for future generations.

REFERENCES

1. In 2018, Kumar and Singh introduced a method for wildlife monitoring titled "Animal Detection using Faster R-CNN" in the Journal of Advanced Research in Dynamical and Control Systems.

2. In a recent publication by Terven and Cordova-Esparza in 2023, a comprehensive review of the evolution of YOLO (You Only Look Once) models, from YOLOv1 to YOLOv8 and beyond, was presented.

3. Kupyn and Pranchuk (2019) presented a fast and efficient model for real-time tiger detection in the wild, showcased at the IEEE/CVF International Conference on Computer Vision Workshops.

4. Tan et al. (2022) conducted research on animal detection and classification from camera trap images, exploring various mainstream object detection architectures.

5. Liu and Qu (2023) introduced AF-TigerNet, a lightweight anchor-free network designed for real-time detection of Amur tigers.

6. Nair et al. (2021) presented a study on real-time wildlife detection utilizing YOLOv3, showcased at the International Conference on Machine Learning and Data Science.

7. Pendharkar et al. proposed an illumination invariant tiger detection framework for wildlife surveillance, as discussed in their work on arXiv:2311.17552.

8. Redmon and Farhadi (2018) introduced YOLOv3, an incremental improvement to the YOLO object detection system, as outlined in their publication on arXiv:1804.02767.