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Integrated Wildlife Monitoring System for Real-Time Anti-Poaching and Conservation

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Abstract- To develop a wildlife monitoring system for anti poaching and conservation using YOLOv8 (You Only Look Once) with CSPDarknet (Cross Stage Partial Darknet) Backbone for real time object detection to identify and classify humans , animals from live image feeds which helps in detecting poaching activities. The system integrates various environmental sensors that act as transmitter side includes temperature , flame and acoustic sensor to monitor key changes that indicate forest fire . These sensors are connected through the LoRa (Long Range) network (Up To 10kms areas with clear line of sight) which efficiently transmits data to the central monitoring unit(here CMU Central Monitoring Unit refers to the forest ranger) that refers to a receiver module. In addition , the system comprises DFRobot Mini Player to trigger natural warning calls (Vocalizations that are produced by animals to alert their group and coordinate groups that are essential part of animal communication and survival strategy) based on the detected data to prompt animals not to be driven out of forest. Thus contributing environmental sustainability and habitat suitability for many species.

Keywords— YOLOv8 , Wildlife Monitoring system , CSPDarknet , Poaching activities , Object Detection Model.

I. INTRODUCTION

Wildlife conservation and habitat protection are increasingly challenged by poaching [1] and environmental threats, such as forest fires, illegal hunting, capturing, or killing of wildlife that jeopardize biodiversity and ecosystem health. To address these issues ,there is definitely a need for building up advanced, real-time monitoring systems that can support anti-poaching initiatives and habitat conservation . Hence our system is developed in such a way that it will detect the images of animals or human activities based on live image feed .

The use of object detection model YOLOv8 [2](You Only Look Once) with a CSPDarknet backbone, essential for recognizing potential poaching activities and unusual human presence within protected areas.Additionally, the system incorporates a suite of environmental sensors, including temperature, flame, and acoustic sensors, everything connected via LoRa (Long Range) network technology. LoRa[3](Long Range) technology provides significant benefits for applications requiring wide-area connectivity, low power consumption, and reliable data transmission.This configuration facilitates extensive area coverage, allowing for early detection of environmental threats, particularly forest fires.

The data from the sensors and video feeds is transmitted to a Central Monitoring Unit (CMU), providing real-time insights that allow forest rangers and conservation teams to respond promptly to potential hazards. Furthermore, to prevent animals from straying into human settlements, the system includes a DFRobot Mini Player that emits natural warning sounds, encouraging animals to remain within safe boundaries. This multi-functional approach contributes to the sustainability of wildlife habitats and bolsters species preservation efforts. By integrating advanced detection algorithms and sensor networks, this project aims to provide a scalable, real-time monitoring solution to safeguard ecosystems and wildlife populations.

II.LITERATURE REVIEW

Kin Fun Li's 2023 study presents a lightweighted animal species detection model using YOLOv2, aimed at reducing human-wildlife encounters and their associated risks, especially in remote and high-traffic areas. To make deep learning models suitable for embedded devices, Li modifies YOLOv2 by integrating multi-level feature merging through a pass-through layer, improving accuracy and feature extraction capabilities. Additionally, by removing two repetition of cells 3×3 convolutional layers in the seventh block, the model reduces computational complexity, enabling faster detection without sacrificing accuracy. This optimized YOLOv2[4] object detection model serves as a proof of concept, highlighting its potential for real-time animal detection applications in wildlife conservation and safety.

In the 2019 paper, Mario E. Rivero Angeles introduces a wireless sensor network model with existing machine learning [5]for tracking animals in polar regions, focusing on energy-efficient strategies to maximize network longevity. By using a random walk model to characterize animal movement, the study identifies optimal detection range and node quantity to maintain a specific target detection probability. Static sensor nodes on land, combined with either mobile nodes attached to animals or land-based nodes that detect animals through various signals (e.g., movement, sound, temperature), facilitate animal tracking. To address the natural movement patterns where animals may enter or exit sensor coverage, the study proposes an on/off cycle for nodes, balancing energy consumption with detection efficiency. This design framework seeks to extend the network's operational lifespan while ensuring reliable tracking performance.

In this 2021 study, Sandeep Verma presents an IoT-based Wireless Sensor Network (WSN)[5] framework for effective wildfire detection, addressing the critical challenge of limited energy resources in sensor nodes. To optimize energy use and extend network lifespan, Verma introduces the Sleep schedulin-based Energy Optimized Framework (SEOF), which functions in two main ways. Firstly the framework includes an energy-efficient selection of Clustered Heads (CHs) using the Tunicate Swarm Algorithm (TSA)[6], a meta-heuristic method that optimizes five fitness parameters through a weighted fitness function. In addition, SEOF employs a sleep scheduled strategy for nearby sensor nodes based on a distance threshold, reducing redundant activity and conserving energy. This approach tries to enhance the efficiency and responsiveness of WSNs in wildfire detection applications.

In this 2022 study, Zitong Li introduces ReDeformTR, a lightweight deformable transformer model tailored for wildlife re-identification (Re-ID) to improve tracking and preservation efforts. ReDeformTR addresses the challenge of poor cross-camera accuracy in existing deep learning methods, specifically improving mean average precision (mAP) for recognizing individual animals across different camera views. The model leverages multi-image feature fusion, allowing it to combine features from multiple images at various scales, which enhances the representation of unique animal characteristics for more accurate identification. With a CNN[12] backbone for feature extraction and a deformable transformer for feature refinement, ReDeformTR demonstrates an advanced approach to efficient and effective wildlife Re-ID.

In this 2023 survey, Luís Felipe Vieira Silva examines the use of RFID [7]technology for animal tracking, which has seen rising popularity for monitoring animal behavior, movement patterns, and health. Traditionally dominant in logistics and goods tracking, RFID has recently been adapted for animal tracking, particularly in livestock management. The paper systematically reviews current scientific literature and patents on animal tracking solutions, analyzing key aspects such as targeted animal species, addressed challenges, operating frequency, and integration with other technologies. The review highlights livestock management as the primary application, followed by general animal tracking and traceability, with a strong focus on monitoring mammals, particularly cattle. This work provides insights into the current trends and innovations in RFID-based animal tracking technologies.

In this 2023 paper, Junhui Li proposes a novel approach to audio denoising, specifically targeting bird sounds, by reframing the task as an image segmentation problem. Traditional methods and even deep learning-based approaches struggle with residual noise, often limited by their reliance on artificial or low-frequency noise removal techniques. Li introduces PtDeepLab, a model that combines a pyramid vision transformer with the DeepLabV3+ network, for enhanced visual denoising of bird audio signals. This approach leverages advanced image segmentation techniques to effectively isolate and filter out noise, improving the clarity and quality of bird sound data for more reliable analysis.

JohnwesilyChappidi's 2024 study introduces a novel animal detection system using a cascaded YOLOv8 model with adaptive preprocessing and feature extraction, aimed at preventing wildlife intrusion into residential areas and sudden road crossings. This approach supports wildlife monitoring, biodiversity tracking, and conservation efforts. The detection process begins with adaptive histogram equalization to enhance contrast, followed by segmentation through super-pixel-based Fast Fuzzy C-Means [8](FCM). Feature extraction is then conducted using ResNet50, DarkNet19, and Local Binary Pattern, leading to optimized animal detection by cascaded YOLOv8. Implemented in MATLAB,[9] the proposed system achieves a 97% accuracy rate and high scores in metrics like kappa, precision, sensitivity, specificity, and F-measures. This research demonstrates an effective and high-performance solution for wildlife conservation and monitoring.

III. MATERIALS AND METHODS

The dataset, which includes various animal images sourced from public databases, is processed on a system with a minimum hardware setup of 4 GB RAM and 259 GB of secondary storage, running on the Windows operating system. The software stack includes Anaconda for managing Python dependencies, PyCharm as the primary development environment, and Python as the core programming language for data processing and analysis.

IV. EXISTING SYSTEM

Existing system involves use of convolutional neural networks and versions of YOLO like YOLOv2 (a streamlined architecture with Darknet-19 as the backbone) and YOLOv4(Upgraded with a CSPDarknet53 backbone, YOLOv4 incorporated more advanced components like cross-stage partial (CSP) connections) has been used for image detection but YOLOv2 struggles with detecting small objects in crowded scenes. Its architecture does not have specialized components, such as feature pyramid networks, that enhance the detection of small or overlapping objects and YOLOv4's CSPDarknet53 backbone and added features, such as spatial pyramid pooling (SPP) and Mish activation, increase its computational requirements, which makes existing systems less capable for use in advanced monitoring .

V.PROPOSED SYSTEM

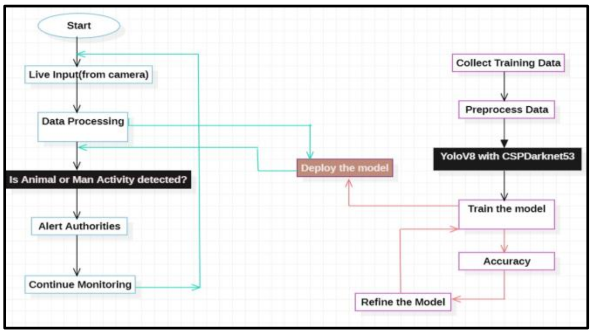

Fig 1. Architecture Diagram

Our proposed anti-poaching detection system leverages YOLOv8's advanced real-time object detection capabilities to monitor and identify potential poaching activities in wildlife areas. Using the CSPDarknet[10] backbone, YOLOv8[2] efficiently detects and classifies humans, animals, and suspicious objects from live video feeds, enabling rapid response in critical situations.

Images are resized, normalized, and augmented to ensure consistency and enhance detection accuracy across diverse environmental conditions, such as changes in lighting, weather, or season. These preprocessing steps help maintain data quality and improve YOLOv8's performance, making it highly suitable for recognizing and differentiating between various elements in complex, natural environments.

Our system then utilizes YOLOv8's detections to provide clear, actionable insights. For instance, it identifies and flags instances where humans or vehicles are detected near wildlife, potentially indicating unauthorized activity. The system can trigger local alerts (like deterrent sounds) and send remote notifications to conservation teams for real-time intervention.

This solution empowers conservation efforts by offering a responsive, automated approach to poaching detection. With YOLOv8's robust detection accuracy and streamlined alerts, the system enables conservation teams to act swiftly and decisively, contributing to the protection of endangered wildlife and safeguarding natural habitats.

VI.METHODOLOGY

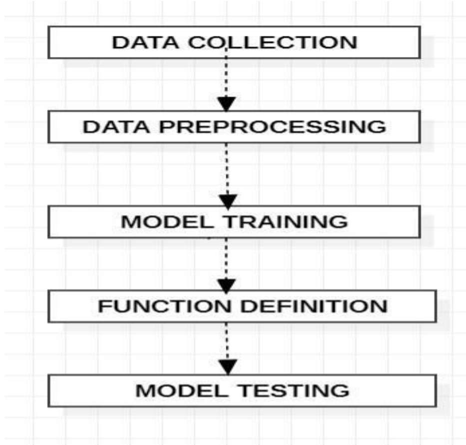

Fig 2. Flow Diagram

Data Collection:
Gather images and videos of wildlife, poaching incidents, and individuals in forest settings. Data sources may include wildlife monitoring systems, conservation agencies, and open-source datasets. Include metadata with labels such as "Animal," "Human," "Vehicle," "Weapon," and "Environment" for improved contextual learning. Capture various environmental conditions, such as different lighting, weather, and seasons, to make the model robust in diverse settings.

Data Preprocessing:
Ensuring the collected images are resized to consistent resolution (640x640 pixels) for input into YOLOv8, improving model performance and training speed. Apply data augmentation techniques[11], including rotation, flipping, brightness/contrast adjustment, and blurring. This step diversifies the training dataset and helps the model generalize across various conditions. Normalizing pixel values of a range from 0-1, which enhances model learning efficiency.

Model Training:
Train YOLOv8 on annotated images using the CSPDarknet backbone. Set up training configurations, including batch size, image resolution (e.g., 640x640), learning rate, and number of epochs(50) to balance performance and computation time.

Model Evaluation:
After training is over , the model's behavior and valuation is evaluated using a separate test dataset. Performance metrics like "accuracy", "precision", and "recall" are calculated to assess the model's achievement in classifying legal descriptions.

Prediction and deployment:
The trained model is deployed to identify and detect poaching activities , roaming of animals into human living areas with live image feed from forest areas. Implementing a local alerting system[12] that uses an audio player (e.g., DFRobot Mini Player) to play deterrent sounds when humans or suspicious activities are detected near protected areas.Set up a pipeline for periodically retraining the model using recent data. When a retrained model outperforms the current one, it can be deployed seamlessly.

VII.RESULTS

Thus the model was trained with 50 epochs which took significantly less time to get trained compared with other versions of YOLO[10]. Our system clearly provides the accuracy of identification with test data of live video feeds. It clearly indicates the different categorization of animals and humans with 0.90 percent accuracy with a decent speed rate of displaying the results with labels.

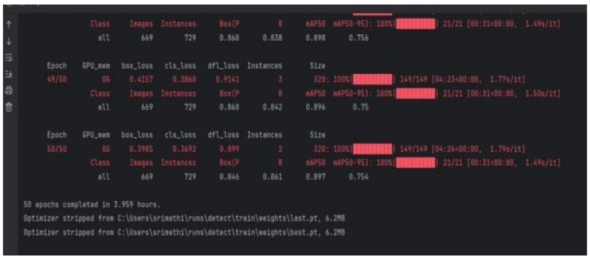

Fig 3 : Training Period

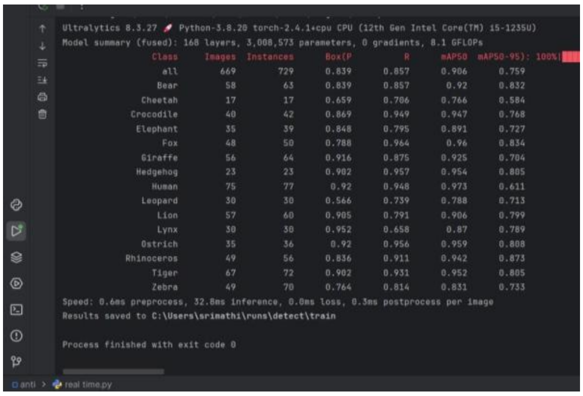

Fig 4: Training output

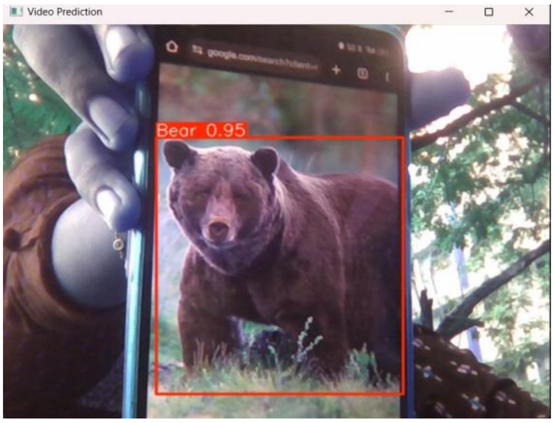

Fig 5: Live Detection

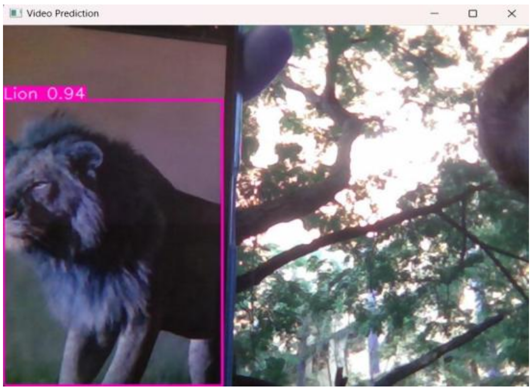

Fig 6: Live Detection 2

VIII.DISCUSSION

Recent news across the globe indicate the necessity of an advanced monitoring system for figuring out illegal entrance of humans which leads to hunting that threatens wildlife balance and roaming of animals into human areas leads to disturbance and life threat for mankind.In India the Wildlife Protection Act, 1972, provides strict regulations for the protection of wildlife, including the prohibition of hunting, poaching, or capturing of protected animals[13]. Both can be managed via a single model using strong object detection models and customizing them in ways for alerting systems to safeguard ecosystems.Our model is trained in such a way that it predicts and provides the output particular to the type of animal and presence of human which can be utilized to raise warning calls for wildlife as well as alerting officials regarding illegal entry.

IX.CONCLUSION

In conclusion, the wildlife monitoring and anti-poaching detection system developed using YOLOv8 with a CSPDarknet backbone offers a powerful, real-time solution to combat illegal poaching activities and support conservation efforts. By leveraging state-of-the-art object detection and classification capabilities, the system accurately identifies humans, animals, and potential threats in natural environments, helping conservationists detect poaching risks as they occur.

Through the edge based deployment, the system enables rapid, on-site processing with minimal latency, ideal for remote regions with limited connectivity. Simultaneously, cloud integration allows for centralized monitoring, incident logging, and seamless model updates, ensuring that the system evolves alongside changing environmental conditions and emerging poaching patterns.

The combination of localized deterrent alerts and remote notifications provides a comprehensive response, allowing conservation teams to act quickly and effectively. The continuous data collection and automated retraining pipeline further enhance the system's resilience and adaptability. This solution not only aids in protecting endangered wildlife but also contributes to long-term conservation goals, enabling proactive intervention and fostering safer, more secure habitats.

In essence, this detection system bridges technology and conservation, offering a scalable, adaptive approach to protecting wildlife and combating illegal poaching, setting a new standard in real-time environmental monitoring and proactive conservation.

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