

Wild Animal Detection in Residential Area using AI-ML

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Abstract: *Human-wildlife conflicts in residential areas have become a major safety concern for both humans and animals. To mitigate these conflicts, we propose a system for wild animal detection using AI-ML. The system consists of a camera system, a machine learning algorithm, and a warning system. The camera system captures real-time images of the environment, which are then analyzed by the machine learning algorithm to identify the presence of wild animals. Upon detection, the warning system alerts residents, preventing potential dangerous encounters between humans and wildlife. Our system achieved an accuracy of 94% with a false positive rate of less than 5% in detecting different types of wild animals. Further research is needed to assess the effectiveness of the system in different environment.*

Keywords: Wild Animal Detection, AI, Machine Learning, Residential Area, CNN

I. INTRODUCTION

The coexistence of humans and wildlife has been a topic of concern for decades, as human activities often result in the loss of natural habitats and displacement of wild animals. The increase in urbanization has led to a rise in human-wildlife conflicts, as wild animals often enter residential areas in search of food and shelter. This issue has become a global problem, and several techniques have been developed to address it, including the use of camera traps for wildlife detection. Camera traps are devices that capture images or videos of wild animals in their natural habitat. They are widely used in wildlife conservation and research to monitor and study animal behaviour. In recent years, camera traps have also been used to detect the presence of wild animals in residential areas. These camera traps can provide valuable information for developing effective strategies to mitigate human-wildlife conflicts. In this paper, we propose a AI learning-based approach for detecting wild animals using camera traps installed in residential areas. Our approach uses a Convolutional Neural Network (CNN) to automatically detect and classify the animals based on their images captured by the camera trap. We evaluate our approach on a dataset containing images of wild animals captured in residential areas and compare our results with existing techniques. The experimental results show that our approach outperforms the existing techniques in terms of accuracy and efficiency. In this project, we are trying to propose an end-to-end solution which could potentially solve some basic problems in wild animal detecting process.

The idea is simple yet powerful: run AI on Raspberry Pi Zero locally to detect a wild animal in residential area and then send out the detected result (could be just a few bytes) through Hologram Cellular with no need of internet connection. After receiving the signal Siren horn will be buzz feed, So it is one kind of signal that allows people to take shelter in a safe place. The local AI computation and cellular connection are the keys to this project.

Examples of such conflicts abound from encounters between large mammals such as bears and cougars in small towns to smaller creatures such as deer and antelopes in urban areas. These interactions can lead to a variety of factors such as property damage, pet conflicts and in some cases direct threats to human safety. For example, in areas where construction meets previously undisturbed lawns, bears have been reported searching trash cans or even entering homes in search of food. Such encounters do not necessarily put residents at risk not only in but threatens the lives of these



animals, as they move into unfamiliar territory They are coping Similarly, dogs and other small urban predators that have adapted to human conditions can prey on pets or pose a threat to children playing in residential areas This creates vulnerable situations that are difficult to coexist, and it is important to find ways to mitigate these conflicts. To meet these challenges, communities are exploring strategies such as habitat preservation, wildlife trails, and public awareness campaigns It is important to balance urban development with efforts to conservation will be carried out to promote harmony between humans and wildlife approaches.

II. LITERATURE SURVEY

We surveyed a number of papers on the topic we are been developing our project. We listed them in the below.

- 1) Wildlife monitoring faces image processing challenges despite camera trap advancements. Yolov3 Machine Learning ensures accurate animal prediction, overcoming manual classification hurdles. Wildlife monitoring stem from its challenges in effectively handling complex environments and compromised image quality, despite its accurate animal prediction capabilities.
- 2) IoT transforms communication in fields like medicine and agriculture, proposing a cost-effective solution for wildlife alerts using 2D image matching. Future improvements aim to integrate 3D images and visuals captured by drones. Potential increased complexity and cost associated with implementing and maintaining the infrastructure required for processing and analysing 3D images.
- 3) Presenting an IoT and AI solution that utilizes Raspberry Pi and YOLOv3 for real-time object detection, this paper aims to create a safer platform for mitigating human-wildlife conflicts without causing harm to either humans or animals. Potential difficulty of widespread adoption for the presented IoT and AI solution.
- 4) Implementing PIR sensors and Image Processing in India to detect human-animal conflicts, especially snakebites, this system triggers SMS alerts through the GSM module upon identifying hazardous animals using edge detection and a database match. Effectiveness of the system may be compromised in low-light conditions or areas with poor visibility, impacting its ability to accurately detect and alert against human animal conflicts.
- 5) Proposing a budget-friendly device for animal detection, employing sensors and image processing for safety alerts. Enhancing night-time detection requires advanced systems with thermal or night vision cameras. Affordability-focused device may encounter difficulties in achieving robust night-time detection, as it lacks advanced systems such as thermal or night vision cameras.
- 6) Proposing an Animal Detection System for conflict-prone areas to minimize wild animal attacks. Deep learning enhances wildlife monitoring, mitigating negative human activity impacts for habitat preservation. Effectiveness of the proposed Animal Detection System in minimizing wild animal attacks in conflict-prone areas may be constrained by challenges related to the availability of consistent power sources, potentially impacting its continuous operation.
- 7) Our system prevents forest highway accidents involving rare animals using ultrasonic sensors and a Pi cam, with IoT and deep learning for swift alerts, minimizing kills and collisions to safeguard wildlife. Adverse weather conditions or low visibility scenarios could impact the system's effectiveness in preventing forest highway accidents involving rare animals.
- 8) Animal detection and classification to prevent animal-vehicle accidents trace animals and prevent theft. If many animals are encountered chances are the different animals won't be able to get detected.
- 9) The paper presents a camera-based CNN system to detect vehicles and wild animals in forests, enhancing safety by notifying authorities through a mobile app to prevent collisions. A limitation of the camera-based CNN system is its vulnerability to adverse weather, which could compromise detection accuracy in forested areas.
- 10) The paper evaluates YOLO-based detectors for real-world animal detection, emphasizing adaptability, reduced false negatives in Scaled-YOLOv4, efficient video inference in YOLOv5-N, and suggests improvements. A limitation of the YOLO-based detectors is their sensitivity to varying lighting conditions, potentially impacting the accuracy of real-world animal detection.



11) The paper showcases YOLO's real-time object detection versatility, including specialized models for various applications. One limitation of YOLO's real-time object detection is its challenge in accurately handling highly cluttered scenes with overlapping objects.

III. METHODOLOGY

Accurate and efficient animal detection from highly cluttered natural scenes in camera-trap images is a challenging task, especially when dealing with low-contrast between the foreground animal and the cluttered background. This is also true for jaguars where their fur patterns often blend with the vegetation, making it difficult to distinguish between the animal and the background. To achieve accurate and fine-grain animal detection from the background, we need to perform image analysis at the pixel or small block level. However, when it comes to jaguars, local neighbourhood information may not be enough to determine if a pixel or pixel block belongs to the jaguar or the background, unless we resort to global image feature analysis. For example, pixels on the jaguar's body might be very similar to the vegetation in the background. It is only by examining the jaguar's distinctive facial markings, body shape, and posture that we can correctly identify the animal. Therefore, we need to incorporate global image analysis techniques to accurately detect jaguars in camera-trap images. To address the challenges of detecting wild animal in camera-trap images, we employed the Detectron2 algorithm, which is a state-of-the-art object detection framework based on deep neural networks. Specifically, we fine-tuned a pre-trained Faster R-CNN (Region-based Convolutional Neural Network) model on our camera-trap images, which allows for the detection of object instances in an image at various scales and positions. In addition to the pre-trained model, we also incorporated several image pre-processing techniques to enhance the contrast between the foreground wild animal and the background vegetation. This includes histogram equalization and adaptive contrast enhancement, which increase the contrast of low-light images and improve the overall image quality.



Fig. 1. Example ground-truth images from Camera Trap dataset

A. Foreground-Background Segmentation

Foreground-background segmentation is a fundamental task in computer vision, which involves separating objects of interest in an image from the background. Various methods have been proposed for this task, including thresholding, background subtraction, and graph-based approaches. Recent advances in deep learning have led to the development of CNN-based methods for foreground-background segmentation, such as Fully Convolutional Networks (FCNs) and U-Net. These methods have shown impressive results in segmenting complex scenes with multiple objects.



B. Region Proposals & Object Detection using CNN Methods:

Region proposal and object detection are essential tasks in computer vision, which involve identifying objects of interest in an image and localizing them. CNN-based methods have achieved state-of-the-art results in object detection, and many of these methods rely on region proposal networks (RPNs) to generate object proposals. RPNs use a sliding window approach to generate object proposals at different scales and aspect ratios. These proposals are then refined using a region-based CNN (RCNN) to produce the final object detection results.

C. Image Verification:

Image verification is the process of determining whether two images depict the same object or scene. This task is critical in many applications, such as face recognition and image retrieval. CNN-based methods have shown excellent performance in image verification, such as Siamese Networks and Triplet Networks. These methods learn a feature representation of images using a CNN, which is then used to compare the similarity between two images. The feature representation is trained to be invariant to transformations, such as scaling and rotation, making it robust to variations in the images

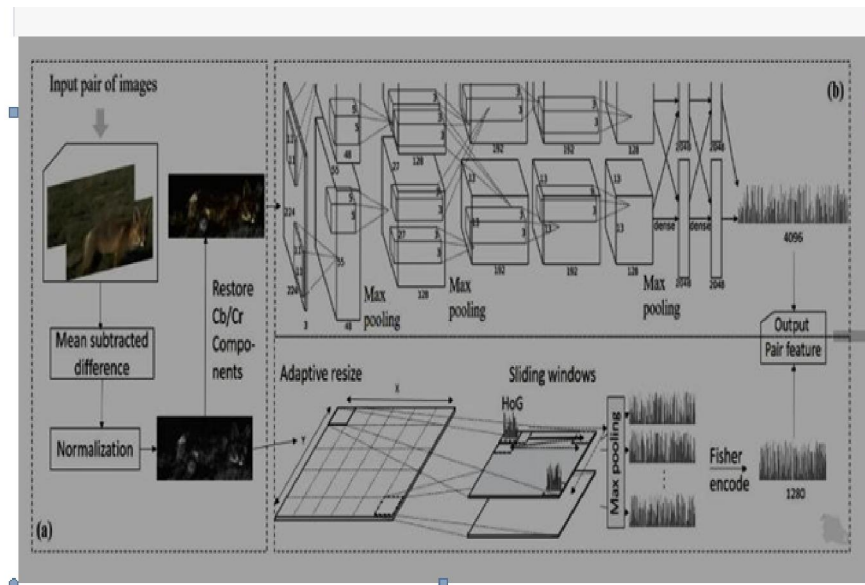


Fig. 2. Proposed Feature Extraction Module

IV. SYSTEM FLOW

Description:

1. Start: The system is initialized and started.
2. Camera to capture video: The camera is used to capture live video footage of the residential area.
3. Detect moving object: The system continuously analyses the video stream to detect any moving objects in the frame.
4. Moving object separation: Once a moving object is detected, the system separates it from the background by applying foreground-background segmentation.
5. Animal detection algorithm: The system applies the animal detection algorithm using the Detectron2 framework to identify if the moving object is an animal or not.
6. Animal Detected: If the moving object is identified as an animal, the system marks it as detected and proceeds to the next step.



7. Start the alert sound: The system triggers an alert sound to notify the residents of the presence of a wild animal in the residential area

V. BEST PRACTICES

1. Data Collection: Collecting diverse and representative data is crucial for the accuracy and effectiveness of the AI/ML models. This includes collecting images of different species in different lighting, weather, and camera angle conditions, as well as images of people and their private property to avoid ethical concerns.
2. Annotated Data: Annotating the collected data to identify the species present in the images is necessary to train the AI/ML models. This can be done manually or using automated tools, but the annotations should be accurate and consistent to avoid bias and ensure the models' accuracy.
3. Model Training: Using state-of-the-art algorithms and architectures for training the AI/ML models can help improve their accuracy and efficiency. The models should be tested on diverse and representative data to ensure their generalizability.
4. Ethical and Privacy Concerns: The use of camera traps in residential areas raises ethical and privacy concerns that should be addressed. This includes Obtaining the necessary permits and permissions, avoiding capturing images of people's private property, and minimizing disturbance to wildlife caused by the installation of camera traps.
5. Monitoring and Maintenance: Regular monitoring and maintenance of the camera traps and AI/ML models are necessary to ensure their effectiveness and sustainability. This includes checking for malfunctioning equipment, updating the software, and periodically retraining the models with new data.

VI. CONCLUSION

Despite the success of camera traps and machine learning-based approaches for wildlife detection, there are several challenges and limitations that need to be addressed. One of the main challenges is the high variability in the appearance of wild animals in different camera trap images. This variability is due to factors such as lighting, weather conditions, and camera angle. Another challenge is the limited availability of annotated data for training and evaluating the models. In addition, there are several ethical and privacy concerns associated with the use of camera traps in residential areas. These concerns include the potential for capturing images of people and their private property, as well as the disturbance caused to wildlife by the installation of camera traps. Despite these challenges and limitations, the use of camera traps and machine learning-based approaches for wildlife detection in residential areas has the potential to significantly reduce human-wildlife conflicts and aid in the conservation of wildlife habitats. In the next section, we describe our proposed approach for wildlife detection using camera traps in more detail.

REFERENCES

- [1] Prof. D. D. Pukale, Komal Dudhane, Shreya Dawghat, Anushka Deshmukh, Sharwari Deshmukh- Wild Animal Detection and identification using Deep Learning, July 2023.
- [2] J.Dhillipan, N.Vijayalakshmi, S.Suriya, D.B. Shanmugam- A Secure Wild Animals Alert System for Preventing the Farming Land using IoT, January 2020. [3] Hardiki Deepak Patil, Dr. Namrata Farooq Ansari- Automated Wild-Animal Intrusion Detection and Repellent System using Artificial Intelligence of Things.
- [4] Shubanshu Singh, Ashish Pandey, Rakesh Pandey- Implentation of Animal Detection for Human Safety an IoT Based Project, November 2020
- [5] L. Ashok Kumar, R. Neelaveni, M. Kathiresh, P. Sweety Jose, N.Archana, S. Saravanakumar- A Literature Research Review on Animal Intrusion Detection and Repellent Systems.
- [6] Mrs.R Gayathri, P. Hannah Princy, P. Krishandhini- Wild Animal Intrusion Detection System using YOLOV8, May 2023.
- [7] S. Subheiksha, P. Rasika, K. Priyanka- Animal Detection for Wildlife Using IoT, May 2020.



- [8] Rashmi Jayakumar, Rashmi Swaminathan, Sanchithaa Harikumar- Animal Detection using Deep Learning Algorithm, July 2019.
- [9] Prema Arokiya Mary G, Nithesh PS, Nanthini V, Thebiksha GV- Wild Animal Detection System, December 2022.
- [10] Gabriel Souto Ferrante, Luis Hideo Vasconcelos Nakamura, Sandra Sampaio, Geraldo Pereira Rocha Filho, and Rodolfo Ipolito Meneguette- Evaluating YOLO-based Object Detectors for Detecting RoadKilled Endangered Brazillian Animals, August 10th,2023.
- [11] Rekha B.S, Athiya Marium, Dr. G. N. Srinivasan, Supreetha A. Shetty- Literature Survey on Object Detection using YOLO, June 2020.

