© April 2025 | IJIRT | Volume 11 Issue 11 | ISSN: 2349-6002

Wild Animal Detection

Mohamed S[1], Praveen kumar R[2], Sri ram V[3], Vasantha ruban BT[4]
[1,2,3,4] *Hindusthan College of Engineering and Technology, Coimbatore, India.*

***Abstract*—Animation detecting and monitoring has always been a challenging topic and an active research area. Most of the current animal detecting and monitoring processes rely on commercial wild camera trap to take wild animal pictures which are triggered by some sort of sensor techniques. However, those taken images still need human to collect and get analysed with tremendous amount of effort. In a wild environment, the cost for deploying, collecting, analyzing is quite significant. With the recent progress of AI technique, there are mature tools that we can use to analyse the collected images. However, there are still no good stories of how we can utilize the AI output to really solve the wild animal detecting and monitoring problem.**

I. INTRODUCTION

Animal monitoring and analysis have been prominent areas of research for several decades. In this project, the focus is on monitoring and analyzing animals by detecting them in natural scenes captured by camera-trap networks. These image sequences are often complex and cluttered, which poses significant challenges for accurate animal detection, often resulting in low detection accuracy and high false positive rates. To address this issue, we utilized a camera-trap dataset containing potential animal regions generated through multilevel graph cut techniques in the spatiotemporal domain. These regions are then passed through a verification step that determines whether each segment contains an animal or background. We developed an animal detection system based on YOLO-extracted Deep Convolutional Neural Network features. These high-quality features are subsequently classified using advanced machine learning algorithms such as support vector machines, k-nearest neighbors, and ensemble trees. Our extensive experiments demonstrate that the proposed model achieves a detection accuracy of 91.4% on a standard camera-trap dataset.

Visual recognition has been gaining popularity in biodiversity preservation and management. Since launching our AI for Good initiative, we have been working with biodiversity researchers and practitioners to deliver Animal image recognition machine learning models and tools. Our first foray into this area was our project for Wild Detect, which aligned with one of our goals at to use data science consulting to aid in the preservation and management of our planet's Animal and environment. The goal was to build a model for visual recognition of specific kinds of animals.

The objective of wild animal detection using artificial intelligence (AI) is to develop a smart, automated system capable of detecting, identifying, and classifying wild animals from images or video feeds with high accuracy and speed. This project aims to harness the capabilities of modern AI technologies, particularly deep learning and computer vision, to create a solution that can operate effectively in real-time and under varying environmental conditions. Traditional wildlife monitoring methods, such as manual patrolling, field observations, or camera trap reviews, are often labor-intensive, time-consuming, and inefficient. The proposed AI-based system seeks to overcome these limitations by enabling continuous and automated wildlife surveillance. The use of convolutional neural networks (CNNs) and other machine learning algorithms allows the system to learn from large datasets and recognize patterns unique to different animal species. This can help in identifying animals even in challenging conditions such as low light, dense forests, or partial visibility.

One of the core objectives is to improve the accuracy of species classification, which is crucial for ecological research, biodiversity studies, and conservation planning. Another key goal is to minimize human-animal conflicts by detecting the presence of potentially dangerous animals near human settlements, farms, or roads and generating timely alerts. This system can be particularly useful in forest reserves, wildlife sanctuaries, and areas prone to human-wildlife interaction. Additionally, it can aid anti-poaching initiatives by detecting suspicious movements or unauthorized human activity in protected zones. By integrating AI with camera traps, drones, or surveillance systems, the solution aims to offer non-invasive monitoring that protects wildlife without disturbing their natural habitat.

II. LITERATURE SURVEY

Chen et al. (2014) developed a camera-trap image recognition framework using low-level features like color histograms and texture descriptors to detect animals in natural habitats. While effective in simple scenarios, their method struggled in cluttered environments due to limited feature representation.

Norouzzadeh et al. (2018) leveraged deep learning, specifically convolutional neural networks (CNNs), to classify and detect wildlife in millions of camera-trap images. Their work demonstrated the power of deep features in handling the variability in wild scenes, achieving performance that rivaled human annotators.

Tabak et al. (2019) explored the use of machine learning models trained on features extracted from ResNet architectures to automate species classification from camera-trap images. Their findings highlighted the importance of transfer learning and large, labeled datasets for effective wildlife monitoring.

Beery et al. (2020) introduced the Caltech Camera Traps dataset and benchmarked several object detection models, including Faster R-CNN and YOLO, under challenging conditions such as occlusion, low lighting, and camouflage. Their study emphasized the need for robust models capable of generalizing across different environments and species.

III. METHODOLOGY

Existing System:
Modern wild animal detection systems utilize a blend of traditional methods and emerging technologies to observe wildlife within their natural environments. A commonly used approach involves camera trap motion-sensitive cameras strategically installed in forests and conservation areas to record images or videos when animals pass nearby. These visual recordings offer valuable insights into animal behavior, population dynamics, and migration patterns. While much of the collected data is still examined manually by researchers, some systems now integrate basic artificial intelligence or machine learning techniques to assist with species recognition and data organization.
Additionally, the use of **drones** equipped with high-resolution or thermal cameras is on the rise. These drones are capable of surveying vast or difficult-to-reach terrain efficiently, providing live visual data on animal presence and movements.

Proposed System:
The proposed system for wild animal detection using AI aims to create an automated, intelligent, and real-time monitoring solution that addresses the limitations of existing methods. At the core of the system is the integration of deep learning models capable of recognizing various animal species from images, videos, and sounds. High-resolution cameras and thermal sensors will be installed in forested and border areas, continuously feeding data into the AI model.
To ensure wide coverage and scalability, the system will utilize drones and IoT-enabled camera traps deployed in remote and high-risk zones. These devices will be equipped with real-time data transmission capabilities, allowing for instant alerts and live monitoring. An edge computing layer will be added to process data locally when internet connectivity is poor, reducing response delays.
The system will also include an alert mechanism connected to a centralized dashboard. Whenever a wild animal is detected near human settlements, farms, or highways, instant notifications will be sent to forest officials, local residents, or automated sirens. This will help prevent human-wildlife conflicts and reduce the risk of accidents or crop damage. The dashboard will also display maps, animal tracking logs, and predictive analytics based on AI models, assisting authorities in decision-making and deployment of field teams. Additionally, the proposed system will support cloud-based data storage and AI training updates, allowing for continuous learning and improvement of detection accuracy. It will also facilitate collaboration between conservationists, researchers, and government bodies by enabling data sharing and remote access.

System Components:
Software:
- Firmware Development
- Cloud Integration
- Web Application

Algorithm:
The algorithm for this Wild animal detection tracking system consists of several key steps:
1. Initialize the camera trap and load the pre-trained object detection model (e.g., YOLO).
2. Wait for motion detection or set time intervals to capture images.
3. Capture an image or video frame from the camera.
4. Preprocess the image (resize, normalize).
4. Run the image through the deep learning model to detect animals.
5. Apply Non-Maximum Suppression and filter low-confidence detections.
6. Save the annotated image and log detection data (species, time, location).
7. Display or send notifications (optional).
8. Loop back to step 2.

Workflow:
The workflow of the proposed system can be described as follows:
1. Initialization: Activate the camera trap system and load the deep learning model (e.g., YOLO) onto the processing unit (edge device or server).
2. Image Capture: When motion is detected or at predefined intervals, the camera trap captures an image or video frame.
3. Preprocessing: The captured image is resized, normalized, and prepared for input into the detection model.
4. Animal Detection: The image is passed through the deep learning model, which detects animals, draws bounding boxes, and assigns confidence scores.
5. Post-Processing: The system applies Non-Maximum Suppression to filter overlapping detections and removes results below the confidence threshold.
6. Data Logging: Detected species, timestamps, and location data are stored locally or uploaded to a cloud platform (e.g., Firebase, AWS, or custom database).
7. Display/Notification: The results can be displayed on a local dashboard, mobile app, or used to send alerts (e.g., for endangered species).
8. Data Retrieval: Researchers can access the detection records via a web or mobile application for further use.
9. Analysis: Collected data is analyzed to study species behavior, population trends, activity patterns, and habitat usage.

IV. SYSTEM ARCHITECTURE AND WORKING

The wild animal detection system utilizes motion-activated camera traps placed in natural habitats to capture images or video whenever animal movement is detected. These images are then sent to an edge device or server where they undergo preprocessing before being analyzed by a deep learning model like YOLO, which identifies and classifies animals based on learned visual features. This approach enables real-time detection of various species without disturbing their environment.
Once detection is complete, the system applies post-processing to refine results and logs important data such as species, timestamp, and location to a cloud platform or local storage. The results can be accessed through a user-friendly dashboard, allowing researchers and conservationists to monitor wildlife activity, analyze patterns, and receive alerts for specific animals or rare sightings, making the entire monitoring process more efficient and data-driven.

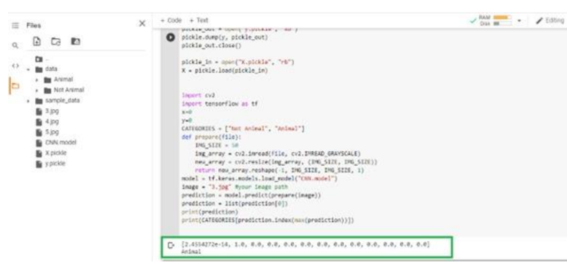

Figure 1: code of wild animal detection

V. CONCLUSION AND FUTURE WORK

The proposed wild animal detection system provides an efficient, automated solution for monitoring wildlife using camera traps and deep learning models. By leveraging advanced object detection algorithms like YOLO, the system can accurately identify animals in real-time, reducing manual effort and improving the reliability of data collection in remote or dense forest environments. This approach enhances wildlife conservation efforts by offering continuous monitoring, behavior tracking, and valuable insights into species movement and population trends.

In the future, the system can be extended with advanced features such as multi-species tracking across video frames, integration of thermal or night vision imaging for low-light conditions, and the use of drones for broader area surveillance. Additionally, incorporating AI-powered species recognition with GPS-based movement prediction could further support conservation research and anti-poaching activities. Expanding the dataset and improving the model's ability to generalize across different terrains and animal types will also contribute to more scalable and robust wildlife monitoring solutions.

REFERENCES

[1] Fang, Y., Du, S., Abdoola, R., Djouani, K., & Richards, C. (2016). Motion based animal detection in aerial videos.Procedia Computer Science, 92, 13-17.

[2] Jaskó, G., Giosan, I., & Nedevschi, S. (2017, September). Animal detection from traffic scenarios based on monocular color vision. In Intelligent Computer Communication and Processing (ICCP), 2017 13th IEEE International Conference on (pp. 363-368). IEEE.

[3] Nguyen, H., Maclagan, S. J., Nguyen, T. D., Nguyen, T., Flemons, P., Andrews, K., ... & Phung, D. (2017, October). Animal recognition and identification with deep convolutional neural networks for automated Aanimal monitoring. In Data Science and Advanced Analytics (DSAA), 2017 IEEE International Conference on (pp. 40-49). IEEE.

[4] Parham, J., Stewart, C., Crall, J., Rubenstein, D., Holmberg, J., & Berger-Wolf, T. (2018, March). An Animal Detection Pipeline for Identification. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1075- 1083). IEEE.

[5] Parham, J., Stewart, C., Crall, J., Rubenstein, D., Holmberg, J., & Berger-Wolf, T. (2018, March). An Animal Detection Pipeline for Identification. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1075- 1083). IEEE.

[6] Xue, W., Jiang, T., & Shi, J. (2017, September). Animal intrusion detection based on convolutional neural network. In Communications and Information Technologies (ISCIT), 2017 17th International Symposium on (pp. 1-5). IEEE.

[7] Zhu, C., Li, T. H., & Li, G. (2017, October). Towards automatic wild animal detection in low quality camera-trap images using two-channeled perceiving residual pyramid networks. InComputer Vision Workshop (ICCVW), 2017 IEEE International Conference on (pp. 2860-2864). IEEE.

[8] Zhang, T., Wiliem, A., Hemsony, G., & Lovell, B. C. (2015, April). Detecting kangaroos in the wild: the first step towards automated animal surveillance. In ICASSP (pp. 1961-1965).

[9] Villa, A. G., Salazar, A., & Vargas, F. (2017). Towards automatic wild animal monitoring: Identification of animal species in camera-trap images using very deep convolutional neural networks. Ecological informatics, 41, 24-32.

[10] Xue, C., Wang, P., Zhao, J., Xu, A., & Guan, F. (2017). Development and validation of a universal primer pair for the simultaneous detection of eight animal species. Food chemistry, 221, 790-796.

[11] Kumar, S., & Singh, S. K. (2016). Monitoring of pet animal in smart cities using animal biometrics. Future Generation Computer Systems.