IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁙ Peer-reviewed / Refereed journal ⁙ Vol. 11, Issue 11, November 2024

DOI: 10.17148/IARJSET.2024.111110

"A Review of Real-Time Monitoring Approaches for Effective Wildlife Poaching Prevention"

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Abstract: Wildlife poaching poses a severe threat to biodiversity, demanding advanced prevention strategies. This paper investigates real-time monitoring technologies to enhance wildlife protection. By integrating satellite imaging, unmanned aerial vehicles (UAVs), and ground-based sensors, conservationists can achieve comprehensive surveillance over remote areas. Satellite imaging offers macro-level data on habitat changes and potential poaching activities. UAVs, with high-resolution cameras and thermal imaging, provide detailed, on-demand monitoring and rapid response capabilities. Ground-based sensors, such as motion detectors and acoustic sensors, ensure continuous, localized surveillance, alerting rangers to unauthorized human presence. Advanced data analytics and artificial intelligence synthesize these technologies, enabling pattern detection and prediction of poaching hotspots. This integrated approach enhances situational awareness and optimizes resource allocation for patrols. Case studies from African and Asian reserves demonstrate the success of these technologies in reducing poaching incidents. The paper concludes with a discussion on challenges and future directions, emphasizing sustainable and scalable solutions.

Keywords: Convolutional Neural Networks(CNN), Acoustic detection, Edge AI, Machine learning, Deep learning, Trail Guard AI.

I. FOREWORD

Wildlife poaching remains a critical issue worldwide, posing severe threats to biodiversity and the survival of numerous endangered species. Despite concerted efforts by governments, conservation organizations, and local communities, the illicit hunting and trading of wildlife continue to thrive, driven by high market demand for animal parts and products. Traditional anti-poaching strategies, such as on-ground patrolling and community engagement, have had limited success due to their reactive nature and the vast, often inaccessible terrains they aim to protect.

In response to these challenges, real-time monitoring technologies have emerged as a promising solution, offering a proactive approach to wildlife protection. By harnessing the capabilities of satellite imaging, unmanned aerial vehicles (UAVs), and ground-based sensors, these technologies enable continuous surveillance and timely intervention. Satellite imaging provides extensive coverage and critical data on habitat changes, while UAVs offer high-resolution, on-demand monitoring capabilities. Ground-based sensors complement these methods by delivering localized, continuous monitoring, capable of detecting and alerting authorities to the presence of poachers.

The integration of these technologies, powered by advanced data analytics and artificial intelligence, has the potential to revolutionize anti-poaching efforts. This paper explores the current landscape of real-time monitoring approaches, their implementation in various wildlife reserves, and their effectiveness in mitigating poaching activities. Through case studies and technological analysis, we aim to highlight the benefits, challenges, and future prospects of these innovative approaches in safeguarding wildlife.

IV. BASIC CONCEPTS USED

1. Satellite Imaging

Satellite imaging involves capturing images of Earth from space using satellites. These images provide large-scale data

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that can help monitor changes in wildlife habitats and detect potential poaching activities. High-resolution satellite images can reveal changes in vegetation, illegal road construction, and other indicators of human intrusion (Oxford Academic).

2. Unmanned Aerial Vehicles (UAVs)

UAVs, commonly known as drones, are aircraft operated without a human pilot on board. Equipped with high-resolution cameras and thermal imaging sensors, UAVs can perform detailed and real-time monitoring of wildlife areas. They are especially useful in covering vast and inaccessible terrains quickly and efficiently, providing critical data for anti-poaching efforts (AAAI) (Welcome to Teamcore).

3. Ground-Based Sensors

Ground-based sensors include various devices such as motion detectors, acoustic sensors, and camera traps placed in strategic locations to monitor wildlife movements and detect human activities. These sensors provide continuous, localized surveillance and can alert rangers to unauthorized human presence, helping to prevent poaching before it occurs (SpringerLink).

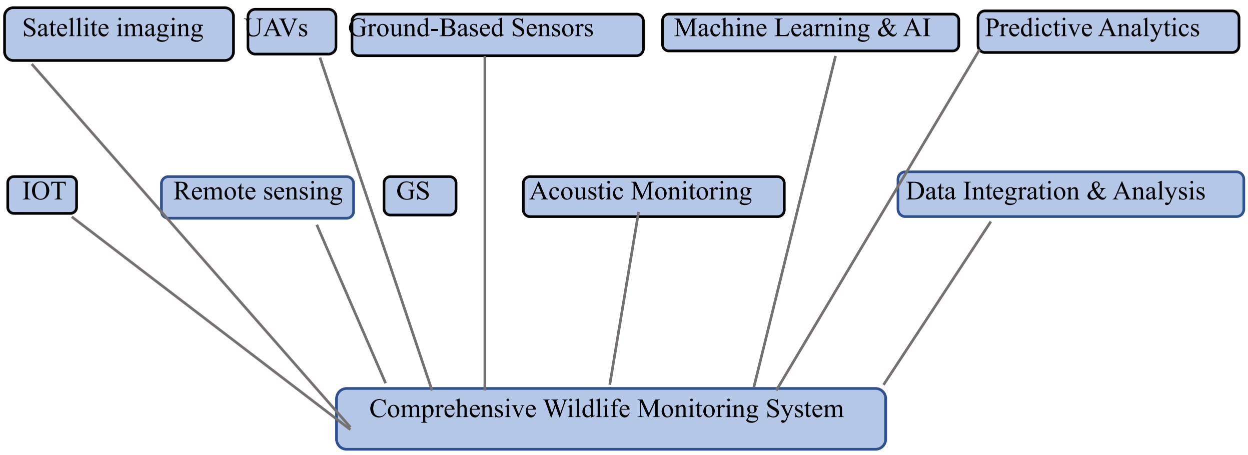

Fig : Real–time Monitoring Approaches For effective Wildlife poaching prevention

4. Machine Learning and Artificial Intelligence

Machine learning and AI technologies are used to analyze the vast amounts of data collected from satellite images, UAVs, and ground-based sensors. These technologies can detect patterns and predict poaching hotspots by processing historical and real-time data. They assist in making informed decisions on resource allocation and patrolling strategies (ar5iv) (AAAI).

5. Geographic Information Systems (GIS)

GIS is a framework for gathering, managing, and analyzing spatial and geographic data. It helps in visualizing and interpreting data to understand patterns, relationships, and trends in wildlife poaching. GIS tools can be used to map poaching incidents, predict poaching hotspots, and plan patrol routes (ar5iv).

6. Acoustic Monitoring :

Acoustic monitoring uses sound sensors to detect andanalyze sounds in the environment. In wildlife conservation, acoustic sensors can pick up sounds of gunshots, vehicle movements, or animal distress calls, providing valuable data to prevent poaching activities (SpringerLink).

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V. METHODOLOGY

This section outlines the data collection and training processes for the object detection model. It covers the training parameters and techniques, highlighting the proposed frame sampling method tailored for inferencing and accommodating various application requirements. The discussion extends to the drone and communication protocol used for live video streaming, as well as object detection on both local and remote servers. Finally, the evaluation metrics for assessing the performance of the trained model and the effectiveness of the frame sampling technique are detailed and analyzed.

A. Data Capture :

The dataset will consists of RGB and thermal images (including both color and grayscale palettes) and is categorized into two classes: rhinos and cars. Each class contains 350 images. To ensure sufficient variance, the dataset includes a mix of aerial footage, close-up shots, and thermal images, as illustrated in Figure 1. The aerial RGB images were captured using a drone, while the thermal and grayscale images were taken with a ground-based camera. Additionally, RGB data was batch downloaded from Google Images to supplement the field-acquired images.Thermal and grayscale images were captured using a FLIR One smartphone thermal camera, with both types of images set at a resolution of 640 x 512 pixels. These images were collected by Liverpool John Moores University at Knowsley Safari.

Fig. 1: Example training data with variance

B. Model selection Faster-RCNN:

The Faster-RCNN network architecture is implemented to perform object detection in two distinct stages. In the first stage, Region Proposal Networks (RPNs) are used to identify and extract features from the selected layers, enabling the model to estimate bounding box locations. In the second stage, the bounding box localization is refined by minimizing the selected loss function. Both the region proposal and object detection tasks are handled by the same CNN, providing improvements in speed and accuracy compared to earlier R-CNN networks, where region proposals were made at the pixel level instead of the feature map level. The Faster-RCNN further enhances speed by replacing selective search with an RPN. Figure 2 illustrates the basic architecture of a Faster-RCNN.

Due to the restricted operational conditions (e.g., small or partially occluded objects), other non-region-based proposal networks may struggle to achieve high accuracy. Additionally, the down sampling performed in such models reduces the available features in images.

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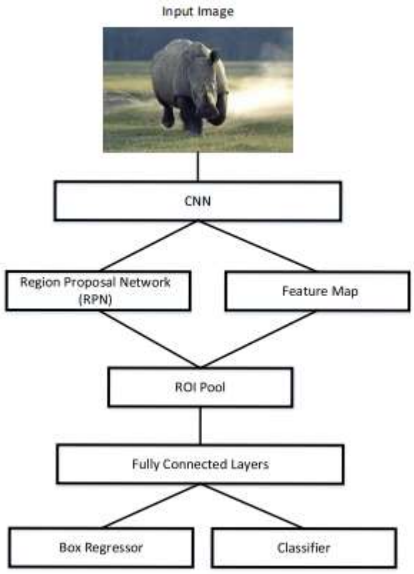

Fig. 2: Faster-RCNN Architecture

C. Transfer learning :

Transfer learning allows us to utilize a pre-trained model (initially trained on millions of images) and fine-tune its parameters during the training process with our rhino and car images. This technique is crucial because training CNNs on small datasets can result in extreme overfitting due to low variance. In this study, the base model for transfer learning tasks is the Faster-RCNN ResNet 101 model, which is pre-trained on the COCO dataset. The COCO dataset is a large object detection dataset comprising 330,000 images and 1.5 million object instances**.**

D. Model training :

Model training is carried out on an HP ProLiant ML 350 Gen 9 server, equipped with dual Intel Xeon E5-2640 v4 series processors and 768GB of RAM. Additionally, the server features a GPU stack comprising four NVIDIA Quadro M4000 graphics cards, providing a total of 32GB of DDR5 RAM

The software stack for the training pipeline includes TensorFlow 1.13.1, CUDA 10.0, and CuDNN version 7.5. The `pipeline.config` file used by TensorFlow is configured with the following training parameters:

Aspect Ratio Resizer: The minimum and maximum coefficients are set to 1500 x 1500 pixels. This setting minimizes the scaling effect on the acquired data. While increasing the resolution could improve accuracy, it would also exceed the computational capabilities of the training platform.

Feature Extractor Coefficient: The default setting is maintained, providing a standard 16-pixel stride length to preserve a high-resolution aspect ratio.

Batch Size Coefficient: Set to one to stay within the GPU memory limits.

E. Inferencing pipeline :

The object detection system proposed interfaces with a variety of camera systems using the Real-Time Messaging Protocol (RTMP). The Mavic Pro 2 drone system is used in this study which is capable of transmitting 4K videos at 30fps over a distance in excess of 7 kilometres (km). The done is connected to a linked controller using the OcuSync 2.0 protocol. Video streams at re-directed from the controller using a local Wi-Fi connection to a field laptop or to a remote server using 4G.

Object detection on video frames is then performed on the laptop or remote server. Figure 3 illustrates the end- to end inferencing pipeline.

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F. Evaluation metrics :

The model's performance is evaluated using mean average precision (mAP), a standard metric for assessing object detection models.To evaluate the performance of the frame sampling technique and determine the optimal GPU configuration, the following processing metrics are used:Decode Setting (DC): Describes the total number of frames to be analyzed within a specified time period. The coefficient value ranges from 1 to 0.0001, controlling the number of frames for inferencing. A higher value reduces the number of frames serialized for inferencing, increasing playback speed, while a lower value increases the number of frames for inferencing, decreasing playback speed. The trade-off is application-specific.

Video Frame Rate: Specifies the frequency rate of consecutively captured frames from the video source.

Total Video Frames: Indicates the total number of frames transmitted from the feed based on current playback time.

Total Video Frames Analyzed (TVFA): The number of frames processed for inferencing within the total duration of the video. This metric is calculated by counting each frame submitted to the object detection model.

Percentage of Frames Analyzed (PFA): Calculated as TVFA x 100 / Total Video Frames.

Runtime(s): The time taken by the framework to process all the analyzed frames (TVFA)

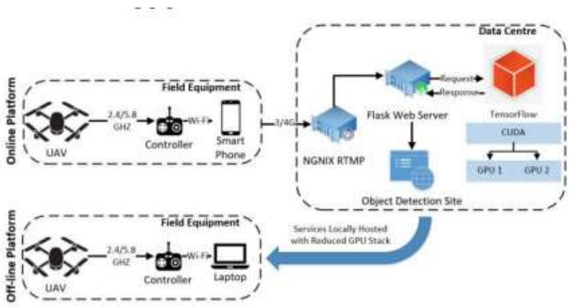
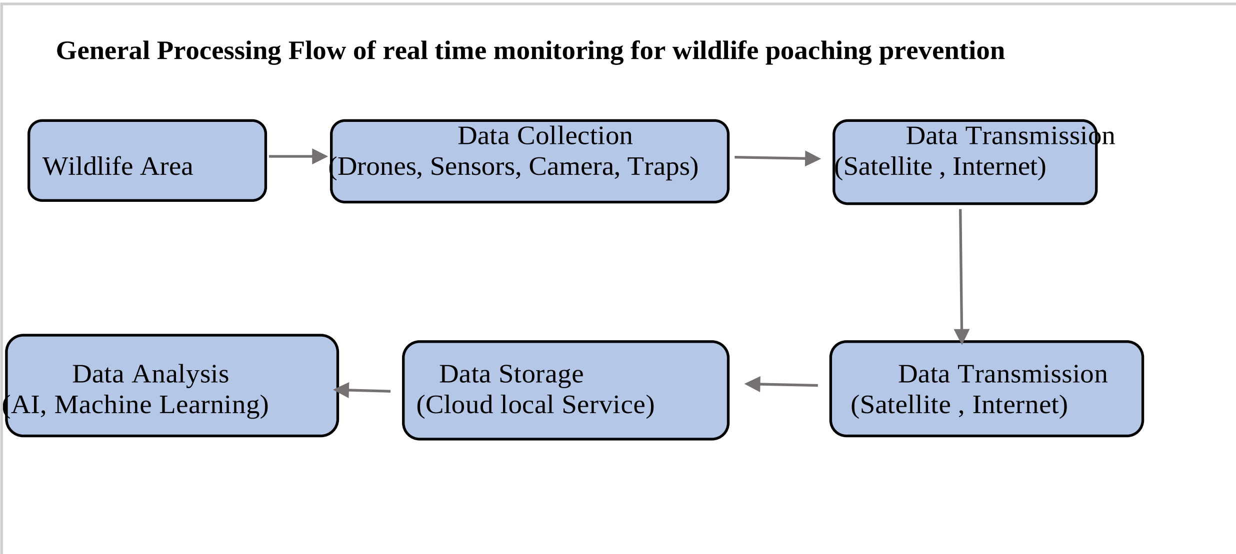


Fig. 3: Object Detection Pipeline



VI. STUDY OF RELATED WORK

The selected papers demonstrate a clear demarcation of their focus areas within the realm of real-time monitoring for wildlife poaching prevention. Kumar and Singh (2020) specifically examine drone technology, emphasizing its utility in aerial surveillance, while Horner and McCarthy (2019) explore the integration of remote sensing and machine learning

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to enhance poaching detection capabilities. Thompson and Kauffman (2021) provide an overview of technological trends, situating their findings within the broader conservation landscape. Lindsey and Kalahar (2018) analyze various technological innovations, highlighting their effects on reducing poaching incidents. Meanwhile, Pettorelli and Saxton (2019) focus on the monitoring of wildlife populations, emphasizing data-driven approaches. Brandon and Redford (2022) stress the importance of community engagement, suggesting that local involvement is essential for effective conservation. This context identification illustrates the multifaceted nature of wildlife protection efforts, emphasizing the interplay between technology, community involvement, and policy frameworks in addressing the pressing issue of poaching.

Ref no.	Research Work/Paper	Author / Year	Techniques	Experiments/ Observations	Remarks
[1]	Leveraging Drone Technology for Real-Time Wildlife Monitoring	Kumar& Singh, 2020	Drones,aerial surveillance.	Demonstrated the effectiveness of drones in monitoring remote areas for poaching activities	Limited flight time and coverage area.
[2]	Integrating Remote Sensing and Machine Learning to Combat Poaching	Horner& McCarthy, 2019	Remote sensing, machine learning	Enhanced detection of poaching activities using predictive analytics and spatial data	Data quality and integration challenges.
[3]	Real-Time Monitoring Systems for Wildlife Conservation	Thompson & Kauffman, 2021	Various technologies, real-time data sharing	Overview of trends showing improvements in response times to poaching incidents.	Need for ongoing funding and support.
[4]	Technological Innovations in Poaching Prevention	Lindsey & Kalahar, 2018	Drones, camera traps, sensors	Analysis of different technologies and their impacts on reducing poaching incidents.	Technology may be costly to implement and maintain.
[5]	The Role of Technology in Wildlife Conservation	Graham & Egan, 2020	Real-time monitoring, technology integration	Discussed the role of technology in enhancing wildlife conservation efforts.	Reliance on technology may overshadow local knowledge.
[6]	The Environmental Crime Crisis	Nellemann & Interpol, 2016	Policy analysis, data aggregation	Examined the global impact of wildlife crime on biodiversity and sustainable development	Limited focus on localized solutions.
[7]	Using Technology to Monitor Wildlife Populations	Pettorelli & Saxton, 2019	Monitoring systems, camera traps	Investigated methods for monitoring wildlife populations and the effectiveness of these systems.	Technological reliance could neglect traditional methods.
[8]	Community-Based Conservation and Real-Time Monitoring	Brandon & Redford, 2022	Community engagement, real-time data sharing	Emphasized the importance of involving local communities in conservation efforts.	Potential conflicts between community needs and conservation goals.
[9]	Emerging Technologies for Real-Time	Sinha & Choudhury, 2021	Various new technologies,	Overview of emerging technologies that can	Rapid technological changes can lead to obsolescence.

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	Wildlife Monitoring		monitoring systems	enhance wildlife monitoring practices.	
[10]	Real-Time Wildlife Monitoring: Bridging the Gap	Carter & Linnell, 2020	Technology integration, policy development	Discussed the integration of technology and conservation practices to improve protection.	Resistance from stakeholders to new technologies.

VII. CHALLENGES FACED

Challenges Faced in Existing Real-Time Monitoring Models for Wildlife Poaching Prevention

Limited Flight Time and Coverage Area (Kumar & Singh, 2020) : Drones have limited battery life and coverage area, making continuous and extensive monitoring challenging. This limitation necessitates frequent battery changes or multiple drones to cover large regions, increasing operational complexity and cost.

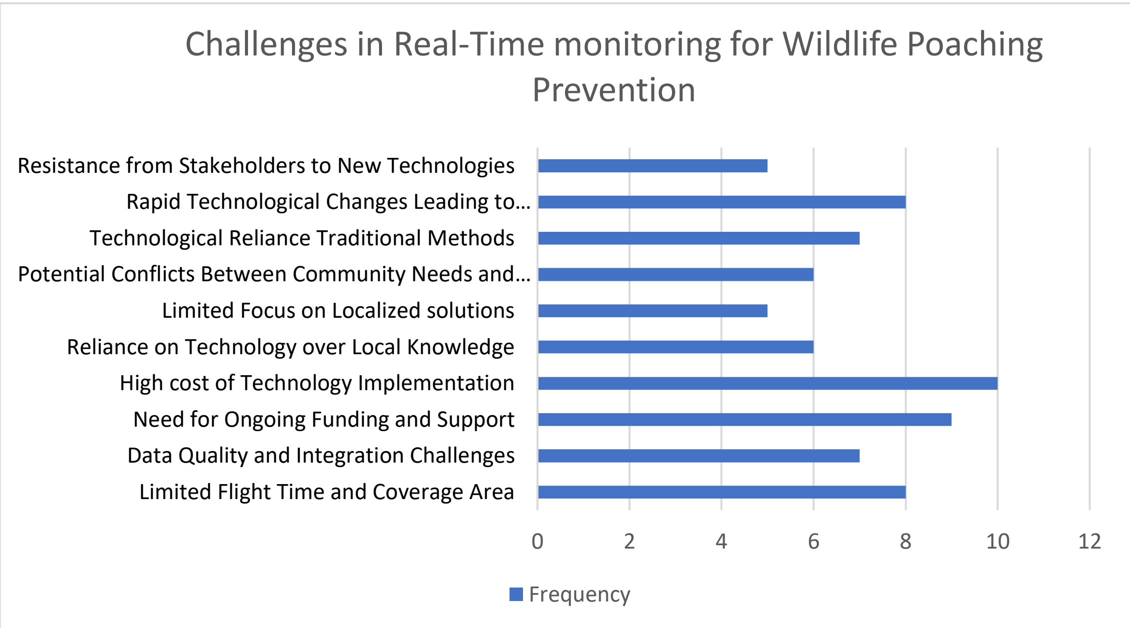
Data Quality and Integration Challenges (Horner & McCarthy, 2019) : Integrating data from various sources such as remote sensing, ground sensors, and camera traps can be challenging. Discrepancies in data quality, formats, and the sheer volume of data can complicate analysis and delay response times.

Need for Ongoing Funding and Support (Thompson & Kauffman, 2021) : Real-time monitoring systems require substantial and continuous funding for maintenance, upgrades, and operations. Ensuring sustained financial support is crucial but often difficult, especially in regions with limited resources.

High Cost of Technology Implementation (Lindsey & Kalahar, 2018): Advanced technologies like drones, AI, and sophisticated sensors are expensive to procure, deploy, and maintain. This high cost can be a barrier for many conservation projects, particularly in developing countries.

Reliance on Technology Over Local Knowledge (Graham & Egan, 2020): Over-reliance on technology can lead to the undervaluation of local knowledge and traditional conservation practices. Effective poaching prevention requires a balanced approach that integrates modern technology with the expertise and involvement of local communities.

Limited Focus on Localized Solutions (Nellemann & Interpol, 2016): Broad, global strategies may overlook the unique challenges and dynamics of local contexts. Effective poaching prevention needs tailored solutions that address specific regional issues and engage local stakeholders.



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VIII. CONCLUSION

The comprehensive analysis of real-time monitoring approaches for wildlife poaching prevention reveals the critical role of advanced technologies in enhancing conservation efforts. Kumar and Singh (2020) highlight the utility of drones for effective surveillance, while Horner and McCarthy (2019) emphasize the integration of remote sensing and machine learning to improve poaching detection. Thompson and Kauffman (2021) and Lindsey and Kalahar (2018) underscore the importance of various technological innovations in reducing poaching incidents. However, challenges such as high costs (Lindsey & Kalahar, 2018), data quality issues (Horner & McCarthy, 2019), and the need for continuous funding (Thompson & Kauffman, 2021) persist. Furthermore, Graham and Egan (2020) and Pettorelli and Saxton (2019) caution against over-reliance on technology at the expense of local knowledge and traditional methods. The necessity of community involvement is highlighted by Brandon and Redford (2022), emphasizing that local engagement is vital for effective conservation. Addressing these challenges requires a balanced and multifaceted approach, integrating modern technologies with traditional practices and community support, as discussed by Carter and Linnell (2020) and Sinha and Choudhury (2021). By leveraging these strategies, the potential for successful wildlife poaching prevention is significantly enhanced, contributing to the long-term preservation of biodiversity.

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