International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct-2026, PP 01-06

Ai In Wildlife Monitoring: A Review Of Camera-Trap Vision, Individual Re-Identification, Bioacoustics And Edge-Based Anti-Poaching Systems

Patole Omkar Jagdish[1] Prof. M. R. Kumbhoje[2] Prof. M. C. Kolse[3] Prof. S. K. Said[4]
Department of Artificial Intelligence and Data Science
Jaihind College of Engineering
Pune, Maharashtra, India

Abstract—Automated wildlife monitoring is central to biodiversity conservation, protection of endangered species, habitat preservation and reduction of human–wildlife conflict. Conventional approaches that rely on manual inspection of camera-trap images and field acoustic recordings create large processing backlogs, delay responses to threats and suffer false positives from moving vegetation. This paper reviews AI for wildlife monitoring. It examines deep convolutional networks for detecting, classifying and counting animals in camera-trap images, generalization across new locations, detectors that filter empty images, individual re-identification of striped and spotted animals such as tigers and leopards using deep embeddings, bioacoustic monitoring of birds and other species, and detection of threats such as gunshots and chainsaws. Anti-poaching decision support and drones with thermal detection are discussed, along with deployment on solar-powered edge devices with compressed models. A multi-tier architecture comprising field sensing, edge inference, connectivity, a conservation intelligence platform and ranger response is proposed, together with research gaps, objectives, a comparison of methods and challenges such as domain shift, rare species, power and connectivity in forests. The review concludes that AI can turn monitoring data into timely conservation action.

Index Terms—Wildlife monitoring, camera traps, species classification, animal re-identification, bioacoustics, anti-poaching, edge AI, conservation

I. Introduction

India's forests and protected areas host tigers, leopards, elephants and many other species, and their conservation depends on knowing where animals are, how populations change and where threats occur. Camera traps and acoustic recorders collect enormous amounts of data, but reviewing millions of images and hours of audio by hand can take months, delaying both research and responses to poaching.

AI can process these data automatically. Tuia *et al.* [1] described perspectives in machine learning for wildlife conservation, emphasizing the need for collaboration between ecologists and AI researchers. Camera-trap capture–recapture methods, introduced for tigers by Karanth [2], rely on identifying individuals, a task that deep learning can now assist.

This paper reviews AI techniques for wildlife monitoring and proposes an edge-based architecture for real-time conservation intelligence.

II. Theoretical Background

2.1 Monitoring Data Sources

Fig. 1 summarizes data sources (camera traps, acoustic sensors, drones, GPS collars) and AI tasks (species classification, counting, re-identification, sound classification and threat detection).

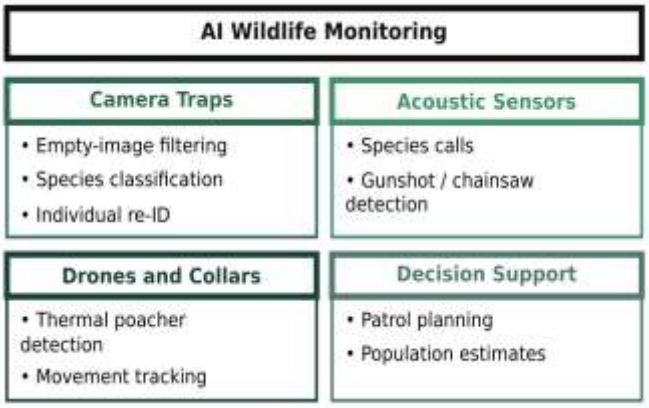


Fig. 1. Wildlife monitoring data sources and AI tasks.

2.2 Individual Identification

Many big cats have unique stripe or rosette patterns. Deep metric learning maps images of the same individual close together in an embedding space, so new images can be matched to known animals.

III. Survey of Existing Approaches

Norouzzadeh *et al.* [3] trained deep CNNs on millions of Snapshot Serengeti camera-trap images and automatically identified, counted and described animals with accuracy comparable to volunteer crowds, potentially saving years of human labour. Tabak *et al.* [4] trained species classifiers on images from multiple North American sites and released tools for ecologists.

Beery *et al.* [5] showed that models often fail at new camera locations because they learn background cues, an important generalization problem. Beery *et al.* [6] later developed a detector, now widely known as MegaDetector, that finds animals, people and vehicles and filters empty images, greatly reducing review effort.

For acoustics, Stowell [7] reviewed deep learning in computational bioacoustics, and Kahl *et al.* [8] presented BirdNET for identifying bird species from audio recordings at scale.

For protection, Fang *et al.* [9] deployed PAWS, which uses machine learning and game theory to plan ranger patrols where poaching is likely, and Bondi *et al.* [10] detected poachers and animals in thermal drone video in near real time. Modern YOLO detectors [11] and model compression [12] enable such models on low-power devices. Table I summarizes these works.

TABLE I Summary of Literature Survey

Sr. No.	Ref.	Year	Methodology	Findings	Research Gap
1	[2]	1995	Camera-trap capture–recapture	Tiger population estimation	Manual identification
2	[9]	2016	PAWS patrol planning	Field-deployed anti-poaching aid	Data from past patrols
3	[3]	2018	Deep CNNs on Snapshot Serengeti	Automated identification and counting	Single ecosystem
4	[5]	2018	Generalization study	Exposed location bias	Analysis study
5	[10]	2018	SPOT thermal drone detection	Near-real-time poacher detection	Drone endurance
6	[4]	2019	Species classifier for ecologists	Accessible tools	Regional species
7	[6]	2019	MegaDetector pipeline	Filters empty images at scale	Detection, not species
8	[8]	2021	BirdNET bioacoustics	Large-scale bird identification	Birds only

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct-2026, PP 01-06

IV. Comparative Study

Table II compares methods. Empty-image filtering saves the most effort, species classifiers support surveys, re-identification supports population estimates, acoustics detect hidden species and threats, and thermal drones support night patrols.

TABLE II Comparison of Wildlife Monitoring Methods

Method	Purpose	Data Need	Edge Feasibility
Empty-image detector	Reduce review effort	Medium	High
Species classifier	Biodiversity surveys	High	Medium
Re-ID embeddings	Population estimates	Medium	Medium
Bioacoustic CNN	Species and threats	Medium	High
Thermal drone detector	Night anti-poaching	Medium	Medium

V. Research Gaps

- G1: Models trained in one region generalize poorly to new habitats and camera placements.
- G2: Rare and endangered species have few training images.
- G3: Real-time alerts are limited by power and connectivity in remote forests.
- G4: Individual re-identification is mature for only a few species.
- G5: Integration of AI outputs with ranger operations is often weak.

VI. Aims and Objectives

1. 1) To review AI methods for camera-trap, acoustic and drone-based wildlife monitoring.
2. 2) To examine individual re-identification and threat detection.
3. 3) To propose an edge-based wildlife monitoring architecture.
4. 4) To compare methods in accuracy, data needs and deployment feasibility.
5. 5) To identify challenges and future directions.

VII. Proposed Architecture

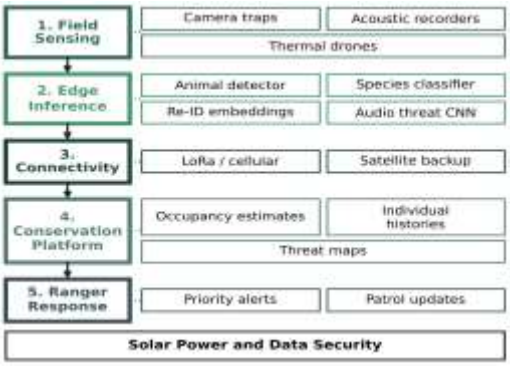


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed edge-based wildlife monitoring architecture.

7.1 Field Sensing Layer

Camera traps with infrared flash, acoustic recorders and thermal drones are deployed along trails and boundaries.

7.2 Edge Inference Layer

Solar-powered devices run a compressed detector to discard empty images, a species classifier, a re-identification embedding model for big cats and a 1-D CNN that detects gunshots and chainsaws in audio.

7.3 Connectivity Layer

Only detections and alerts are transmitted over LoRa, cellular or satellite links, saving power and bandwidth.

7.4 Conservation Intelligence Platform

Detections are aggregated into occupancy and population estimates, individual histories and threat maps.

7.5 Ranger Response Layer

High-priority alerts, such as gunshots or people in core zones at night, are sent to ranger teams with location; patrol plans are updated.

VIII. Process Flow and Evaluation

Fig. 3 outlines the workflow. Re-identification compares the embedding of a new image f(x) with stored embeddings $f(x_i)$ of known individuals using distance

$$d = \|f(x) - f(x_i)\|_2 \quad (1)$$

and a match is declared when d falls below a threshold. Models are trained with a triplet loss

$$L = max(0, d(a,p) - d(a,n) + m) \quad (2)$$

which pulls images of the same individual (anchor a, positive p) together and pushes different individuals (negative n) apart by margin m.

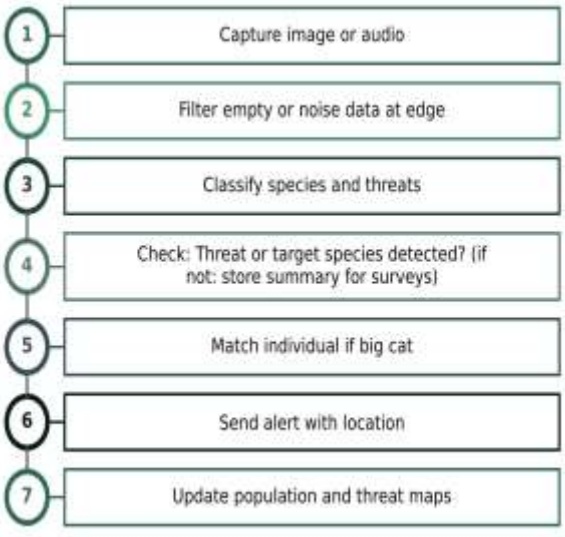


Fig. 3. Wildlife monitoring and alert workflow.

IX. Limitations and Future Scope

Table III summarizes challenges. Future directions include self-supervised and few-shot models for rare species, satellite imagery for habitat change, community-based monitoring apps and AI-assisted mitigation of human–elephant conflict.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Domain shift	Diverse training sites; adaptation
Rare species	Few-shot and self-supervised learning
Power in forests	Solar devices; duty cycling
Connectivity	Edge filtering; LoRa / satellite
Operational use	Ranger-friendly alerts and training

X. Conclusion

AI is transforming wildlife monitoring from slow manual review into rapid, automated analysis. The reviewed literature shows that deep learning accurately detects, classifies and identifies animals in camera-trap images, that bioacoustic models monitor species and threats, and that drones and patrol planning support anti-poaching. Edge deployment and close collaboration with conservation teams will turn these capabilities into timely protection of wildlife.

10.1 Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

References

1. D. Tuia et al., “Perspectives in machine learning for wildlife conservation,” Nat. Commun., vol. 13, Art. no. 792, 2022.
2. K. U. Karanth, “Estimating tiger Panthera tigris populations from camera-trap data using capture–recapture models,” Biol. Conserv., vol. 71, no. 3, pp. 333–338, 1995.
3. M. S. Norouzzadeh et al., “Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning,” Proc. Natl. Acad. Sci. USA, vol. 115, no. 25, pp. E5716–E5725, 2018.
4. M. A. Tabak et al., “Machine learning to classify animal species in camera trap images: Applications in ecology,” Methods Ecol. Evol., vol. 10, no. 4, pp. 585–590, 2019.
5. S. Beery, G. Van Horn, and P. Perona, “Recognition in terra incognita,” in Proc. ECCV, 2018, pp. 456–473.
6. S. Beery, D. Morris, and S. Yang, “Efficient pipeline for camera trap image review,” arXiv:1907.06772, 2019.
7. D. Stowell, “Computational bioacoustics with deep learning: A review and roadmap,” PeerJ, vol. 10, Art. no. e13152, 2022.
8. S. Kahl, C. M. Wood, M. Eibl, and H. Klinck, “BirdNET: A deep learning solution for avian diversity monitoring,” Ecol. Inform., vol. 61, Art. no. 101236, 2021.
9. F. Fang et al., “Deploying PAWS: Field optimization of the protection assistant for wildlife security,” in Proc. AAAI Conf. Artif. Intell. (IAAI), 2016, pp. 3966–3973.
10. E. Bondi et al., “SPOT poachers in action: Augmenting conservation drones with automatic detection in near real time,” in Proc. AAAI Conf. Artif. Intell. (IAAI), 2018.

11. G. Jocher, A. Chaurasia, and J. Qiu, “Ultralytics YOLOv8,” 2023. [Online]. Available: https://github.com/ultralytics/ultralytics

12. S. Han, H. Mao, and W. J. Dally, “Deep compression: Compressing deep neural networks with pruning, trained quantization and Huffman coding,” in Proc. ICLR, 2016.