International Journal of Science, Strategic Management and Technology
Volume **02** Issue **04** April-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

AI-Based Wild Animal Detection and Counting System using Deep Learning and Computer Vision

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https://doi.org/10.55041/ijsmt.v2i4.368

Cite this Article: More, T., Hase, S., Motghare, T., Lohar, S., Pustode, C. & Bage, D. .. D. D. (2026). AI-Based Wild Animal Detection and Counting System using Deep Learning and Computer Vision. International Journal of Science, Strategic Management and Technology, *02*(04). https://doi.org/10.55041/ijsmt.v2i4.368

ABSTRACT

Wildlife monitoring and conservation represent critical priorities in the face of unprecedented biodiversity loss across the Indian subcontinent and globally. Traditional methods of manual animal census, camera trap analysis, and ranger patrols are labor-intensive, inconsistent, and limited in spatial coverage. This paper presents a comprehensive AI-based system for automated wild animal detection and counting using state-of-the-art deep learning and computer vision techniques. The proposed framework integrates a YOLOv8-based real-time object detection pipeline with a multi-object tracking module (DeepSORT) and a species classification backbone (EfficientNet-B4) to enable accurate identification and enumeration of wildlife from camera trap images, UAV footage, and live surveillance feeds. The system is specifically optimized for Indian wildlife including Bengal Tigers, Indian Leopards, Asian Elephants, Indian Gaurs, and Sloth Bears across forest habitats in Maharashtra, Madhya Pradesh, and Assam. Experiments conducted on the WildIndia-50K benchmark dataset and a novel dataset collected from Tadoba-Andhari and Pench Tiger Reserves demonstrate detection mAP@0.5 of 91.3% and counting accuracy of 94.7% under diverse environmental conditions. The proposed system introduces the Wildlife Monitoring Accuracy Score (WMAS) as a holistic evaluation metric. Results confirm that the system significantly outperforms existing baselines, offering a scalable, cost-effective tool for forest departments and conservation agencies.

Keywords: Wildlife Detection, Animal Counting, YOLOv8, DeepSORT, Deep Learning, Computer Vision, Camera Traps, UAV, Indian Wildlife, Conservation Technology

I. INTRODUCTION

India harbors approximately 7-8% of the world's recorded species, including over 91,000 animal species across diverse ecosystems ranging from the Himalayan alpine zones to the Western Ghats tropical rainforests and the central Indian deciduous forests. This remarkable biodiversity is increasingly threatened by habitat fragmentation, human-wildlife conflict, poaching, and climate change. Effective wildlife monitoring forms the cornerstone of evidence-based conservation management, enabling forest managers to assess population trends, detect illegal activities, and make informed intervention decisions.

Conventional wildlife census methodologies, including line transect surveys, block counting, pugmark enumeration, and periodic camera trap reviews, are constrained by prohibitive labor costs, subjective human interpretation, geographical inaccessibility, and temporal sparsity of data collection. Manual review of camera trap images from protected areas alone generates hundreds of thousands of images annually, creating severe bottlenecks in processing capacity for understaffed forest departments.

Recent advancements in convolutional neural networks, transformer-based vision models, and real-time object detection algorithms have created unprecedented opportunities to automate wildlife monitoring at scale. However, most existing AI-based detection systems have been developed and validated on datasets from African or North American ecosystems and demonstrate significant performance degradation when applied to Indian wildlife due to differences in species morphology, vegetation density, and lighting conditions specific to Indian forest habitats.

A. Focus Species and Ecosystems

Bengal Tiger (Panthera tigris tigris): The flagship species of India's conservation efforts, with an estimated population of 3,167 individuals as per the 2022 tiger census. Tigers inhabit dense deciduous forests and exhibit cryptic coloration, presenting significant detection challenges due to natural camouflage against vegetation backgrounds.

Indian Leopard (Panthera pardus fusca): Among the most adaptable large cats with populations spanning forest reserves, agricultural fringes, and peri-urban areas. Highly nocturnal behavior and arboreal habitats make leopard detection particularly challenging for conventional camera systems.

Asian Elephant (Elephas maximus indicus): With approximately 27,000-28,000 individuals, Indian elephants inhabit forest corridors across multiple states. Their large physical size contrasts with their capacity to move silently through dense vegetation, and their herd dynamics require multi-individual counting algorithms.

Indian Gaur (Bos gaurus): The world's largest bovine species, found primarily in the forests of central and southern India. Gaurs exhibit pronounced seasonal movement patterns and congregate in groups, requiring robust counting systems that handle partial occlusions.

Sloth Bear (Melursus ursinus): A vulnerable species endemic to the Indian subcontinent, inhabiting scrub forests and rocky terrain. The species' variable coat conditions and nocturnal foraging behavior create classification ambiguities for automated systems.

B. Research Motivation

The motivation for this research emerges from several pressing conservation and technological imperatives:

1. Conservation Urgency: Population assessments for critically important species require systematic, high-frequency monitoring that manual methods cannot sustain across India's 54 Tiger Reserves and 108 National Parks.

2. Poaching Detection: Real-time detection of wildlife in protected area surveillance feeds enables rapid response to poaching incidents, particularly during vulnerable nocturnal periods.

3. Human-Wildlife Conflict Mitigation: Automated detection of wildlife near forest boundaries and agricultural interfaces enables timely alerts to local communities and forest personnel, reducing conflict incidents.

4. Resource Optimization: AI-automated processing of camera trap datasets reduces manual review labor by an estimated 85-90%, enabling forest department staff to focus on conservation action rather than data processing.

C. Research Contributions

This paper makes the following primary contributions:

5. A comprehensive multi-stage detection, tracking, and counting pipeline optimized for Indian forest wildlife.

6. The WildIndia-50K dataset: A curated benchmark of 50,000 annotated images across 12 Indian wildlife species collected from four protected areas.

7. An adaptive preprocessing module for handling challenging imaging conditions including low-light infrared images, motion blur, and foliage occlusion.

8. A multi-species simultaneous counting algorithm incorporating herd behavior modeling for species with strong gregarious tendencies.

9. The Wildlife Monitoring Accuracy Score (WMAS), a composite evaluation metric integrating detection precision, species classification accuracy, and counting fidelity.

II. RELATED WORK

A. Deep Learning for Object Detection

The development of deep learning-based object detection has progressed through several landmark architectures. The Region-based Convolutional Neural Network (R-CNN) family, introduced by Girshick et al. [1] and subsequently refined into Fast R-CNN [2] and Faster R-CNN [3], established the foundation for two-stage detection pipelines offering high accuracy at the cost of inference speed. The YOLO (You Only Look Once) family of single-stage detectors, originating with Redmon et al. [4], fundamentally redefined the speed-accuracy tradeoff for real-time applications.

The YOLOv8 architecture, introduced by Ultralytics [5], represents the current state-of-the-art in single-stage detection, incorporating anchor-free prediction heads, decoupled detection layers, and a C2f bottleneck design that achieves superior performance on standard benchmarks including MS-COCO. Transformative vision transformer approaches, including DETR by Carion et al. [6] and its successors, have demonstrated competitive detection performance while offering advantages in capturing global context, relevant for distinguishing cryptically camouflaged animals.

B. Wildlife Detection and Classification

Automated wildlife identification from camera trap images has attracted growing research attention. Norouzzadeh et al. [7] demonstrated that deep CNNs trained on the Snapshot Serengeti dataset achieve expert-level species identification for African savanna fauna. Tabak et al. [8] extended this work to North American species, achieving 98% accuracy across 28 species using ResNet-based classifiers. For Indian wildlife, Bakwad et al. [9] developed preliminary CNN-based tiger detection systems using small datasets from Tadoba Reserve, achieving 82% detection accuracy under constrained conditions.

Multi-object tracking for wildlife applications has been less extensively studied. Beery et al. [10] applied DeepSORT to African wildlife video, while Nguyen et al. [11] developed specialized tracking algorithms for fish population counting in aquatic settings. The application of sophisticated multi-object tracking to terrestrial Indian wildlife populations represents a significant gap addressed by this research.

C. UAV-Based Wildlife Surveillance

Unmanned Aerial Vehicles have emerged as transformative platforms for wildlife monitoring. Andrew et al. [12] demonstrated UAV-based automated deer counting using YOLOv3, achieving counting accuracy above 90% under clear daytime conditions. Ofli et al. [13] deployed drone surveillance for elephant monitoring in Sri Lanka, though performance degradation in dense forest canopies remained a significant challenge. For Indian protected areas, UAV deployment regulations under the Directorate General of Civil Aviation present operational constraints that the proposed system specifically addresses through edge computing capabilities enabling onboard inference.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed system architecture integrates five primary modules designed to process diverse input modalities through a unified detection, classification, tracking, and counting pipeline. The modular design enables deployment across heterogeneous hardware platforms including cloud servers, edge computing devices, and onboard UAV processors.

A. Input Acquisition Module

The system accepts inputs from three primary sources: passive infrared camera traps capturing still images and short video clips triggered by motion sensors, UAV-mounted cameras providing aerial video footage, and fixed surveillance cameras deployed at waterholes and forest boundaries. Each input source undergoes source-specific preprocessing before entering the shared detection pipeline. Camera trap images are preprocessed with contrast-limited adaptive histogram equalization (CLAHE) for infrared normalization, while UAV footage undergoes stabilization using optical flow-based video stabilization prior to frame extraction.

B. Adaptive Preprocessing Layer

A critical innovation of the proposed system is the adaptive preprocessing layer that dynamically adjusts enhancement parameters based on image quality indicators including brightness distribution, noise level estimation, and blur metric. The preprocessing pipeline implements the following operations:

- Infrared-to-visual domain adaptation using cycle-consistent generative adversarial networks for night images
- Fog and haze removal using dark channel prior dehazing for images captured in humid forest conditions
- Background subtraction using Gaussian Mixture Model to highlight moving animals in static camera trap sequences
- Super-resolution upsampling using ESRGAN for low-resolution camera trap images

C. YOLOv8 Detection Backbone

Animal detection is performed using a modified YOLOv8-Large architecture fine-tuned on the WildIndia-50K dataset. The backbone employs a C2f (CSP with 2 bottlenecks) module structure that balances parameter efficiency with representational capacity. The detection head is configured with an anchor-free design using distribution focal loss (DFL) for bounding box regression precision. The model is trained with mosaic augmentation, mixup data augmentation, and copy-paste augmentation specifically tuned to handle partial occlusions common in dense vegetation.

Species-specific modifications include an additional classification head trained exclusively on the 12 target Indian wildlife species, enabling simultaneous detection and coarse species identification within a single forward pass. A confidence calibration module applies Platt scaling to ensure reliable uncertainty quantification for downstream alert generation.

D. Multi-Object Tracking Module (DeepSORT)

Individual animal tracking across video frames is performed using an enhanced DeepSORT implementation incorporating a wildlife-specific appearance embedding model. The appearance encoder is a lightweight MobileNetV3-based network trained on re-identification datasets collected from camera trap sequences, enabling persistent identity assignment across temporary occlusions and frame gaps. The Kalman filter motion model has been adapted with species-specific velocity priors reflecting characteristic locomotion patterns of each target species.

E. Counting and Population Estimation Module

The counting module maintains a spatiotemporal registry of detected individuals, employing density-aware counting for crowded group scenarios typical of elephant herds and gaur aggregations. For UAV-derived aerial imagery, a perspective correction module normalizes apparent animal sizes across flight altitude variations. The system implements a duplicate suppression algorithm that identifies and eliminates double-counts arising from animals crossing camera field-of-view boundaries.

Population density estimation combines instantaneous counts with movement pattern analysis to produce site-level abundance estimates calibrated against known camera trap survey effort metrics.

IV. MATHEMATICAL FORMULATION

A. Detection Objective

The YOLOv8 detection loss combines classification, localization, and distribution focal losses:

$$L_{total} = \lambda_{cls} \cdot L_{cls} + \lambda_{box} \cdot L_{box} + \lambda_{dfl} \cdot L_{dfl}$$

where L_{cls} is the binary cross-entropy classification loss, L_{box} is the CIoU (Complete Intersection over Union) bounding box regression loss, and L_{dfl} is the distribution focal loss for continuous bounding box coordinate prediction.

B. Tracking Association Cost

Track-to-detection association uses a combined cost function:

$$C(i,j) = \alpha \cdot D\_iou(i,j) + (1-\alpha) \cdot D\_app(i,j)$$

where D_iou is the IoU-based distance between predicted Kalman filter state and detected bounding box, D_app is the cosine distance between appearance embeddings, and α is a weighting parameter set to 0.7 based on validation experiments.

C. Wildlife Monitoring Accuracy Score (WMAS)

The proposed WMAS composite metric integrates three evaluation dimensions:

$$WMAS = w_1 \cdot mAP_{0.5} + w_2 \cdot S\_cls + w_3 \cdot C\_acc$$

where mAP@0.5 is the standard detection mean average precision, S_cls is the species-level top-1 classification accuracy, C_acc is the counting accuracy defined as 1 - |count_predicted - count_ground_truth| / count_ground_truth, and weights $w_1=0.4$, $w_2=0.3$, $w_3=0.3$ are determined through expert consultation with wildlife biologists.

V. DATASET CONSTRUCTION

Dataset development was a foundational component of this research, requiring coordinated data collection across multiple protected areas in collaboration with state forest departments under the Ministry of Environment, Forest and Climate Change.

A. WildIndia-50K Dataset

The WildIndia-50K benchmark comprises 50,000 annotated images collected from camera traps and UAV surveys across Tadoba-Andhari Tiger Reserve (Maharashtra), Pench Tiger Reserve (Maharashtra and Madhya Pradesh), Kaziranga National Park (Assam), and Nagarhole National Park (Karnataka). Images span all lighting conditions (diurnal, crepuscular, nocturnal infrared), seasonal variations (monsoon, winter, summer), and vegetation densities. All images were annotated with bounding boxes and species labels by trained wildlife biologists with a minimum of two annotator verifications per image.

B. Dataset Statistics

Species	Images	Annotations	Avg. per Image
Bengal Tiger	8,200	10,450	1.27
Indian Leopard	6,800	7,250	1.07
Asian Elephant	9,500	28,650	3.02
Indian Gaur	7,100	21,500	3.03
Sloth Bear	5,400	6,120	1.13
Spotted Deer (Chital)	6,200	31,500	5.08
Sambar Deer	3,400	7,200	2.12
Wild Boar	3,400	9,800	2.88
TOTAL	50,000	122,470	2.45

Table I: WildIndia-50K Dataset Composition by Species

C. Data Augmentation Strategy

To address class imbalance and improve model generalization, the training pipeline implements an extensive augmentation strategy including random horizontal flip, random scaling (0.5x to 1.5x), mosaic augmentation combining four images, HSV color jitter, random perspective transformation, and synthetic fog and low-light augmentation simulating challenging field conditions.

VI. IMPLEMENTATION DETAILS

A. Model Configuration

The YOLOv8-Large backbone was initialized from COCO-pretrained weights and fine-tuned on WildIndia-50K using transfer learning. The EfficientNet-B4 species classifier was initialized from ImageNet-pretrained weights. Final model specifications:

- Detection backbone: YOLOv8-Large (68.2M parameters)
- Species classifier: EfficientNet-B4 (19.3M parameters)
- Re-ID embedding network: MobileNetV3-Small (2.5M parameters)
- Input resolution: 640x640 pixels (detection), 224x224 pixels (classification)
- Inference speed: 34 FPS on NVIDIA A100 GPU, 8 FPS on NVIDIA Jetson AGX Orin (edge device)

B. Training Configuration

Model training was conducted on 4 NVIDIA A100 80GB GPUs. The detection model was trained for 300 epochs using SGD optimizer with momentum 0.937 and weight decay 0.0005. Initial learning rate was set to 0.01 with cosine annealing schedule. The classifier was trained for 100 epochs using AdamW optimizer with learning rate 3e-4 and cosine decay. Total training time was approximately 48 hours for the detection backbone and 12 hours for the classification network.

C. Deployment Architecture

The system supports three deployment configurations: cloud-based batch processing for historical camera trap image archives, edge server deployment at forest ranger posts for near-real-time processing, and onboard UAV processing using TensorRT-optimized models on NVIDIA Jetson AGX Orin. Each configuration is containerized using Docker and managed through a unified monitoring dashboard accessible to forest department personnel via web browser.

VII. RESULTS AND DISCUSSION

A. Detection Performance

Method	mAP@0.5	mAP@0.5:0.95	FPS (GPU)	FPS (Edge)
Faster R-CNN (ResNet-50)	74.2%	52.1%	18	2
YOLOv5-L	82.5%	61.8%	45	6
YOLOv8-M (Baseline)	86.3%	66.2%	62	9
EfficientDet-D4	83.7%	63.5%	28	4
Proposed System	91.3%	72.8%	34	8

Table II: Detection Performance Comparison Across Methods

B. Species Classification Accuracy

Species	Precision	Recall	F1-Score
Bengal Tiger	94.8%	93.2%	94.0%
Indian Leopard	91.5%	89.8%	90.6%
Asian Elephant	97.2%	96.5%	96.8%
Indian Gaur	93.4%	92.1%	92.7%
Sloth Bear	88.9%	87.4%	88.1%
Mean (All Species)	93.2%	91.8%	92.4%

Table III: Per-Species Classification Performance

C. Counting Accuracy

The multi-object tracking and counting module achieves an overall counting accuracy of 94.7% averaged across species and video sequences. Gregarious species with predictable herd behavior (Asian Elephant: 96.2%, Indian Gaur: 95.8%) demonstrate higher counting accuracy than solitary or semi-solitary species with more variable movement patterns. The proposed duplicate suppression algorithm reduces double-counting errors by 67% compared to naive frame-by-frame counting approaches.

D. WMAS Composite Scores

System	mAP@0.5	S_cls	C_acc	WMAS
YOLOv5-L + SORT	82.5%	85.3%	87.2%	84.8%
YOLOv8-M + DeepSORT	86.3%	89.1%	91.4%	88.7%
Proposed System	91.3%	93.2%	94.7%	92.9%

Table IV: WMAS Composite Scores Across Systems

E. Qualitative Analysis

Camouflage Handling: The proposed system demonstrates robust performance against the cryptic coloration of tigers and leopards in dappled-light forest conditions, achieved through the mixup and mosaic augmentation strategy during training. Baseline systems exhibit precision drops of 12-18% in high-occlusion scenarios compared to 6% for the proposed system.

Nocturnal Performance: The infrared domain adaptation module enables consistent nighttime detection with mAP@0.5 of 87.6%, compared to 71.3% for baseline systems without domain adaptation, representing a critical capability for monitoring nocturnal species.

Herd Counting: Elephant herd counting in aerial UAV footage demonstrates the effectiveness of the perspective correction module, achieving accuracy within 2 individuals for herds up to 25 members, compared to errors of 5-8 individuals for systems without perspective normalization.

VIII. DISCUSSION

A. Transfer Learning Effectiveness

Initialization from COCO-pretrained weights and progressive fine-tuning on WildIndia-50K demonstrates the value of transfer learning for wildlife-specific detection. Ablation experiments show that random weight initialization requires 3.2x more training data to achieve equivalent mAP@0.5 performance. Species with limited training examples (Sloth Bear: 5,400 images) benefit most substantially from pretrained feature representations, achieving classification F1-scores only 5.9% below species with twice the training data.

B. Edge Deployment Considerations

The TensorRT-optimized edge deployment achieves 8 FPS throughput on NVIDIA Jetson AGX Orin, enabling near-real-time processing of camera feeds at remote ranger posts without cloud connectivity dependency. Model quantization to INT8 precision reduces memory footprint by 75% with only 1.8% mAP degradation, enabling deployment on resource-constrained embedded platforms.

C. Failure Case Analysis

Systematic analysis of detection failures identifies three primary failure categories: extreme partial occlusion where less than 15% of animal body is visible (38% of false negatives), species confusion between Indian Leopard and juvenile Bengal Tiger in low-resolution night images (22% of misclassifications), and double-counting during rapid directional changes that confuse the Kalman filter motion model (19% of counting errors). Future work will specifically address each failure mode.

IX. LIMITATIONS

Several limitations are acknowledged in the current system:

- Geographic Specificity: The WildIndia-50K dataset primarily covers four protected areas in three states. System performance on novel ecosystems such as mangrove habitats (Sundarbans) or high-altitude forests (Himalayan protected areas) has not been systematically validated.
- Species Coverage: The current system covers 8 of the 12 target species with high performance. Rare and cryptic species such as the Snow Leopard and Indian Wild Dog require additional targeted data collection.
- Individual Re-identification: The system performs population counting but does not implement individual animal re-identification across sessions, limiting applicability for long-term mark-recapture population estimation.
- Connectivity Dependency: Cloud deployment configurations require reliable internet connectivity that is frequently unavailable in remote forest interiors.
- WMAS Calibration: Weight parameters in the WMAS metric were determined through expert consultation and require empirical validation against independent wildlife biologist assessments.

X. CONCLUSION

This research presents a comprehensive AI-based framework for automated wild animal detection and counting, specifically optimized for Indian forest wildlife across diverse environmental conditions. By integrating YOLOv8-based detection, EfficientNet species classification, and DeepSORT multi-object tracking within an adaptive preprocessing pipeline, the system achieves state-of-the-art performance on the WildIndia-50K benchmark with detection mAP@0.5 of 91.3% and counting accuracy of 94.7%.

The system addresses critical gaps in existing wildlife monitoring technology through its adaptive infrared preprocessing, perspective-corrected aerial counting, and edge computing deployment capabilities. The introduced Wildlife Monitoring Accuracy Score (WMAS) provides a unified evaluation framework that better reflects operational requirements of wildlife management compared to isolated technical metrics.

By enabling scalable, automated, and cost-effective wildlife monitoring, the proposed system offers meaningful contributions to conservation management across India's protected area network. Forest departments equipped with this technology can shift from reactive to proactive conservation management, enabling timely responses to population changes, poaching threats, and human-wildlife conflict events.

XI. FUTURE WORK

10.Individual Re-identification: Integration of deep metric learning for individual animal identification to support mark-recapture population estimation without physical tagging.

11.Behavioral Analysis: Extension of the tracking module to perform automated behavioral classification including threat posture detection, mating behavior recognition, and human-wildlife conflict anticipation.

12.Acoustic Integration: Fusion of camera-based detection with acoustic monitoring using bioacoustic deep learning models to improve detection in dense vegetation where visual systems are limited.

13.Satellite Imagery: Integration of satellite remote sensing data for landscape-scale habitat analysis and movement corridor identification.

14.Community Engagement: Development of citizen science mobile applications enabling local forest community members to contribute wildlife sightings and validate AI detections.

15.Rare Species Adaptation: Specialized low-shot learning modules for rare and critically endangered species with limited training data availability.

16.Real-Time Alert System: Integration with forest department communication infrastructure to deliver automated anti-poaching alerts based on unusual animal behavior patterns detected by the system.

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