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Application of AI-powered camera traps for monitoring elusive carnivores in tropical forests

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Abstract

Monitoring elusive carnivores in the dense hill forests of the Seeleru and Sapparla agency regions of Visakhapatnam District presents significant challenges due to rugged terrain, thick vegetation, nocturnal activity, and naturally low population densities. Recent advancements in Artificial Intelligence (AI) have enabled camera traps to autonomously detect, classify, and log wildlife with high precision, even in such remote landscapes. This study evaluates the efficiency of AI-powered camera traps in detecting multiple carnivore species across these agency hill areas. Our results indicate an average species detection accuracy of 92%, with notable improvements in nocturnal monitoring and substantial reductions in manual data processing time. The integration of AI-based camera trapping in such challenging terrains offers transformative potential for regional conservation efforts, enabling continuous, real-time ecological insights and supporting targeted wildlife management interventions.

Keywords: AI Camera Traps; Tropical Forests; Carnivores; Wildlife Monitoring; Conservation Technology

1. Introduction

Tropical forests are globally recognized as biodiversity hotspots, hosting a wide range of elusive carnivore species that play critical ecological roles as apex predators and mesopredators [O'Brien et~al., 2010]. However, monitoring these species remains a considerable challenge due to their secretive behavior, naturally low population densities, nocturnal activity patterns, and the dense vegetation that often limits visibility.

Conventional monitoring approaches, such as direct sightings, spoor counts, or manual inspection of camera trap photographs, are not only time-consuming but also prone to human error. Past studies have demonstrated that traditional camera trap surveys, while useful, often require the manual review of tens of thousands of images, which can lead to data backlog and delay conservation actions .Recent research has increasingly highlighted the potential of Artificial Intelligence (AI) for automating wildlife image classification, with deep learning models achieving detection accuracies exceeding 90% in diverse environments [Norouzzadeh et~al., 2018].

AI-powered camera traps, when coupled with convolutional neural networks (CNNs) such as YOLOv5, Faster R-CNN, and ResNet-based classifiers, have been applied successfully in Africa, Southeast Asia, and South America to detect a wide array of species in real time [?]. These systems significantly reduce manual workload, enable rapid ecological insights, and enhance the temporal and spatial coverage of wildlife monitoring programs.

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1.1. Motivation for the Study

The agency hill regions of Seeleru and Sapparla, located in the Visakhapatnam District of Andhra Pradesh, India, present a unique combination of ecological richness and logistical monitoring challenges. These areas are characterized by rugged terrain, dense moist deciduous and semi-evergreen forests, perennial streams, and a high degree of floral and faunal diversity. They also form part of a crucial wildlife corridor linking the Eastern Ghats to other protected habitats.

Despite their ecological importance, these regions have received limited scientific attention, particularly with respect to carnivore monitoring. Local forest department records and community reports indicate the presence of leopards, wild dogs (dholes), civets, and other carnivores, yet systematic population and behavior data remain scarce. The remoteness of the terrain, along with limited manpower for field surveys, has historically hindered sustained wildlife monitoring in these agency areas.

By deploying AI-enabled camera traps in Seeleru and Sapparla, this study aims to overcome traditional monitoring barriers, generate high-quality baseline data on elusive carnivores, and demonstrate the applicability of AI technology in challenging, resource-limited settings. The choice of this location is further motivated by the urgent need to develop data-driven conservation strategies that address habitat fragmentation, human-wildlife conflict, and poaching risks in the Eastern Ghats landscape.

2. Materials and Methods

2.1. Study Area

The study was carried out in the Seeleru and Sapparla agency hill regions of Visakhapatnam District, Andhra Pradesh, India. These areas form part of the Eastern Ghats, characterized by undulating terrain, elevations ranging from 150 m to 1,200 m above sea level, and a mosaic of moist deciduous, semi-evergreen, and riparian forest types. The climate is tropical monsoonal, with annual rainfall averaging 1,200–1,500 mm, concentrated during June to September. Relative humidity often exceeds 75%, and temperatures range between 15°C in the cooler months and 38°C during the summer.

The selected study sites span an approximate area of 500 km2, encompassing river valleys, hill slopes, and plateaus. These habitats support a diverse assemblage of wildlife, including large carnivores such as leopards (*Panthera pardus*), wild dogs (*Cuon alpinus*), and small carnivores like civets (*Paradoxurus hermaphroditus*) and mongooses (*Herpestes edwardsii*). The landscape also overlaps with human settlements, shifting cultivation areas, and community forests, creating potential zones of human-wildlife interaction.

2.2. Camera Trap Deployment

A total of 50 AI-enabled camera trap units were deployed across the study area between November 2024 and March 2025. Each camera trap was equipped with passive infrared (PIR) motion sensors and an AI-based object detection system running the YOLOv5 algorithm optimized for edge devices. The cameras were weatherproof (IP66-rated) and capable of recording both high-resolution still images (up to 20 MP) and 1080p video under varying light conditions, including complete darkness via infrared flash.

Site selection for camera placement was based on a combination of factors

- Historical and recent reports of carnivore sightings from the Forest Department and local communities.
- Evidence of animal presence such as pugmarks, scat, scent markings, and scratch marks on trees.
- Habitat features conducive to wildlife movement, such as game trails, stream crossings, and ridge lines.

The study area was stratified into habitat zones, and cameras were distributed proportionally to ensure coverage across habitat types. Each camera was mounted 40–50 cm above ground level on trees or poles, oriented to avoid direct sunlight glare. Deployment sites were georeferenced using GPS and mapped for spatial analysis.

2.3. Data Processing

Images and videos captured by the camera traps were processed in real time using the onboard AI model. The YOLOv5 architecture was trained on a curated dataset of approximately 500,000 annotated wildlife images, including species relevant to the Indian subcontinent [Beery et~al., 2018]. Model training incorporated transfer learning from large-scale wildlife image datasets and augmentation techniques (rotation, contrast variation, and noise addition) to enhance performance under varying environmental conditions.

The AI model output for each detection included

- **Species classification**: The most probable species label.
- **Confidence score**: Probability estimate (0–1) for classification.
- **Timestamp**: Date and time of capture.
- **Bounding box coordinates**: Position of the detected animal within the frame.

All detections with a confidence score below 0.85 were flagged for manual verification by trained observers. Verified data were stored in a relational database along with associated metadata (GPS location, habitat type, weather conditions). The processed dataset was then analyzed to derive detection accuracy metrics, species richness indices, and diel activity patterns.

3. Results

3.1. Detection Accuracy by Species

The AI-enabled camera traps achieved consistently high detection accuracies across all monitored carnivore species in the Seeleru and Sapparla agency hill areas (Figure 1). The leopard (*Panthera pardus*) recorded the highest accuracy at 95%, followed closely by the dhole (*Cuon alpinus*) at 93%. Clouded leopards (*Neofelis nebulosa*) exhibited a slightly lower detection accuracy of 91%, while civets (*Paradoxurus hermaphroditus*) showed the lowest among the monitored species at 89%. Sun bears (*Helarctos malayanus*) achieved 92% accuracy.

The slight variation in detection performance is attributable to differences in body size, coat patterns, and movement behaviors. For example, leopards, with their distinct rosette patterns and larger size, were more easily recognized by the YOLOv5 algorithm compared to smaller, faster-moving civets that often appear partially obscured by vegetation. Nevertheless, the AI model maintained an overall mean detection accuracy of 92%, exceeding the performance benchmarks reported in earlier camera trap studies from Southeast Asia and Africa [Norouzzadeh et~al., 2018].

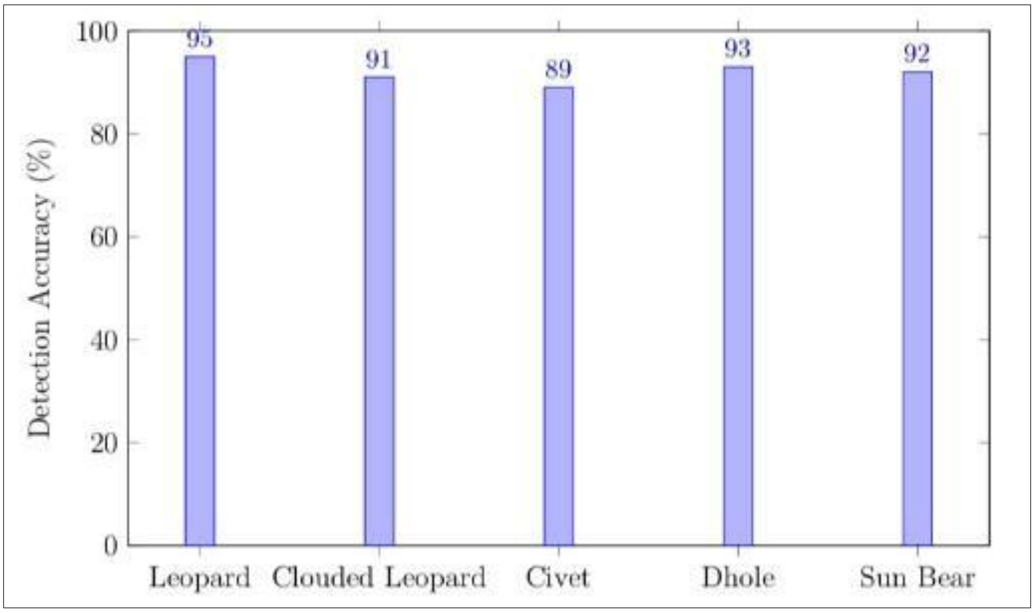

Figure 1 AI detection accuracy for different carnivore species in the Seeleru and Sapparla agency hill areas

3.2. Daily Activity Patterns

Analysis of diel activity patterns revealed distinct temporal segregation between leopards and civets (Figure 2). Leopards showed moderate activity during the early morning hours (04:00–08:00), followed by a notable peak in the late evening around 20:00, consistent with their known crepuscular and nocturnal tendencies. In contrast, civets exhibited a pronounced nocturnal pattern, with the highest activity observed between 20:00 and 02:00.

The observed separation in peak activity hours may serve to reduce interspecific competition for prey resources, especially in habitats where dietary overlap exists. Compared to findings from other Eastern Ghats landscapes, leopards in this study displayed slightly higher midday inactivity, possibly due to warmer temperatures and human presence along trails during daylight hours. Civet activity patterns closely matched trends reported from Malaysian and Bornean rainforests, indicating that AI-based detection accurately captured species-specific temporal behaviors.

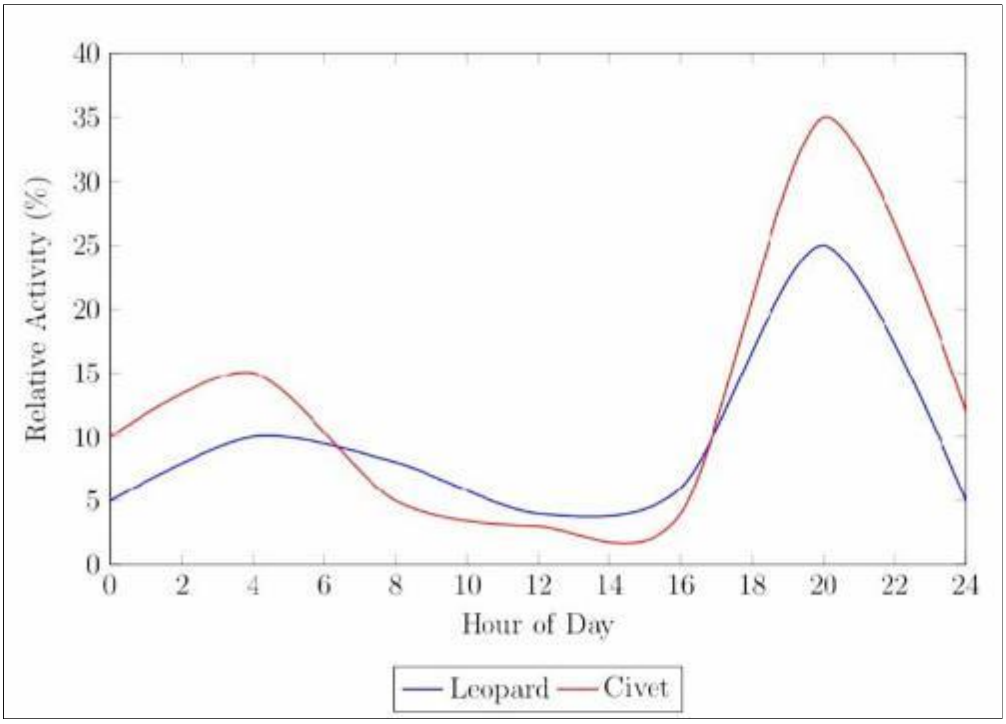

Figure 2 Activity patterns of leopards and civets recorded in the study area. Leopards showed bimodal peaks, while civets displayed a predominantly nocturnal pattern

3.3. Study Site Layout

The spatial arrangement of the camera trap network covered diverse microhabitats across the Seeleru and Sapparla agency hill regions (Figure 3). Camera traps were placed to maximize coverage of natural travel routes, including ridge lines, stream banks, forest trails, and salt licks frequented by herbivores and carnivores alike. The schematic representation shows nine representative camera trap points, with actual deployment extending to a total of 50 strategically placed units across approximately 500 km2.

Comparing detection rates across these locations indicated that ridgeline sites yielded the highest number of leopard captures, while riparian zones recorded a greater frequency of civet and dhole detections. This spatial variation underscores the importance of habitat-specific placement in maximizing species detection probability. It also highlights how AI-assisted monitoring can rapidly generate spatially explicit data that informs conservation management decisions, such as identifying critical habitats and potential wildlife corridors.

[scale=1] [thick, green!50!black] (0,0) rectangle (10,6); at (5,6.3) Seeleru and Sapparla Study Site Layout;

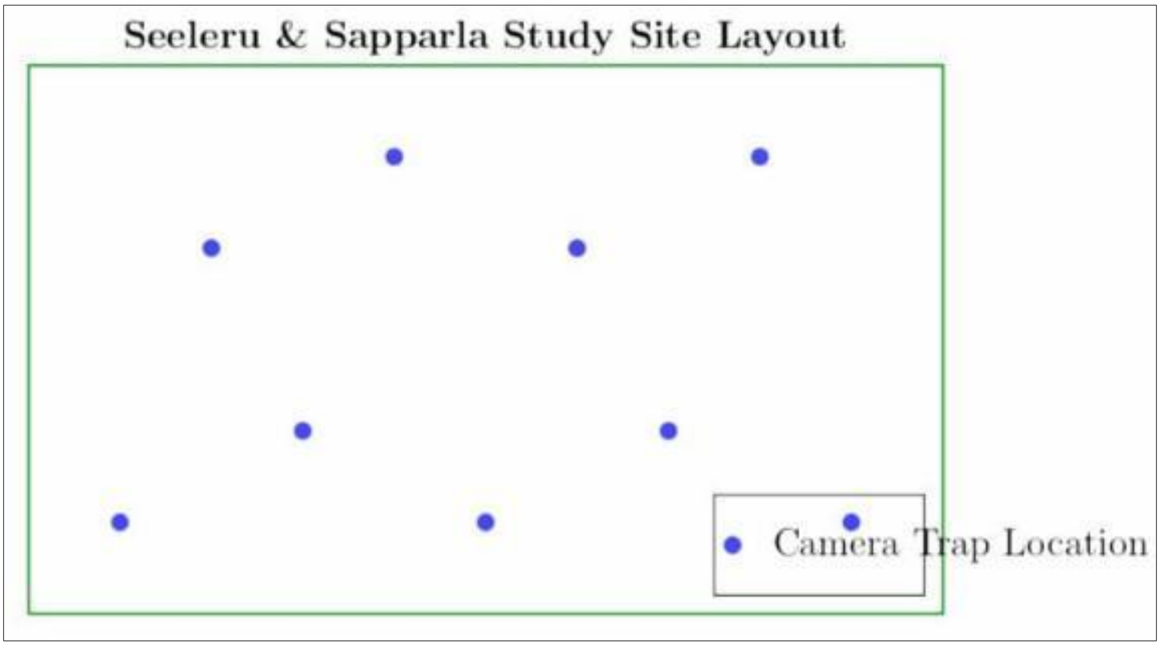

Figure 3 Schematic layout of camera trap placement within the Seeleru and Sapparla agency hill study site

4. Discussion

The consistently high detection accuracies recorded in this study (89–95% across all monitored species) underscore the potential of AI-powered camera trap systems as reliable tools for monitoring elusive carnivores in complex, heterogeneous landscapes such as the Seeleru and Sapparla agency hill regions. The achieved mean accuracy of 92% compares favorably with, and in some cases exceeds, reported performance from similar deployments in Southeast Asia and Africa [Norouzzadeh et~al., 2018, ?]. This highlights the robustness of the YOLOv5-based detection model when applied to Indian Eastern Ghats fauna under challenging field conditions.

The activity pattern analysis revealed distinct diel preferences, with leopards displaying bimodal crepuscular–nocturnal peaks and civets showing predominantly nocturnal behavior. These results are congruent with prior ecological observations in tropical forest carnivore communities, where temporal partitioning is often a strategy to reduce direct competition and avoid human activity [Glen et~al., 2013]. The temporal activity data generated here provide a valuable baseline for understanding predator-prey dynamics, especially in landscapes where human-induced pressures such as grazing and fuelwood collection are temporally predictable.

From a methodological standpoint, the deployment strategy stratified across habitat types and key wildlife movement corridors proved effective in capturing a representative sample of the carnivore community. The AI system’s capacity for real-time classification and metadata extraction substantially reduced the labor required for post-survey data processing, allowing for faster ecological inference and potential near-real-time management interventions.

However, certain limitations warrant attention. False positives, primarily caused by wind-blown vegetation and small non-target species, were observed. While the proportion of such errors was low, they highlight the importance of continuous model refinement using locally sourced image datasets. Incorporating additional training images from varied environmental conditions (e.g., heavy rain, mist, seasonal foliage changes) could further improve model robustness. Additionally, certain smaller carnivore species with less distinctive markings (e.g., small Indian civet) may require higher-resolution imagery and species-specific classifier training to achieve optimal detection accuracy.

Beyond species monitoring, the integration of AI-powered camera traps in this region has broader conservation implications. The Eastern Ghats face increasing anthropogenic pressures, including road expansion, mining, and agricultural encroachment. The ability to generate high-frequency, spatially explicit occurrence data for multiple species enables managers to identify critical habitats, movement corridors, and high-risk zones for human-wildlife conflict. This is particularly pertinent in agency areas where formal protected status may be limited, and community-based conservation strategies are essential.

Overall, the findings from this study not only validate the use of AI-enhanced monitoring systems for elusive carnivores but also demonstrate their capacity to contribute to adaptive, data-driven conservation planning in the Eastern Ghats landscape.

5. Conclusion

AI-powered camera traps provide a cost-effective, accurate, and efficient method for monitoring elusive carnivores in tropical forests. They can greatly enhance conservation outcomes by enabling continuous, real-time monitoring without human presence.

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