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Drone-based deep learning system for accurate camel counting in desert rangelands with integration into Sarebanyar platform

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Abstract Data-driven herd management is essential for scientific herd management in arid and semi-arid regions; however, traditional counting methods are labor-intensive, time-consuming, and prone to significant human error. This study proposes a drone-based deep learning framework for automated counting and monitoring of camel herds under prevailing desert conditions. Aerial videos were collected from nine camel herds across multiple regions in Iran using unmanned aerial vehicles (UAVs). A dedicated dataset was constructed from extracted video frames and annotated using polygon-based labeling. Two detection strategies were comparatively evaluated, including body-without-head and head-only detection. Object detection models were trained using the YOLOv8 architecture and tested under different training data scales to analyze the effect of dataset size on counting performance. Experimental results showed that head-based detection showed promising robustness under the tested conditions, although a fully controlled comparison with body-based detection would require matched training data. Expanding the training dataset from 100 images (≈900 frames) to 220 images (≈1800 frames) led to substantial improvements in detection stability and counting accuracy. Using the expanded dataset, the proposed system achieved > 98% counting accuracy in multiple real herds, including large groups containing up to 271 camels, with 1 counting error. The trained model was successfully integrated into the Sarebanyar App, enabling automated processing of newly acquired UAV videos and direct storage of results within an operational management workflow. The findings demonstrated that combining the UAV imaging, optimized region-of-interest selection, and diverse real-world training data enables a robust, scalable, and economically efficient solution for intelligent livestock monitoring in harsh desert environments, providing a practical pathway toward AI-driven smart herd management systems.

Keywords: Drone, counting, camel, Deep Learning

Introduction

Camel husbandry is an important component of livestock production in arid and semi-arid regions, where camels contribute to food security, rural livelihoods, and the sustainability of desert-based agricultural systems. In Iran, camel herds represent a valuable livestock resource, and their effective management depends on access to timely and reliable information on herd size, spatial distribution, movement patterns, and animal health. Recent work has shown that ICT-based systems can support online monitoring, phenotyping, and rangeland assessment in camel production systems, highlighting the growing role of digital tools in camel husbandry management (Bitaraf Sani et al., 2025).

At present, herd counting and monitoring in major camel-breeding regions still rely largely on traditional manual approaches. These methods are inherently limited for extensive herds, since visual counting can be affected by human error, especially when animals are dispersed over large areas or move dynamically during observation. Manual surveys are also labor-intensive, time-consuming, and costly, particularly in remote desert landscapes where access is difficult and repeated field presence is required. In addition, periodic censuses do not provide continuous monitoring, making it difficult to detect events such as mortality, disease, changes in herd distribution, or movement patterns in a timely manner. Close human proximity during counting may also disturb the animals and reduce both welfare and counting accuracy (Figure 1).

Figure 1. Aerial view of a free-ranging camel herd in desert rangeland illustrating spatial dispersion and counting challenges

The need for more efficient monitoring solutions has encouraged the development of digital approaches based on unmanned aerial vehicles (UAVs) and machine learning. UAVs offer rapid acquisition of aerial imagery, broad spatial coverage, and reduced field burden, making them attractive for monitoring large livestock populations in difficult environments. Reviews in precision agriculture have emphasized the value of UAVs for high-resolution remote sensing and scalable field observation, demonstrating their growing relevance beyond crop systems into broader agricultural monitoring tasks (Zhang and Kovacs, 2012; Maes and Steppe, 2019). In addition, UAV-based high-throughput phenotyping studies have shown that aerial imaging combined with artificial intelligence can support automated trait extraction and counting tasks (Ampatzidis et al., 2019). Similarly, UAV RGB imagery has been successfully used for automated counting applications in agricultural contexts, reinforcing the potential of image-based detection pipelines for large-scale monitoring (Liu et al., 2022).

Concurrently, advances in deep learning-based object detection have improved the balance between accuracy and real-time inference. In particular, YOLOv8 has been presented as a strong object detection framework for fast and accurate visual analysis, making it suitable for rapid processing of aerial data (Sohan et al., 2024). Such methods are especially promising for livestock monitoring because they can automate detection and counting from UAV footage with greater speed and consistency than manual observation.

Despite these promising developments, camel-specific automated counting remains underexplored. Most existing studies and practical systems have focused on other livestock species or general remote-sensing applications, leaving a clear gap in camel monitoring under real desert conditions. Camels also present unique detection challenges, including body shape variation, partial occlusion, background similarity, and changing herd density. For this reason, a camel-focused solution is still needed to evaluate whether aerial deep learning methods can perform reliably in real-world herding environments.

In response to this gap, the present study proposes a UAV-based deep learning framework for automated camel counting and monitoring. The system was designed to analyze aerial video data and support direct integration with the camel management software platform Sarebanyar, thereby linking remote sensing with practical herd management workflows. The main objective of this study was to assess whether deep learning-based aerial detection can provide a reliable and scalable solution for camel counting in operational field conditions and to examine how different representation settings influence the performance.

Materials and methods

Study design and field data collection

Aerial data acquisition was conducted through close collaboration with local camel owners and herd managers in central and eastern regions of Iran. Field campaigns were carefully scheduled prior to the daily grazing period, when animals naturally exited the enclosure, allowing controlled and sequential observation without disturbing normal herd behavior. All recording procedures complied with animal welfare considerations, and no physical interaction or behavioral manipulation of animals was performed during data collection. Data for this study were collected from nine herds in Yazd and South Khorasan provinces (Table 1).

The rearing system of these herds was extensive and they had daily grazing in specific pastures.

Table 1. Characteristics of the nine camel herds in Yazd and South Khorasan provinces

Province	City	Local name	Area (ha)	Herd size (N)	Rangeland (ha)/camel	Mean of SAVI	Daily grazing (km)
Yazd	Ardakan	*Allah_abad*	10000	166	60.24	0.01	19.43
		Eskanbilo	9254	188	49.22	0.01	21.33
		Hoze_Sinesefid	6129	139	44.09	0.01	24.88
		Chahe_Choghondar	4669	68	68.66	0.009	23.89
		Saghand	4200	72	58.33	0.02	19.25
		Godare_Jangah	4500	77	62.50	0.01	21.30
	Mehriz	*Fahraj*	1381	106	13.02	0.03	17.22
	Khatam	*Cheshmeh-shor*	9506	272	34.49	0.04	15.67
South Khorasan	Tabas	*Diheshk*	3700	76	48.68	0.04	16.62

The final acquisition protocol positioned the UAV directly above the herd gate, ensuring that each camel passed through a constrained passage and appeared only once in the recorded scene, thereby minimizing double-counting errors.

UAV configuration and imaging setup

The UAV was positioned 7–8 meters above the herd gate, providing a near-vertical viewing geometry that balanced field coverage, image clarity, and counting reliability. In addition to gate-based recordings, supplementary footage from open rangelands was collected exclusively for robustness testing under unconstrained environmental conditions. Videos were captured using four different imaging devices with a minimum spatial resolution of 4K and a frame rate of 30 frames per second (fps). The use of multiple devices introduced variations in sensor characteristics and imaging conditions, improving dataset generalization.

Dataset preparation and annotation

Video frames were randomly extracted to avoid temporal bias and redundancy. Annotation was performed using the CVAT platform, employing polygon-based object labeling to precisely delineate camel body structures (Huang et al, 2024) (Figure 2). To ensure dataset diversity, frames were selected from multiple videos representing different herd sizes, lighting conditions, and viewing angles. Special attention was given to capturing head appearances from a wide range of orientations. Frames were intentionally selected so that camel heads were represented across nearly all observable viewing angles, including frontal, lateral, partially occluded, and tilted poses. Furthermore, recordings from different provinces enabled inclusion of varying sunrise angles, shadow patterns, and desert backgrounds, increasing the robustness of the training dataset against environmental variability.

Detection scenarios

Two detection strategies including Body detection excluding the head, and Head-only detection, were evaluated. The body-without-head scenario was motivated by practical observations during annotation. In several videos, calves were present, and the heads of adult camels occasionally overlapped visually with the smaller bodies of calves, causing ambiguity in bounding regions. To address this challenge and investigate whether localized anatomical features could improve counting stability, a head-only detection scenario was introduced and comparatively evaluated. Head + body detection scenario was not tested due to computational and proper annotation limitations.

Model training and experimental setup

All experiments were conducted using the YOLOv8 object detection architecture due to its balance between detection accuracy and real-time inference capability (Sohan et al, 2024). Training was performed for 400 epochs using an 80/20 train–validation split. To investigate the influence of dataset scale on counting performance, two dataset sizes including An initial dataset consisting of 100 training images (approximately 900 extracted frames), and an expanded dataset consisting of 220 images (approximately 1,800 frames) were evaluated. Standard data preprocessing and augmentation techniques inherent to the YOLO training pipeline were applied to improve model generalization under varying illumination and background conditions.

Evaluation metrics

Model performance was assessed using widely accepted object detection metrics, including Precision, Recall, mean Average Precision at IoU threshold 0.5 (mAP50), and mean Average Precision across IoU thresholds from 0.5 to 0.95 (mAP50-95). These metrics enabled evaluation of both localization accuracy and detection robustness under challenging desert imaging conditions.

Software integration and deployment

The best-performing trained model weights were exported and integrated into the Sarebanyar herd management software platform (Bitaraf Sani et al., 2025). A dedicated processing module was developed to automatically analyze incoming UAV videos, perform camel detection and counting, and store prediction outputs directly within the system database. This integration enabled practical operational use, allowing herd managers to generate analytical reports and monitoring records without requiring expertise in computer vision or machine learning.

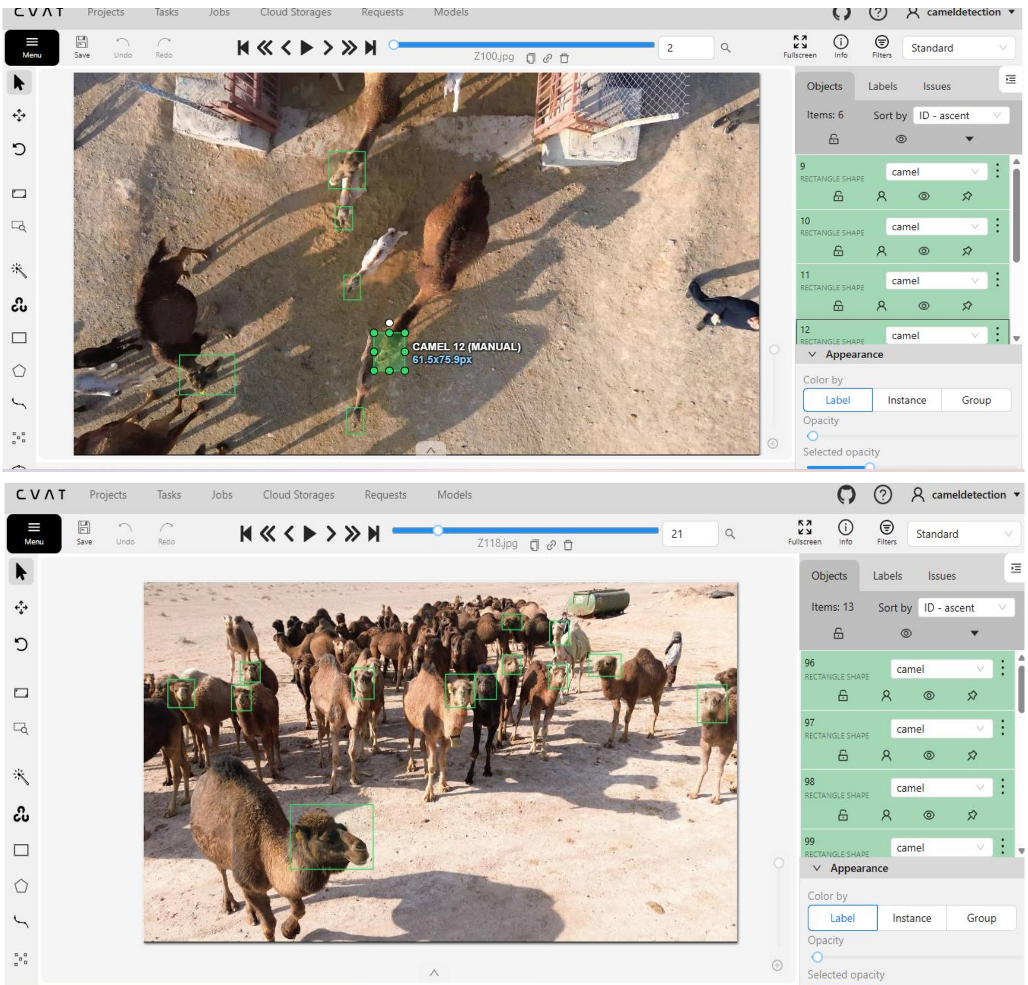

Figure 2. Polygon-based camel annotation performed in the CVAT platform.

Results

Table 2 summarizes the field evaluation results obtained from multiple herds across different locations using two detection strategies and two training dataset sizes. The results demonstrate that counting accuracy was strongly influenced by both the selected detection region and the volume of training data (Table 2).

When the body-without-head detection strategy was trained using the smaller dataset (100 training images, approximately 900 frames), performance was inconsistent across herds. In several cases, substantial undercounting occurred, with accuracies as low as 55.55% observed in Ardakan herd 4. Similar behavior was recorded in Mehriz herd 8, where counting accuracy varied between 64.21% and 82.10%. These fluctuations were primarily associated with dense herd configurations in which animals overlapped spatially, causing partial occlusion of body regions. However, the same strategy achieved near-perfect performance in less crowded scenarios. For example, Ardakan herds 1 and 6 reached 100% accuracy, indicating that body-based detection can perform reliably when animals are well separated. Over counting cases were also observed (e.g., Ardakan herd 5), where predicted counts exceeded real counts, producing accuracies above 100%. These errors were mainly attributed to visual overlap between adult camels and calves, where portions of adjacent bodies were interpreted as separate individuals. In contrast, the head-only detection strategy initially showed weak performance when trained with the smaller dataset.

Severe undercounting occurred in several cases, including complete detection failure in Tabas herd 7 (0% accuracy). This behavior indicates that head detection requires greater visual diversity during training due to variations in orientation, scale, and partial occlusion. A substantial improvement was observed after expanding the dataset to 220 training images (≈1800 frames). Under this condition, head-based detection achieved consistently stable and highly accurate results across all evaluated herds. Multiple experiments reached 100% counting accuracy, including large herds such as Khatam herd 9 containing 271 camels, where the system produced zero counting error. These results confirm that increasing dataset diversity significantly enhances robustness and generalization capability. Overall, the experiments demonstrate that while body-based detection may perform adequately under controlled conditions, head-only detection provides superior stability in real operational environments once sufficient training data are available.

Table 2. Summary of the field evaluation results obtained from multiple herds across different locations using two detection strategies and two training dataset sizes

Herd ID	Location	Detection Target	Training Size	Extracted Frames	Real Count	Predicted Count	Error	Predicted Count/ Real Count (%)
4	Ardakan	Body (without head)	100	~900	72	49	32	55.55
4	Ardakan				72	40	32	55.55
8	Mehriz				95	61	34	64.21
8	Mehriz				95	78	17	82.10
6	Ardakan				188	187	1	99.46
1	Ardakan				68	68	0	100
1	Ardakan				68	68	0	100
6	Ardakan				166	166	0	100
5	Ardakan				77	92	-15	119.48
5	Ardakan				77	98	-21	127.27
7	Tabas	Head only	100	~900	76	0	76	0
7	Tabas				72	1	71	1.38
9	Khatam				271	45	226	16.60
9	Khatam				271	50	221	18.45
2	Ardakan				166	103	63	62.04
8	Mehriz				106	80	26	75.47
8	Mehriz				106	89	17	83.96
2	Ardakan				166	166	0	100
3	Ardakan				139	139	0	100
5	Ardakan	Head only	200	~1800	77	77	0	98
7	Tabas				74	72	2	100
8	Mehriz				106	106	0	100
9	Khatam				272	271	1	99.96
1	Ardakan				66	66	0	100

The comparison between the two dataset scales clearly shows that training data volume plays a critical role in counting reliability. The smaller dataset resulted in unstable predictions and sensitivity to herd density and environmental variability. After dataset expansion, detection performance stabilized across locations, lighting conditions, and herd structures. The improvement can be attributed to the inclusion of camel heads captured from multiple viewing angles, illumination conditions, and background environments across different provinces. This diversity enabled the model to learn invariant visual features, reducing false detections caused by shadows, body overlap, and desert background similarity.

Training of the YOLOv8n model was completed in approximately 0.95 hours. The final model contained about 3.0 million parameters and required 8.1 GFLOPs, demonstrating a lightweight architecture suitable for deployment. On the validation dataset, the model achieved: Precision: 0.927, Recall: 0.788, mAP50: 0.876, mAP50-95: 0.495. Inference speed averaged approximately 2.4 ms per image, enabling near real-time processing capability. In practical deployment, full video processing time depended on hardware configuration and video duration. Under typical operational conditions, processing and reporting required approximately 20-30 minutes, which remains substantially faster than traditional manual counting procedures.

A key outcome of this study is the successful deployment of the trained model within the Sarebanyar herd management platform. The developed module enables a standardized operational workflow: herd owners or service providers record a short UAV video following the acquisition protocol defined in this study (flight height, camera orientation, resolution, and frame rate). The recorded video is then uploaded to the Sarebanyar management panel, where the automated module performs detection, counting, and data storage without requiring technical expertise from the user (Figure 3). The final counting results are reviewed by the system administrator and communicated to camel owners as an official herd report. This approach transforms camel counting into a scalable digital service integrated directly into an existing livestock management ecosystem.

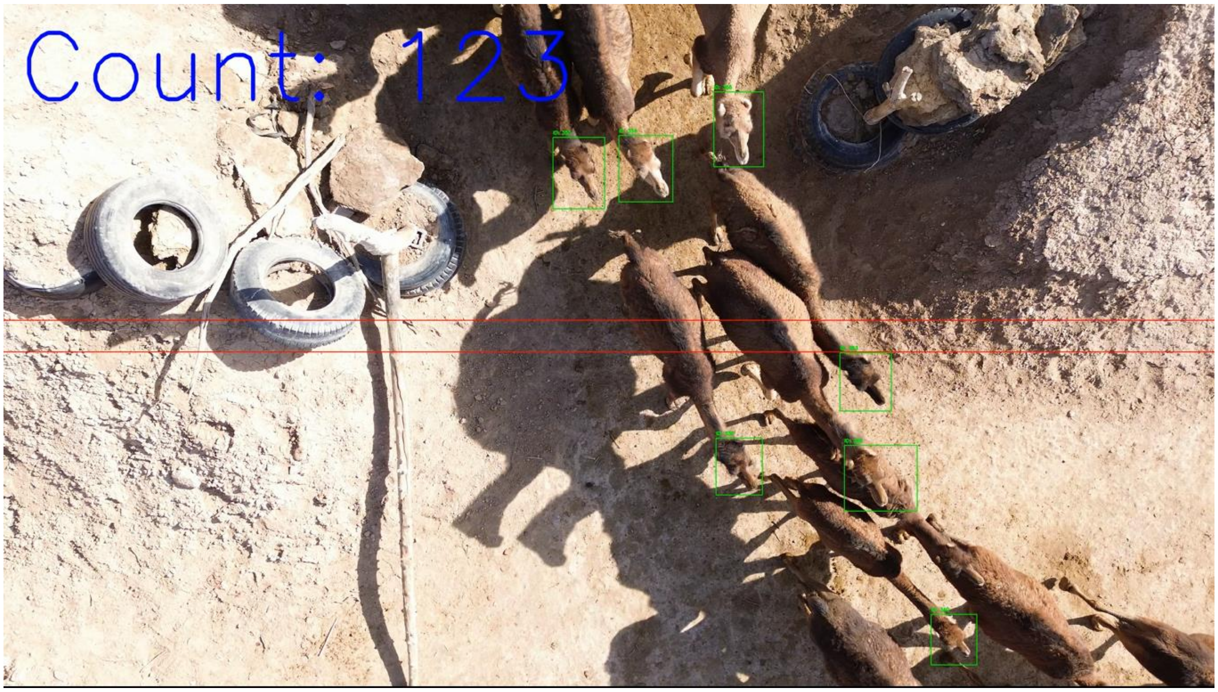

Figure 3. Example of real-time camel counting output generated by the deployed system

Discussion

The results of this study demonstrate that the selection of the detection region is a decisive factor influencing livestock counting accuracy in UAV-based monitoring systems. While object detection models are commonly evaluated based on overall detection metrics, the present findings show that anatomical target selection can significantly affect counting reliability in real operational environments. In aerial gate-view imagery, camel bodies frequently overlap due to herd movement and spatial clustering, leading to partial occlusions and ambiguous object boundaries. These conditions increase both missed detections and duplicate predictions. In contrast, the head region provides a more compact and spatially distinguishable feature, reducing overlap-related ambiguity and improving counting stability once sufficient training data are available.

Unmanned Aerial Vehicles (UAVs) have become a cornerstone technology in precision agriculture due to their ability to provide high-resolution spatial data with flexible temporal acquisition. Compared to satellite imagery, UAV platforms offer superior spatial resolution and on-demand deployment, enabling field-level monitoring of crop growth, stress, biomass, and yield variability (Zhang & Kovacs, 2012; Maes & Steppe, 2019). Recent developments in computer vision and deep learning have further enhanced UAV-based agricultural analytics. Convolutional neural networks (CNNs) have been widely adopted for plant detection, crop counting, and phenotyping applications using RGB imagery (Ampatzidis et al., 2019; Liu et al., 2022). These advancements demonstrate that integrating UAV imaging with data-driven algorithms significantly improves monitoring efficiency, automation, and scalability in agricultural systems. Beyond crop production, UAV systems have increasingly been applied to livestock monitoring in extensive grazing systems. UAVs provide a non-invasive and cost-effective method for observing animals in remote and difficult terrains (Guo et al., 2022).

This observation highlights an important methodological insight: improving counting performance does not necessarily require more complex model architectures, but rather an appropriate representation of the target object. While many previous UAV-based livestock monitoring studies have focused on model optimization or architectural improvements (Liu et al., 2022), our work demonstrates that redefining the detection target itself can yield substantial gains in operational accuracy. Specifically, the head-based detection performed better in our experiments; however, this result should be interpreted cautiously because the two approaches were not always evaluated under identical data-size conditions.

Cattle monitoring has been one of the primary research areas in UAV-based livestock applications. Barbedo (2019) demonstrated the feasibility of detecting cattle in UAV imagery using deep learning techniques under varying illumination and background conditions. Rahman et al. (2020) specifically addressed the challenge of counting clustered cattle in aerial images, highlighting that occlusion and animal aggregation significantly reduce detection accuracy. Zhang et al. (2021) applied Mask R-CNN to livestock classification and counting tasks, reporting improved segmentation performance in dense herds. These studies confirm that UAV-based cattle counting is viable; however, they also underline limitations related to object overlap, background similarity, and varying object scales.

Monitoring smaller livestock species such as sheep introduces additional complexity due to reduced object size and strong clustering behavior.

Another key finding is the strong dependency of counting performance on dataset diversity and size. The transition from the smaller dataset to the expanded dataset resulted in a dramatic increase in robustness and accuracy across all test locations. This confirms that variability in viewing angles, illumination conditions, herd composition, and environmental backgrounds plays a critical role in enabling deep learning models to generalize effectively. Rather than relying solely on increasing network complexity, incorporating representative field data from multiple provinces proved essential for achieving stable real-world performance. This result aligns with recent trends in applied computer vision, where domain diversity is increasingly recognized as a primary driver of deployment success. Research has shown that lightweight object detection architectures such as YOLO variants can achieve promising results, particularly when trained on sufficiently diverse datasets (Zhang et al., 2023). The issue of small-object detection in aerial imagery remains an active research area, with performance strongly influenced by spatial resolution, dataset scale, and feature representation strategies.

UAV-based animal detection has also been widely adopted in wildlife ecology for surveying large mammals and ungulates in remote environments. Guo et al. (2022) provided a comprehensive review of wildlife surveying methods using UAV and satellite imagery, emphasizing the growing role of deep learning in automated animal detection. Thermal imaging combined with machine learning has also been used to detect hoofed animals in challenging terrain (Włodarczyk et al., 2022). These studies demonstrate that environmental contrast, shadow effects, and terrain heterogeneity strongly influence detection robustness—factors particularly relevant in desert ecosystems. The rapid evolution of object detection architectures has significantly improved real-time monitoring capabilities. The YOLO (You Only Look Once) family of detectors introduced a single-stage real-time detection paradigm that balances speed and accuracy (Redmon et al., 2016). Subsequent improvements in anchor-free detection and feature pyramid networks have enhanced performance in small-object scenarios common in UAV imagery (Iskandar et al., 2024).

Beyond algorithmic performance, one of the major contributions of this work lies in demonstrating practical deployment within an operational herd management ecosystem. Unlike many experimental studies that remain confined to laboratory evaluation, the proposed system was successfully integrated into the Sarebanyar management platform, transforming the detection model into a usable service. The workflow enables herd owners to record a short UAV video following standardized acquisition guidelines and obtain automated counting results through the management panel without requiring technical expertise. This transition from research prototype to deployable tool represents a significant step toward real-world adoption of AI-based livestock monitoring.

From an economic perspective, the proposed approach offers substantial advantages over traditional manual counting methods. Conventional herd census operations typically require multiple workers operating for several days under harsh desert conditions, leading to high labor costs and increased human risk. In contrast, the proposed system reduces the process to a short aerial recording followed by automated processing, dramatically lowering operational costs while improving statistical reliability. Feedback obtained from camel breeders further indicated strong acceptance of the system, emphasizing usability and time savings as primary benefits.

At a broader scale, the system also introduces important implications for governmental livestock management and policy planning. Continuous acquisition of UAV recordings across regions enables the creation of a growing digital archive of camel populations. Such datasets can support accurate regional statistics, long-term population monitoring, disease management planning, and evidence-based policy decisions. The ability to simultaneously perform accurate counting and build a visual historical database represents a significant advancement over fragmented and error-prone traditional census approaches.

Despite these promising outcomes, several limitations should be acknowledged. Detection performance may still be affected under extreme lighting conditions, severe occlusion, or rapid animal movement causing motion blur. Furthermore, the current system relies on standardized UAV acquisition parameters; deviations from recommended flight height or camera orientation may reduce accuracy. Future work may focus on adaptive models capable of handling wider acquisition variability, multi-object tracking across video sequences, and automated quality assessment of input videos

Overall, the findings demonstrate that combining optimized detection targets, diverse real-world datasets, and software-level integration can transform UAV-based animal monitoring from a research concept into a scalable and economically viable solution for precision livestock management.

Limitations and future work

This study has several limitations that should be acknowledged. First, the Body (without head) configuration was not evaluated at the training size of 200, which prevents a complete comparison across all experimental settings. Additionally, the head + body scenario was not included in the current experiments. Future studies should evaluate this combined representation using a larger sample size and appropriate annotation to determine whether it can outperform or complement the head-only approach.

Second, although the proposed UAV‑based counting approach performed well under controlled conditions, its applicability in highly extensive rangeland systems may depend on the availability of temporary or permanent aggregation areas. In such settings, future research could investigate decentralized or multi‑point monitoring strategies to support free‑roaming camel herds.

Conclusion

This study demonstrated the efficacy of UAV-based aerial imaging and deep learning for automated camel counting, bridging a critical gap in precision livestock management. By systematically evaluating different morphological representations-namely head-only and body-based models-we established that head-focused detection appears to be a promising approach for robust camel detection in dense herd settings, pending further evaluation under matched training conditions.

The findings suggest that automated aerial monitoring can significantly reduce the labor-intensive nature of traditional manual counting, while simultaneously increasing accuracy in health and inventory management. This approach not only provides a scalable framework for camel husbandry but also offers a template for monitoring other large livestock species in diverse rangeland settings.

However, we must acknowledge certain constraints. First, the comparative performance of the body-only and the combined head+body configurations remains to be fully explored, particularly under varying data-volume conditions; future research with larger, more diverse datasets is required to further optimize these representations. Second, while our method performs reliably in environments where camels are managed in enclosures, its application in vast, free-roaming rangelands requires further development of decentralized or multi-point monitoring strategies. Collectively, this work lays a foundational pathway for integrating advanced computer vision into rangeland management, highlighting the potential for future AI-driven, and autonomous herd surveillance.

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Conflicts of Interest

The authors confirm that there are no recognized conflicts of interest associated with this publication.

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