

Intelligent Aerial-Based Recognition and Positioning System for Camel Grazing

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Abstract—Camels hold significant economic, social, and cultural importance for communities in the Middle East. Traditional camel herding practices in desert areas face numerous challenges, including road accidents, overgrazing, and disease transmission. The use of modern technology, such as drones and health sensors, presents a promising approach for enhancing grazing practices, ensuring sustainability, and boosting productivity. However, several technical challenges need to be addressed, including detecting camels from a high-altitude perspective and tracking camel movement using single-lens drones, which are hindered by inadequate communication and electrical infrastructure. In this paper, we propose a sustainable lightweight artificial intelligence (AI) system to enhance the efficiency of camel grazing within limited resources. The system consists of two components: the first is a new AI deep-learning model for detecting camels. It is trained on a brand new dataset of camel aerial images in desert areas. This model enables the real-time detection of camels in high-altitude drone footage, overcoming challenges such as camouflage and the small size of objects. The second component is a monocular camera-based positioning system for estimating the locations of camels using low-cost civilian drones. The system converts pixel coordinates into geographic coordinates, enabling herders to track the movements of their camels efficiently. The system offers a sustainable solution by utilizing low-cost civilian drones and edge computing, making it accessible to low-income herders and eliminating the high costs associated with GPS collars and satellite connectivity.

Index Terms—non-terrestrial, drone perspective, herding, recognition, positioning

I. INTRODUCTION

Camels are essential to the livelihoods of millions across arid and semi-arid regions, particularly in the Middle East and North Africa. Camels are not only a cultural symbol but also a source of food, fiber, and income. However, traditional camel herding practices face increasing challenges owing to environmental degradation, road safety concerns, and inefficient grazing management. For instance, over 600 road accidents annually in Saudi Arabia are attributed to stray camels, prompting the implementation of stricter regulations and penalties for herders [1].

To address these issues, there is a growing need for intelligent monitoring integrated with non-terrestrial network (NTN) systems that can track camel movements, prevent overgrazing, and improve herding efficiency. Unmanned aerial vehicles (UAVs) offer a promising solution due to their mobility, affordability, and ability to capture high-resolution

imagery over vast desert landscapes [2]. However, deploying UAV-based systems in remote desert environments presents unique challenges, including limited communication infrastructure, harsh environmental conditions, and the difficulty of detecting camels from high altitudes. Researchers have explored various connectivity methods between the ground and satellites by predicting network traffic and preallocating resources to optimize energy consumption, latency, and operational requirements [3]. However, traditional terrestrial networks and electricity infrastructure are often unavailable in remote desert areas. Satellite connections are unsuitable because of their high latency and expensive service charges. Other existing solutions, such as applying Global Positioning System (GPS) collars onto camels or using satellite imaging, are not feasible in resource-constrained desert environments. Utilizing UAVs to establish a non-terrestrial wireless communication system between camels and herders during grazing is more sustainable and cost-effective [4].

Building on the momentum of AI-driven advancements in digital connectivity and network optimization across the Arab world, innovative solutions are being developed to address specific regional challenges, such as the technical obstacles faced in camel husbandry. [5]. Although modern technologies offer viable solutions for developing innovative monitoring systems, camel husbandry faces several technical challenges. First, it is challenging to spot camels in deserts from high altitudes using single-lens civilian drone cameras. The images captured by drones are usually taken from a far distance in the air, causing the camels to appear small in pictures. In addition, camels blend into the desert environment owing to their patterns of sand, rocks, and plants, making them difficult to recognize using traditional methods. Moreover, most datasets of camel pictures focus on ground-level images, and there is a lack of image datasets from high altitudes for camel-image recognition. New datasets from high-altitude perspectives are required to train AI models to recognize camels in deserts. Second, livestock positioning using a civilian UAV equipped with a single-lens camera imposes obstacles. The height of the UAV, as well as the pitch and yaw angles of the camera, affect the field of view and resolution. Variations in altitude can impact the scale, whereas incorrect angles may distort the captured imagery. Owing to their focal length and field of view, single-lens cameras are limited in capturing broad

fields of view, which affects spatial coverage. Additionally, synchronizing the GPS data, flight log data, and video frames is a complex process that requires proper alignment for accurate positioning.

This paper proposes a lightweight, UAV-based camel monitoring system that combines deep learning for aerial camel recognition with a monocular camera-based positioning method. The system is designed to operate in resource-constrained environments and aims to provide a cost-effective and sustainable alternative to GPS collars and satellite imaging. We introduce a new aerial camel dataset, train a YOLO-based detection model, and develop a projection-based positioning algorithm using UAV telemetry data. Our results demonstrate the feasibility of this approach for real-time camel tracking and behavioral analyses.

II. BACKGROUND AND RELATED WORKS

Camel grazing is deeply embedded in the cultural and economic fabric of the Middle East. However, unregulated grazing has led to significant ecological consequences, with studies estimating that over 40% of the Arabian Peninsula's rangelands are degraded due to overgrazing [6]. A recent study showed that the majority of camel owners lack sufficient knowledge and practical behavior [7]. Traditional herding methods rely heavily on manual observation and lack the precision required for sustainable land management. Recent efforts have explored the integration of innovative agricultural technologies, including internet of thing (IoT)-based health sensors and GPS-enabled tracking systems, to modernize livestock management [8], [9].

Target positioning and distance measurements are critical tasks in wildlife and livestock monitoring. Despite their effectiveness, GPS collars and satellite imaging are often prohibitively expensive and impractical for large-scale deployment in remote desert regions of the world. However, providing each animal with a location-tracking device can result in significant costs and energy consumption [10], posing practical challenges for widespread implementation in livestock management. UAVs equipped with monocular cameras offer a more accessible alternative, but they introduce new challenges in object detection and geolocation. Camels are challenging to detect from aerial views because of their natural camouflage and small size in high-altitude imagery. Moreover, monocular cameras lack depth perception, which complicates distance estimation and spatial localization.

Previous research in computer vision has explored various camera models for object detection and distance estimation. Classical models, such as pinhole and perspective projection frameworks, provide a mathematical basis for estimating object positions from 2D images [11]. However, in practical applications, applying this model to estimate the distance to the corresponding target in the sampling camera often requires additional information because objects with the same appearance but different sizes may have the same projection on the camera. The utility of the camera model extends across a broad spectrum of applications in computer vision

and graphics. Different environments and cameras may cause changes in the various parameters. Therefore, appropriate models must be applied and fine-tuned to adapt to the scene. Positioning methods for monocular cameras may require additional prior information or external data from third parties to obtain an accurate distance estimation. Megalingam leverages prior information about target objects and applies similarity principles to calculate the distance to the target using this information [12]. Some studies have proposed deep learning-based approaches for monocular distance estimation, such as DisNet [13], which takes the relative position and size of the target object in the image as input and uses five hidden layers for inference. However, these methods often require extensive training data and are sensitive to changes in camera orientation and focal length.

In the context of livestock monitoring, UAV-based systems have been used to track cattle and sheep. However, few studies have focused on camels, which present unique challenges owing to their size, movement patterns, and desert habitat. Our work contributes to this emerging field by developing a specialized dataset and a lightweight recognition and positioning system tailored for camel herding in desert environments.

III. PROPOSED SYSTEM

To support highly automated and sustainable herding in the camel grazing industry, we introduce a system for intelligent monitoring that relies on a single UAV. The framework comprises two components. First, we employ deep-learning techniques to detect camels from the air using a UAV. Second, we estimate the geographical locations of camels using drone flight data.

A. Camel Recognition from High-Altitude UAV Perspective

In this task, we considered a herd of camels grazing freely in the desert. A drone approaches the camels in motion and captures videos. The background program takes images as input and outputs the possible positions of camels in the picture. Rectangular bounding boxes were used to mark the outer outline of the camels with confidence probabilities.

1) *Dataset*: We identified a typical limitation in existing camel datasets: most images captured from frontal or near-profile angles feature camels that take up more than half of the frame. These images do not efficiently represent the perspective of the UAVs. In aerial videos, camel objects appear compact and occupy only a small portion of the frame. Models trained on current open-source datasets struggle to perform well on aerial videos because of these differences. To address this issue, we created a new dataset using images captured from a high-altitude drone perspective. Our goal is to capture camel imagery from an aerial viewpoint and build a specialized dataset that bridges the gap between conventional camel datasets and the unique visual characteristics seen in aerial videos. This achievement aims to provide reassurance to those involved in aerial video analysis, enriches the diversity of available resources, and serves as a crucial foundation

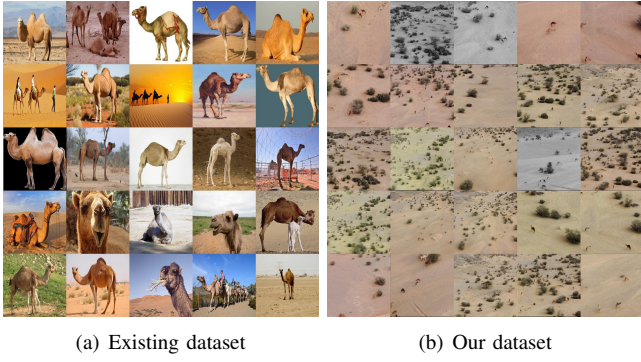


Fig. 1: Datasets Comparison

for training models capable of accurately detecting camels in UAV perspectives.

For each training video segment, we extracted one image every 20 frames and eliminated images with excessive similarity and without camels. We employed image augmentation methods, including random brightness adjustment, contrast adjustment, and noise addition, to further enhance the dataset. Finally, we obtained 1170 training samples after image augmentation. To facilitate training, we resized the image to a resolution of 1080×1080 . Figure 1 shows examples of the existing and our datasets.

2) *Model Design*: Unlike typical object detection tasks, the images in this task were captured from a high-altitude UAV in a bird's-eye view perspective. The target objects are smaller and more challenging to distinguish than those in everyday detection tasks. The distinction between small objects often relies on local features. However, convolutional pooling operations in deep networks may discard shallow-level local information. Therefore, preserving small-scale local features using appropriate methods is crucial for addressing these problems.

Achieving real-time performance that supports video streaming is essential for camel recognition in the desert. The You Only Look Once (YOLO) model employs a one-stage prediction and utilizes predefined anchors to facilitate detection, providing superior real-time capabilities as the foundational model for our camel recognition task. We developed an anchor-based YOLO model, in which the number of final feature maps and anchors determined the output. The model detects the presence of camels in a given image and accurately describes their locations using bounding boxes. The input of the network is a single picture, and its input dimension is $w \times h \times 3$, where w and h represent the width and length, respectively, and 3 represents the three color channels of an RGB image. The output is a vector with the dimension $n \times (c + 4 + 1)$, where n represents the number of all objects in the image, c represents the number of classes of objects in the dataset, and 4 denotes the value of the bounding box (x, y, w, h) , where x, y, w, h indicate the center position of the bounding box and its width and height, respectively. The last dimension represents the confidence probability that an object is inside the bounding box. The loss function of this network comprises three weighted parts: objectness loss, class

loss, and rectangular bounding box loss. The objectness loss, also known as object confidence loss, assesses the prediction performance of the model in terms of confidence probability. It can be modeled as the binary cross-entropy loss (BCE) loss function,

$$\text{BCE}(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)], \quad (1)$$

where $\hat{y}_i$ represents the output of the neural network, and y_i denotes the true label, which has a value of 0 or 1. The class loss measures the accuracy of the classification and is also computed using the BCE loss. The bounding box loss assesses the position of the predicted bounding box and is heavily influenced by the intersection over union (IOU):

$$\text{IOU} = \frac{S_1}{S_2}, \quad (2)$$

where S_1 represents the intersection area between the true bounding box and the predicted bounding box, while S_2 is the combined area of the true bounding box and the predicted bounding box. Additional IOU variants, such as complete intersection over union (CIOU) and generalize intersection over union (GIOU), are also available as optional loss functions in the model.

The YOLO model comprises several crucial submodules, including significant components such as the cross stage partial network (CSPN) and spatial pyramid pooling (SPP). CSPN is a simplified residual network that can enhance the learning ability of convolutional neural network (CNN) and maintain accuracy while being lightweight. SPP incorporates a continuous pooling and residual connection process, which effectively extracts features of different scales. In the detection head, the model includes up- and down-sampling processes in the form of a feature pyramid networks (FPN) and connects different sampling layers through techniques such as skip connection.

Table I presents the details of the model structure. CBL denotes the Conv2d-BN-LeakyReLU layer, which contains a convolutional layer, batch normalization layer, and LeakyReLU activation layer.

TABLE I: Model Network Architecture

Layer	Type	Repeated Times	Layer	Type	Repeated Times
1	CBL	2	13	CSPN	1
2	CSPN	1	14	CSPN	2
3	CBL	1	15	Upsample	1
4	CSPN	1	16	Concatenate	1
5	CBL	1	17	CSPN	2
6	CSPN	1	18	CBL	1
7	CBL	1	19	Concatenate	1
8	CSPN	1	20	CSPN	2
9	SPPF	1	21	CBL	1
10	CBL	1	22	Concatenate	1
11	Upsample	1	23	CSPN	2
12	Concatenate	1	24	Detection Layer	1

B. Camel Positioning by a Single-lens Drone

We encountered challenges in accurately estimating distances owing to the constantly changing perspectives of civilian drones. The varying sizes of our target objects, camels,

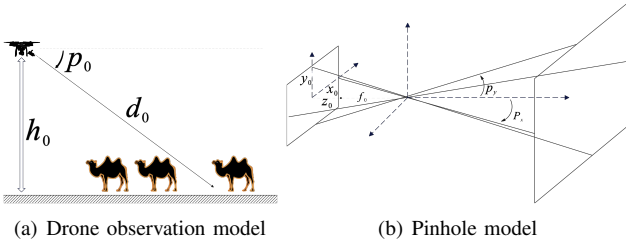


Fig. 2: Drone observation and pinhole models

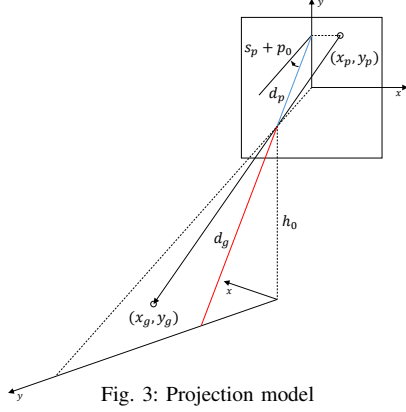


Fig. 3: Projection model

further complicate distance estimation and positioning. To address these issues, we developed a cost-effective positioning method explicitly designed for civilian drones equipped with a monocular camera. We tested this method on the video dataset mentioned earlier and found that accurate animal positioning was possible within an acceptable margin of error. Our approach capitalizes on the agility and accessibility of civilian drones, enhancing their ability to collect data from remote desert terrain. By implementing our algorithms on civilian drones, we can precisely position camels without expensive equipment. We illustrate our method for camel positioning in deserts using a single-lens camera mounted on a UAV and propose a system for tracking camels.

1) *Problem Description*: Figure 2a shows a drone in a hovering state, with its camera oriented at a downward angle, capturing images of camel objects on the ground. Because we focused on observing camels within desert terrain, we adopted the simplifying assumption of a flat ground surface. Let the altitude of the drone be denoted as h_0 . The camera of the drone was adjusted to rotate downward relative to the horizontal axis for ground-level observation. We denote this downward pitch as p_0 . Light rays perpendicular to the imaging plane of the camera pass through the optical center and are directed to the ground. This distance can be expressed as

$$d_0 = h_0 \csc(p_0). \quad (3)$$

Owing to the lack of distance between the camera and camels within the field of view, it is challenging to derive the geographical coordinates corresponding to pixels by directly applying the perspective projection model with the camera's intrinsic and extrinsic parameter matrices. Nevertheless, the flat terrain provided favorable conditions for employing the pinhole model, enabling the calculation of the camel's corre-

sponding geometric coordinates. As illustrated in Figure 2b, we considered a scenario in which the object plane remained parallel to the imaging plane. Light from the objects traverses a small pinhole directly onto the imaging plane. The distance from the camera lens to the imaging plane can be represented as

$$m_0 = z_0 + f_0, \quad (4)$$

where f_0 denotes the default focal length, and z_0 denotes an extra distance that can be altered through human operation and camera settings. The vertical p_y and horizontal p_x pitch angles of the camera's field of view from the center can be expressed as

$$p_y = \arctan\left(\frac{y_0}{m_0}\right), \quad p_x = \arctan\left(\frac{x_0}{m_0}\right), \quad (5)$$

where y_0 and x_0 represent the vertical and horizontal distances from the center of the imaging plane to the upper boundary, respectively.

As shown in Figure 3, we considered the scenario of a single pixel. The coordinates of this pixel in the coordinate system with the center of the imaging plane as the origin are denoted by (x_p, y_p) . We established the camera coordinate system using the vertical projection of the camera onto the ground as the origin, with its positive y-axis direction aligned with the projection of the main perspective on the ground. Light starts from the target pixel and travels through the optical center to reach the ground. The coordinates corresponding to this pixel on the ground can be represented as (x_g, y_g) , satisfying the relationship

$$s_p = \arctan\left(\frac{y_p}{m_0}\right), \quad (6)$$

$$d_g = h_0 \csc(s_p + p_0), \quad d_p = \sqrt{m_0^2 + y_p^2}, \quad (7)$$

$$x_g = \frac{x_p}{d_g} \times d_p, \quad y_g = h_0 \cot(s_p + p_0), \quad (8)$$

where s_p denotes the angle shift from the drone's center of view. d_g denotes the distance from the optical camera to the target, which is the red line in Figure 3. Here, d_p denotes the distance from the optical center of the camera to the pixel position on the imaging plane, which is the blue line shown in Figure 3.

To obtain the target's latitude and longitude coordinates, we need to transform the target into the camera coordinate system to longitude and latitude. The yaw of the UAV based on the true north is denoted by σ . We needed to transform them into a coordinate system with the true north as the positive direction of the y-axis. The new coordinates are denoted as Δx and Δy :

$$\Delta x = x_g \cos \sigma - y_g \sin \sigma, \quad \Delta y = y_g \sin \sigma + x_g \cos \sigma. \quad (9)$$

From this, we can estimate the latitude and longitude of the target by

$$\text{latitude} = \text{lat}_d + \frac{\Delta y}{R}, \quad \text{longitude} = \text{lon}_d + \frac{\Delta x}{R \times \cos(\text{lat}_d)}, \quad (10)$$

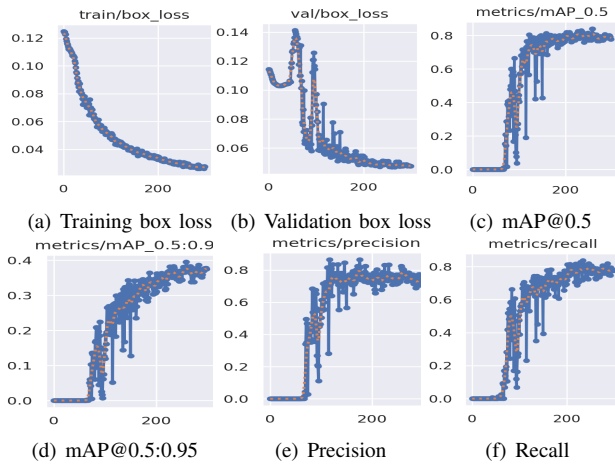


Fig. 4: Model evaluation

where the Earth's radius is denoted as R , and the latitude and longitude of the drone are denoted as lat_d and lon_d . By combining the above equations with the UAV flight data, we can deduce the geographical latitude and longitude coordinates corresponding to the pixel positions.

IV. SYSTEM DEMONSTRATION

In this section, we demonstrate two key components of our proposed system: the camel recognition model from a drone perspective and the camel positioning and geotagging system.

1) *Camel Recognition Model from UAV Perspective:* In this task, we collected new data in deserts and constructed a unique dataset from the drone perspective for camel recognition. Furthermore, we trained a new YOLO-based model to detect camels in the desert from the air.

To construct a new dataset for camel recognition, we used the DJI MAVIC MINI drone to capture approximately three hours of video footage in the deserts of Makkah Province, Saudi Arabia. The parameters and camera specifications of the drone model utilized in our study are detailed in Table II.

TABLE II: Drone Performance Parameters

Performance Parameters	Value
Model Name	DJI MAVIC MINI
Max Speed	13 m/s
Battery Capacity	2400 mAh
Max Flight Time	30 minutes
Diagonal Distance	213 mm
Maximum FOV	83 degree
Video Resolution	FHD:1920×1080 24/25/30/48/50/60p
Max Video Bitrate	40 Mbps

We trained the recognition model for 300 epochs on an NVIDIA A100 GPU, which took approximately eight hours. Figure 4 illustrates the evolution of the evaluation metrics during training. These losses indicate that our model fits the dataset and performs well. Figure 5 shows the performance of the test video examples. The evaluation indicated that our new model yielded satisfactory detection results.

2) *Camel Positioning and Geotagging:* To evaluate the effectiveness of our camel positioning method, we used the aforementioned new dataset, which comprises approximately three hours of aerial footage captured from a drone



(a) Recognition result 1

(b) Recognition result 2

Fig. 5: Camel recognition results in deserts



(a) Original video frame

(b) Estimated camels' locations with drone's FOV

Fig. 6: Result of camels' positioning

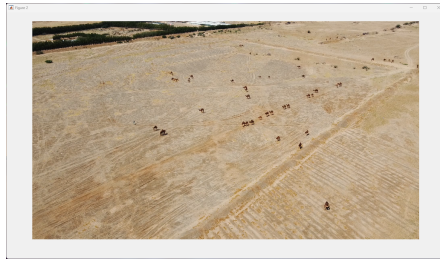
perspective, focusing on camel activities. Initially, we employed a deep learning model to predict the positions of camels in video frames, generating bounding boxes around them. Leveraging the centroid coordinates of these predicted bounding boxes as a reference, our algorithm computes the corresponding geographic coordinates.

Essential flight data, such as the drone's GPS coordinates, altitude above ground level, yaw, and camera pitch, were obtained from telemetry data transmitted during the flights. Figure 6(a) shows a video frame captured by the drone camera. Figure 6(b) shows the outcome of our methodology in the corresponding estimated field of view (FOV) and camels' positions. The trapezoidal box represents the FOV of the drone, and the red points represent the camel positions. The results show that our algorithm is effective in accurately determining the spatial coordinates of camels in aerial footage.

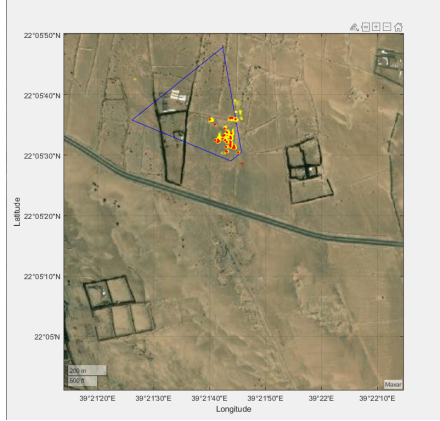
Building on this foundation, we developed a user-friendly system, as shown in Figure 7. The system displays the tracking trajectories of camels, facilitating enhanced data collection and research on camels. As the camels move, their current positions are marked by red points and their previous positions are shown as yellow clouds. This system leverages the calculated geographic coordinates of the camels to map their movements over time. Visualizing these trajectories enables researchers to gain valuable insights into the behavioral patterns and spatial dynamics of camels, allowing for more informed analyses.

V. SUSTAINABILITY ANALYSIS AND DISCUSSIONS

Demonstrating a commitment to sustainability, our proposed system offers a resource-efficient approach for managing herds of camels. By opting for a civilian, low-cost, single-lens drone and a localized processing unit, we minimized initial hardware investments compared to resource-intensive satellite monitoring or the deployment of numerous GPS collars and smart sensors across herds. The implementation of the lightweight YOLO architecture optimizes camel recognition on edge devices, lowering the computational overhead



(a) Original video frame



(b) Estimated camels' locations and tracks with drone's FOV

Fig. 7: Camel recognition and positioning system

and power consumption. The use of open-source frameworks further bolsters sustainability by reducing operational costs, making this solution a viable and accessible option for low-income herders. Table III highlights the advantages of the proposed system over GPS collars, satellite imaging, and other UAV-based methods.

TABLE III: Sustainability Comparison with Existing Solutions

Method	Cost	Scalability	Accuracy	Infrastructure Dependency
GPS Collars	High	Low	High	Low
Satellite Imaging	Very High	Moderate	Moderate	High
Other UAV Systems	Moderate	High	Variable	Low
Proposed Single-Lens Drone System	Low	High	High	None

Although the proposed system demonstrates feasibility, several areas warrant further exploration to enhance its robustness and scalability. We proposed a YOLO model for real-time detection. Future work will include benchmarking quantitative metrics, including the system's frame rate and latency on edge devices, to validate its suitability for live monitoring. Reliance on a single drone limits its coverage and resilience. A multi-drone framework can enhance scalability and fault tolerance by utilizing coordinated flight paths and data fusion strategies. To validate the positioning accuracy, future studies should incorporate error modeling and sensitivity analysis to enhance the understanding of the reliability of projection-

based methods. To cooperate with NTN, future work should explore mesh networking to ensure reliable communication in remote areas without the need for network infrastructure.

VI. CONCLUSIONS

In this paper, we demonstrated a lightweight and sustainable system for an intelligent automated camel grazing system in desert areas. We utilized a civilian single-lens UAV to capture video data from deserts, creating a unique dataset for detecting camels from an aerial perspective. Leveraging deep learning frameworks, we trained and evaluated a model capable of automatically detecting camels effectively. To improve automated positioning, we proposed a lightweight method that incorporates UAV flight parameters to determine the geographical latitude and longitude coordinates of camels accurately. The lightweight architecture and cost-effectiveness of our system make it sustainable in diverse scenarios, not only for camel herding but also for monitoring other livestock or wildlife in challenging terrains. The dataset and positioning framework serve as a foundation for researchers conducting UAV-based ecological studies or precision agriculture.

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