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Livestock Management With Unmanned Aerial Vehicles: A Review

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ABSTRACT The ease of use and advancements in drone technology is resulting in the widespread application of Unmanned Aerial Vehicles (UAVs) to diverse fields, making it a booming technology. Among UAVs' several applications, livestock agriculture is one of the most promising, where UAVs facilitate various operations for efficient animal management. But the field is characterized by multiple environmental, technical, economic, and strategic challenges. However, the use of advanced technological techniques like Artificial Intelligence (AI), Internet of Things (IoT), Machine Learning (ML), Deep Learning (DL), advanced sensors, etc., along with the assurance of animal welfare while operating the UAVs, can lead to widespread adoption of drone technology amongst livestock farmers. This paper discusses livestock management research where UAVs monitor farm animals via detection, counting, tracking animals, etc. In this article, an attempt has been made to elucidate different aspects and broader issues around livestock management while highlighting the associated challenges, opportunities, and prospects. This work is the first review paper on the subject matter with all the necessary information and analysis, to the best of our knowledge. Therefore, the article promises to provide interested researchers with detailed information about the field, guiding future research.

INDEX TERMS Unmanned aerial vehicle, cattle, livestock management, livestock agriculture.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are aircraft designed to fly without a pilot on board, also called mini flying robots, miniature pilotless aircraft, and drones (in this paper UAVs and drones terms are used interchangeably to refer to the same thing). The mutual collaboration of three major components is required to operate such an aircraft system: aircraft body, ground control station, and the sensor support [1], [2]. Their strength is the capability to reach a remote location with minimum time, effort, and energy, without human presence. In addition to their high mobility, low maintenance requirement, and easy deployment, UAVs have also eased the collection of outdoor aerial images and facilitated easy monitoring and analysis. Due to the recent advancement in electronics, communications, and embedded technologies, the fall in prices has increased its availability in the military, commercial and civilian applications. According to the Association for UAV Systems International, over 100 thousand new job opportunities will be created in the UAVs industry by 2025 [3]. By 2027, the estimated global UAV market value will reach $3 billion, led by North America, Asia, and Europe, respectively [4], [5]. The UAV-driven paradigm has been described with its applications and challenges [6].

The world first saw the use of drone technology during the First World War in military applications by the USA and France. However, it has witnessed a vast expansion of applications, global awareness, and a surge in interest in drones over the last few decades. Presently, the commercial drone market has a steady momentum and is expected to get more prominent in the nearest future [7]. The long list of UAV application fields includes, but is not limited

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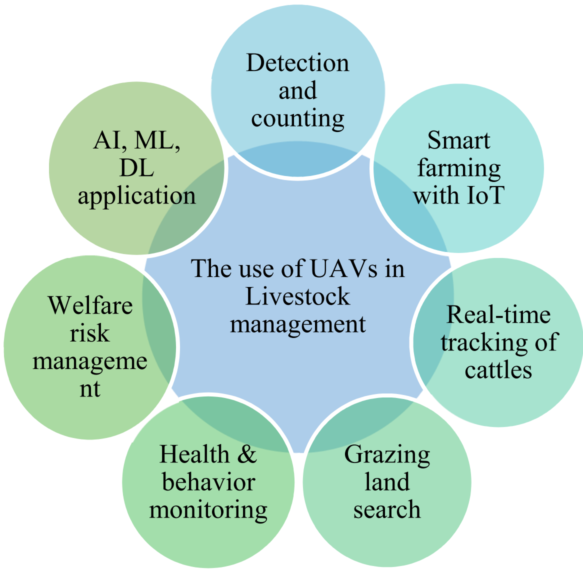

FIGURE 1. Different aspects of livestock management related to UAVs.

to, remote sensing, real-time traffic control, rescue operations, disaster monitoring, the inspection of civil structures, delivery of goods to remote areas, military applications, marine industry, border patrol, agriculture, livestock management, imaging and mapping, aerial photography, journalism, power transmission line and other cables inspection, etc.

One of the most promising sectors for UAV deployment is agriculture, where the farmer gets a bird's eye view of the entire field. Such technology can optimize a farmer's effort by helping him to seamlessly analyze the whole ground, alleviating the hassle of manual inspection. Livestock farming, being an essential part of agriculture, is not an exception. Drones can significantly contribute to monitoring, detecting, and tracking the animals, searching for grazing lands, and reporting any abnormal situation to the farmer to safeguard herds from potential threats [8]. A graphical view of the various aspects of livestock management, where the UAVs play a significant role to modernize the field, is presented in Figure 1.

Significant research has been done on the detection and counting of animals using drone images. Earlier approaches involved the capture of the targeted area's video footage for manual analysis [9]. Later, the process improved in several ways like thresholding [8], sliding window approach [10], thermal imaging [11], etc. With the help of image segmentation, the detection and counting process can be further improved. The challenging task of online tracking of animals is discussed in several articles. The works presented in [12], [13] make use of Long-term Recurrent Convolutional Networks (LRCN) to track the cattle across frames. The work in [14] extends the task of identification and tracking to open-set identification. The identification of misplaced livestock is formulated as an optimization problem to maximize the probability of detection of livestock in [15]. Another research dimension is the coordination and communication between multiple UAVs in tracking tasks, which has been attempted to be solved using a high-speed local network [10], long-distance WiFi access points [16], etc. Besides health monitoring [17], the impact of exploratory agency to ease the process of online monitoring [13], behavior monitoring [18], livestock roundup [19], optimal distribution of cattle [20] in the grazing land, etc. An intelligent surveillance system in [21] monitors the behavior and health issues where drones are used to collect pictures and video clips. An Automatic Veterinary System (AVS) is proposed in [22] for livestock monitoring systems where the customized UAV can work autonomously, without requiring any frequent check by the operator. RFID code, color code band, and various sensors can improve the accuracy and performance of such AVS, where smartphone applications may ease the decision-making process.

With the advancement of sensor technology and connectivity, there have been some research efforts on Internet of Technology (IoT) applications with drones with a particular interest in livestock management [23], [24]. The data collection, analysis and real-time decision-making process are entertained with the use of artificial intelligence (AI), machine learning (ML), and deep learning (DL) tools in this field [25]–[27]. Softwarization of UAV network is described in [28] along with the various application fields and research directions. An exciting research direction focuses on the behavioral changes of cattle in the presence of UAVs. For example, the authors in [29] assessed the heart rate and movement rate of livestock in the presence of UAVs with varying time and flight conditions. Livestock welfare management is also discussed in several papers in recent times while operating with UAVs over cattle fields [30]. However, the above-mentioned issues are surrounded by numerous challenges. Some technical challenges include dealing with the aircraft, sensors, and image processing tools, whereas other strategic challenges constitute government policies, economic constraints, environmental issues, etc.

As a promising field of future research, UAVs and their different application fields are discussed in various review articles. A well-written review paper succinctly reviews the recent development of the addressed issue, summarizes the present status, and suggests directions of future progress. In literature, it has been found that several papers have been written on the use of UAVs in diverse fields. The application of UAVs in the mining industry, forestry application, agricultural modernization, disaster management, ray research, communication network and power transmission line monitoring, remote sensing, mapping and inspection of structural models, etc., are presented in review articles by researchers. A list of review papers written on the use of drones in different applications has been presented in Table 1. However, livestock management using UAVs is not visible among review articles even though many works have been done on the topic.

The key features of this paper are as follows:

TABLE 1. The review papers related to the use of UAVs.

Topic	Reference	Year of publication
3D mapping and modeling	[31]	2013
Forestry applications	[32]	2016
Inspection of bridge and other construction projects	[33], [34]	2018
Remote sensing and photogrammetry	[35]	2019
Precision Agriculture applications	[36], [37]	2019
Monitoring in mining areas	[38]	2019
Structural disaster damage detection and characterization	[39]	2019
Communication network issues	[40]	2020
Inspection of power system transmission lines and fault diagnosis	[41]	2020
Sustainable weed management and spraying technologies	[42]	2021
Ray research	[43]	2021
Smart agriculture management	[7] , [44]	2021
Civil applications	[45]	2019
UAV assistance paradigm	[6]	2020
Software implementation of UAV network	[28]	2020
Cattle and other livestock management	No record	

– It is the first review article on the use of UAVs in livestock management research.
– It discusses different fields related to cattle management where UAVs are being used and presents a detailed literature review on the subject matter.
– It highlights the various kinds of challenges related to the field and itemizes the solutions proposed by different researchers.
– It highlights the broader aspects and the concurrent research directions in UAV based cattle management.
– It identifies the research gaps in the field where more research is needed.

The paper has been structured in the following way: it starts with the general introduction to the topic, which includes the current potentials of the drone industry, different application fields where UAVs are being used, the necessity of using UAVs in the addressed area, the literature view, in short, the list of review papers on the topic and the critical contributions of the article. Section 2 elucidates the different research directions for UAVs in livestock research. The next part, section 3, highlights the challenges impeding the implementation of promising ideas on the topic and the suggested solutions by the researchers. Some of the broader issues, which may make the research field compatible with modern technologies and help overcome the identified challenges, are discussed in section 4. Finally, the concluding remark discusses the research gap as well as the recommendations for future works. The paper structure is summarized in a graphical flow chart, presented in Figure 2.

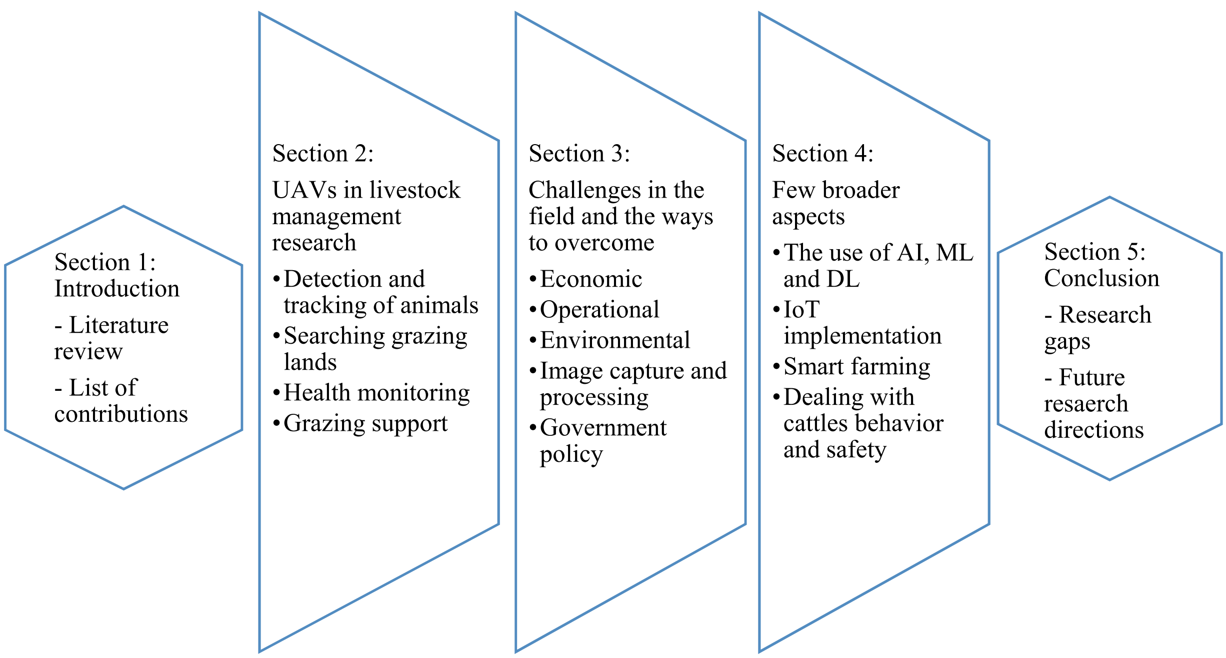

FIGURE 2. Detailed structure of the review process.

TABLE 2. Summary of the articles on livestock detection and counting by UAVs.

Year of publication	Livestock Type	UAV Type	Country	Method	Reference
2016	Cattle	3DR IRIS+	USA	Count manually from captured video	[9]
2017	Cattle	Custom-made	UK	Python `astropy` library to detect thermal image	[11]
2017	Cattle	DJI Inspire M1	UK	Faster-R-CNN with VGG-CNN M-1024	[12]
2018	Cattle	Multirotor	Spain	Apply sliding window on images, use CNN to check whether each window is livestock or not	[10]
2018	Sheep	Information not provided	New Zealand	R-CNN	[10]
2019	Cattle	SenseFly eBee	USA	DisCountNet with SfM	[48]
2019	Cattle	DJI Phantom 4	Japan	YOLOv2 with VisualSFM	[49]
2019	Sheep	Information not provided	UK	Single-Shot Multibox Detector	[26]
2019	Cattle	DJI Matrice 100	UK	YOLOv2	[13]
2019	Cattle	DJI Phantom 4 Pro	Brazil	15 pretrained transfer-learning architectures	[50]
2019	Information not provided	Quadcopter	Information not provided	Segmentation using U-Net and Inception-V4	[51]
2020	Cattle	DJI Mavic Pro	Australia	Segmentation using Mask R-CNN with ResNet-101	[52]
2020	Cattle and Sheep	DJI Mavic Pro	Australia	Segmentation using Mask R-CNN with ResNet-101	[53]
2020	Cattle	DJI Mavic 2 Pro	Brazil	NASNet-Large	[54]
2020	Sheep	Quadcopter	Qatar	Image processing with morphological operators; YOLOv2	[8]
2020	Cattle	DJI Mavic 2 Pro	Brazil	Xception architecture	[55]
2021	Sheep	DJI Phantom 3 Pro	New Zealand	Segmentation using U-Net and custom CNN	[56]
2021	Cattle	DJI Mavic Pro	Brazil	Faster R-CNN with Inception-ResNetV2	[57]

II. DIFFERENT ASPECTS OF USING UAVS IN LIVESTOCK RESEARCH

A review of available literature on UAVs for livestock revealed several areas that dominated the field. Some of the main areas identified are discussed in this section.

A. DETECTION AND COUNTING OF LIVESTOCK

The task of detecting and localizing livestock from the fields can be considered as object detection. These tasks focus on locating livestock from images or videos and count them. Table 2 summarizes all the works done in the field of livestock detection and counting.

The following subsections will discuss about different approaches of cattle monitoring using UAVs:

1) PRIMITIVE APPROACHES

Earlier approaches on livestock detection using UAVs [9] simply captured video footage of the pasture, and human observers were employed to detect and count the livestock manually. This process was beneficial for detecting and counting diseased cattle living in quarantine. To automate the process of detection and counting, [8], [46], [47] applied thresholding on each image frame on the video sequence to separate livestock from the background. Then morphological operations and binary masks were used to remove noisy pixels. Finally, the remaining blobs were counted to get the number of livestock in the frame.

2) R-CNN-BASED APPROACHES

Although these methods were computationally inexpensive, their low accuracy resulted in better systems [10] that relied on the Sliding Window approach to analyze individual frames and detect livestock from fields. The system considered the distance of the UAV from the field to determine the estimated livestock size. Then sliding windows of three sizes

(85%, 100%, 115% of the estimated size) were applied on different frame patches. Each patch was then supplied to a Convolutional Neural Network (CNN) to determine the probability of that patch being livestock or background.

Recent advances in ML and AI-based approaches allowed us to accomplish this task by combining pretrained CNN-based architecture with Region Proposal Networks (RPN). These networks take images or videos as input and produce Regions of Interest (RoIs) as bounding boxes around the livestock. Then the regions are classified using a pre-trained network. For example, [46] uses a modified version of R-CNN [58] to detect and count sheep on a field. The method applied selective search to generate region proposals and CNN for feature extraction from the regions. Then the features are fed to an SVM for classification, and to a linear bounding box regressor to get the confidence value.

[12], [57] utilize Faster R-CNN [59] to detect and localize cattle. Reference [12] uses the VGG-CNN M-1024 network [60] as the pretrained base CNN architecture. In contrast, [57] utilizes Inception-ResNet-v2 [61] to detect cattle. As shown in Figure 3, in Faster-R-CNN, the base network is followed by a trainable RPN and a classifier network. In between the two networks, the RoIPool [62] layer is used. Using the feature map extracted by the base CNN architecture, RPN produces bounding boxes as region proposals. In the case of rectangular bounding boxes, each proposal takes the form of an N $\times$ 5 matrix, where N denotes the number of RoIs. The first column of the matrix denotes the index of the RoI, and the remaining four are the coordinates of the top left and bottom right corners of the proposed bounding box. The RoIPool layer then takes these bounding boxes and resizes them to some predefined size. Sometimes overlapping proposals are discarded to reduce the computational cost using different suppression techniques. The extracted feature maps can be slightly off by 1 or 2 pixels, but that does not reduce the accuracy much. The RoIs are then fed to the classifier network. Based on the classified result and the confidence score, predicted RoIs can be discarded or retained accordingly. In addition to that, [57] computes projections of the image vertices using GPS position and altitude of the drone in relation to the ground before detection. After calculating of the global coordinates of the drones from all the images, by creating a bipartite graph and using maximum flow, duplicate cattle are identified and removed to avoid counting the same cattle multiple times.

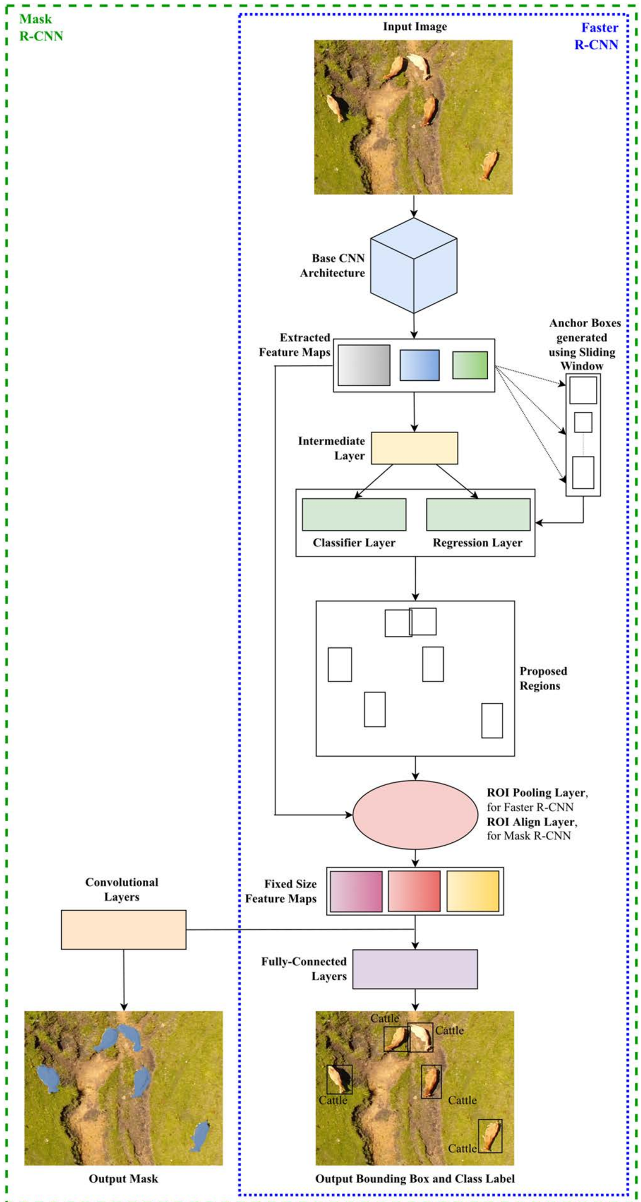

FIGURE 3. The architecture of R-CNN-based approaches for generating bounding boxes and segmentation masks to detect and count livestock (Adapted from [59], [64]. Input image taken from [49]).

3) SEGMENTATION BASED APPROACHES

To further improve upon detection, some works consider this work as image segmentation. For example, in [51], [56], the authors utilized a combination of U-Net [63] and a CNN network to segment livestock images to count them. The U-Net architecture, shown in Figure 4, makes use of a contraction and an expansion part. The contraction phase combines convolution, non-linear activation, and max-pooling layers to down-sample the input livestock image to generate high-resolution features. By concatenating output from the contraction phase, the expansion phase performs up-convolution on those features to extract the segmentation masks for the livestock. In [56], the segmented images are then classified using a seven-layer CNN architecture to ensure the correct livestock count. On the other hand, [51] utilized Inception-V4 [61] to classify the segmented images.

Other works on segmentation-based counting [52], [53] utilize Mask R-CNN [64] to segment cattle from frames of video sequences to count them. They detect the body or the head of cattle, treating the task as image segmentation. Depicted in Figure 3, Mask R-CNN is an extension of Faster R-CNN since most of the baseline architecture is similar. Mask R-CNN corrects the misaligned feature map provided by the RoI Pooling layer by replacing it with the

FIGURE 4. U-Net architecture for livestock segmentation (Adapted from [63]. Input image taken from [49]).

RoIAlign layer. This layer utilizes Bilinear Interpolation to avoid quantization and compute the exact feature map for the cattle to be segmented. The generated segmentation masks are then counted to find the number of cattle.

4) SSD AND YOLO-BASED APPROACHES

The problem with these R-CNN based architectures is that they generate lots of proposal regions by applying classifiers on multiple locations for each image which takes up a lot of processing time. Additionally, they perform poorly for smaller targets [65]. For this reason, some works [26] proposed the use of Single Shot Multibox Detector (SSD) [66] to detect livestock from images captured at 50m altitude. The network is faster than previous R-CNN-based methods as it only requires a single forward pass through the detection network to localize livestock. As seen in Figure 5, the architecture builds upon VGG-16 [67] by replacing its fully connected layers with a set of auxiliary convolutional layers enabling it to gradually decrease input size to extract features in multiple scales. The bounding box around livestock is generated using a CNN architecture considering both the confidence of the network and the distance of the proposed box from the ground truth. The architecture starts with a set of bounding boxes in the input image and based on the confidence values provided by the classifier, the ones with the highest confidence are retained.

To perform faster and more accurate detection, recent works on livestock detection [8], [13], [49] utilize a variant of "You Only Look Once" (YOLO) architecture [65], known as YOLOv2 [68]. This is an improvement over previous architecture YOLOv1 that applies a single neural network on the entire image. As a result, the network can reason about the entire image globally, considering all objects in the image. First, the image is divided into multiple grids for predicting bounding boxes. The architecture produces an area of interest with a corresponding confidence score based on whether

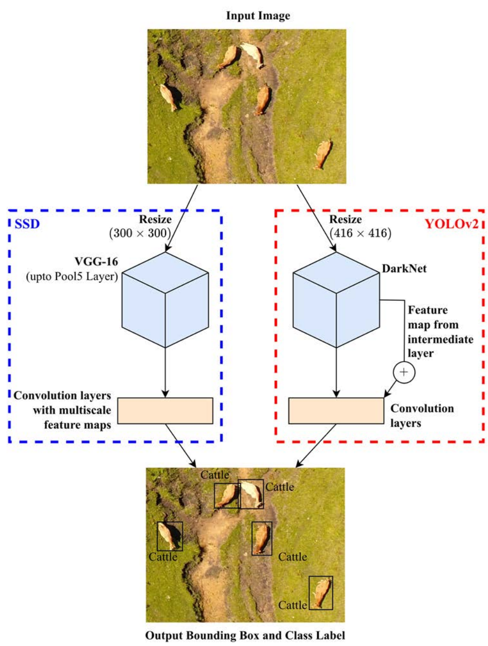

FIGURE 5. SSD and YOLO-based architectures for generating bounding boxes to detect and count livestock (Adapted from [65], [66], [68]. Input image taken from [49]).

the bounding boxes are the center of any object. Based on the class probability map of those confidence scores, final detections are made. YOLOv2 makes several improvements to the baseline architecture. As shown in Figure 5, the architecture utilizes fine-tuned classifier network with high input resolution enabling it to only focus on object detection instead of adjusting to a new resolution. It utilizes k-means clustering to pick better priors.

With the grid cell localized anchors, the model can easily learn to predict better bounding box dimensions. For faster feature extraction, it replaces VGG-16 with Darknet-19 that uses 19 convolutional layers and 5 max-pooling layers reducing the total number of operations to gain speed. By hierarchically classifying the images using directed graph-based ideas from WordNet [69], the model can predict detected objects better. This makes YOLOv2 ideal for livestock detection.

Reference [49] further extended detection and counting using YOLO variants by generating bounding boxes using YOLOv2 and constructing a 3D model of the area using VisualSFM [70], [71], a Structure from Motion (SfM) system to avoid recounting the same cattle multiple times. To estimate the shape of the model, Scale-Invariant Feature Transformation (SIFT) is used to find matching feature points in images to merge them using bundle adjustment. To get the point cloud from the model and the surface from the point cloud, Dense Reconstruction [72], [73], and Screened Poisson Surface Reconstruction [74] are performed. From that, the world coordinate for each cattle location is extracted. Finally, each coordinate containing cattle is matched with a pre-existing list using the Hungarian Algorithm [75]. A similar SfM approach [76] was also followed by [48] to create an orthomosaic reconstruction of the field. The authors used DiscNet to extract foreground information containing cattle. From the extracted foreground features, CountNet is used to generate the per-pixel probability of a cow being in a given pixel, counting the number of cows in the image.

5) DETECTION UNDER VARYING ILLUMINATION CONDITIONS

Considering the varying illumination and contrast of the captured images and the overlap of clustered livestock, color-space transformations, morphological operations and the result produced by CNNs can be utilized. Reference [54] considers the RoI provided by NASNet-Large architecture and generates binary masks to pinpoint the cattle. The authors superimpose the RoI on the original image and convert it to different color channels. Then different masks are generated by applying various thresholding techniques in different channels. By separately counting the masks and combining them, a final count of cattle is generated. In addition to that, to avoid counting the same cattle from multiple images, Speeded Up Robust Features (SURF) [77] and Binary Robust Invariant Scalable Keypoints (BRISK) [78] are applied to identify and match cattle in different images.

6) OTHER APPROACHES

Various deep CNN-based architectures pretrained on the ImageNet Challenge [79] can also be applied for detecting livestock. Reference [50] inspected the performance of pre-trained architectures for two similar-looking cow species in different weather conditions, times of day, soil conditions, etc. They also experimented with the positioning of UAVs. They found that if the ground samples have 2 cm/pixel occupancy in 112 × 112 input images, it provides the best accuracy for most models. Among all the architectures tested, NASNet-Large [80] was the best performing one. The architecture is a combination of Normal Cell and Reduction Cell designed by AutoML [81], which utilizes Reinforcement Learning to develop neural network architectures.

Authors in [55] captured images from an angle to cover more ground at a time and utilized Xception architecture [82] to detect whether cattle exist in image blocks or not. The base architecture relies on pointwise convolution followed by a depthwise convolution that gets rid of non-linearity leading to efficient model parameters. The authors also experimented with the input image size and distance to the cattle. Smaller image blocks are more suitable for detecting distant animals. However, it also increases misdetections since minor anomalies become more prominent. Other approaches to the detection of livestock include thermal images which can help in separating livestock from the background based on the temperature [11].

B. TRACKING LIVESTOCK WHILE GRAZING

Tracking livestock from a video or a sequence of frames introduces an additional temporal dimension to the detection phase. Considering the slow walking speed of livestock, and minimal sudden movements, information of subsequent frames can be incorporated to identify and track them. However, tracking livestock across successive frames can be computationally expensive. In this regard, [47] utilized shape features of the detected contour around goats, such as area, aspect ratio, convexity, contour moment, extent, equivalent diameter, eccentricity, form factor, perimeter, roundness, etc. to track them across frames. These features were then fed through different machine learning-based classifiers to detect the actions.

References [12], [13] make use of Long-term Recurrent Convolutional Networks (LRCN) to track the cattle across frames. For each frame, the visual features are extracted using the pool3-layer of Inception V3 architecture [83]. These features are then fed to LSTMs, which generate IDs for the cattle in the entire input sequence. The recurrent architecture can be seen in Figure 6.

Reference [14] extends the task of identification and tracking to open-set identification. It focuses on a flexible scenario where the system can recognize already seen livestock, and

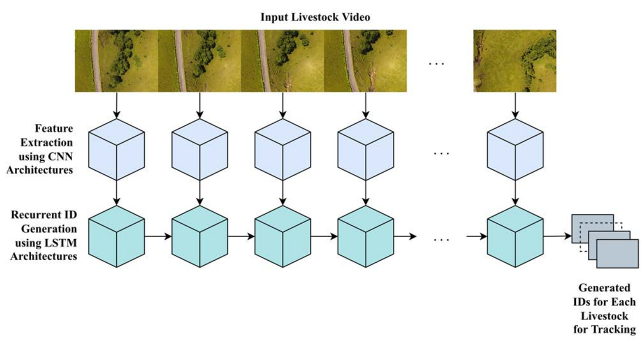

FIGURE 6. Long-term recurrent convolutional network architecture for tracking livestock (Adapted from [12]. Input images taken from [49]).

TABLE 3. Summary of the articles on livestock tracking by drones.

Year of publication	Livestock Type	UAV Type	Country	Method	Reference
2017	Cattle	DJI Inspire M1	UK	LSTM and LRCN with InceptionV3	[12]
2019	Goat	DJI Phantom 3	West Indies	Shape features fed into Machine Learning-based classifiers	[47]
2019	Cattle	DJI Matrice 100	UK	LSTM and LRCN with InceptionV3	[13]
2021	Cattle	Mixed	UK	Map livestock images into class-distinctive latent space	[14]
2021	Simulation	Simulation	Not applicable	Motion-Encoded Electric Charged Particles Optimization	[15]

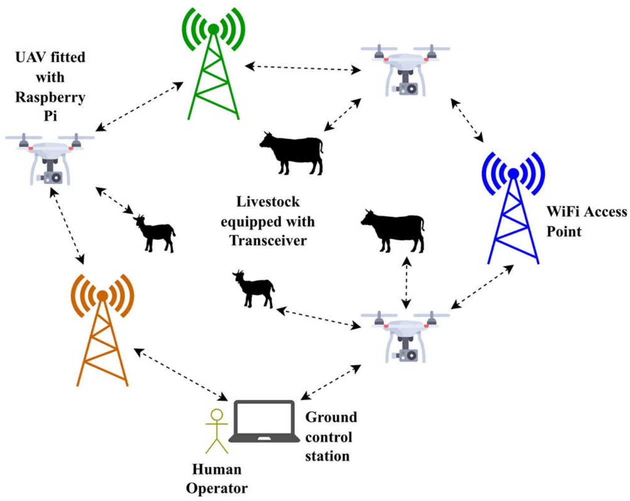

FIGURE 7. Communication among UAVs, Livestock, and ground control station using WiFi access points (Adapted from [10], [85]).

at the same time, identify and re-identify livestock that has not been seen before without further training. The authors consider the task as learning to map livestock images into class-distinctive latent space, where the images of the same livestock are mapped closer and different livestock further. After that, k-Nearest Neighbors clustering is used to find an existing or new cluster for the detected livestock.

Another dimensionality that can be added to tracking livestock is the identification of misplaced livestock. One of the critical challenges in this problem is to locate the missing target as fast as possible. Because the probability of finding the target decreases rapidly with time. Reference [15] approaches this by modeling "it" as an optimization problem to maximize the probability of detection of livestock. It combines the motion-encoding mechanism with Electric Charged Particles Optimization (ECPO) algorithm [84]. The trajectory for searching the target livestock is modeled as a series of UAV paths. These paths are updated using the Motion-Encoded ECPO (ECPO-ME) algorithm. Table 3 presents the summary of articles written on the topic.

C. COMMUNICATION AND EXPLORATORY AGENCY OF UAVS

Communication among UAVs shepherding livestock is crucial for establishing multirotor systems to control large herds. As depicted in Figure 7, paper [10] utilizes a high-speed local network built over long-distance WiFi access points [16] to establish communication with UAVs. These UAVs are controlled using Raspberry Pi model 3, which is a low-cost small board computer. These devices also manage the communication using 76MHz to 108MHz radio frequency band [10]. A ground control station software is set up that facilitates manual control, exchanged information logging among UAVs, status updates for the human controllers, prevention of access to restricted areas, and prevention of collisions. The UAVs can be programmed to cover a particular area by coordinating for minimum overlap and maximum coverage. Similar approach is followed in paper [85], which utilizes GPS collar fitted on cattle and sheep to monitor the livestock's position, health, and behavior as seen in Figure 7. First, the pasture is modeled as a convex polygon. To get an initial estimate of the position of the livestock, the optimal sweeping direction is calculated by following [86]. After determining the GPS coordinates of the livestock, the data is fed to a streaming K-means clustering algorithm to determine the optimal UAV trajectory to minimize the distance between the target livestock group and the UAVs. This reduces the overall flight time of all the UAVs to cover the entire ground while also reducing power consumption. After that, the UAVs periodically cover the whole pasture to collect health and behavior data and update the coordinates of the livestock.

The purpose of UAVs having exploratory agency is to move with the livestock's movement to keep track of them easily. Reference [13] considers this task as a "dynamic traveling salesman" where the cities are discovered on the fly. As illustrated in Figure 8, the authors use a dual-stream deep learning architecture to combine exploration strategies learned from previous experiences with instantaneous sensory inputs. The sensor data capturing the movement of the cattle is interpreted with AlexNet [87] and combined with positional history interpretation using long-term positional memory and a shallow CNN to predict the next action to be carried out by the UAV. The actions are also stored for future use.

The article [88] focuses on utilizing Long-Range Wide-Area Network (LoRaWAN) to locate cattle herds tagged with LoRa transceiver to cover all the herds in an optimal path. The locations are used to model a traveling salesman problem, where a Hamiltonian loop visiting all the locations at most once is determined using a modified version of Particle

TABLE 4. Summary of the articles on communication exploratory agencies of UAVs while tracking livestock.

Year of publication	Livestock Type	UAV Type	Country	Method	Reference
2017	Simulation	Simulation	Not Applicable	Collision avoidance using altitude alteration	[19]
2018	Cattle	Multirotor	Spain	High-speed local network using long-distance WiFi access points to communicate	[10]
2019	Cattle	DJI Matrice 100	UK	Long-Term Positional Memory with AlexNet and a shallow CNN	[13]
2019	Simulation	Simulation	Not Applicable	Streaming k-Means clustering on GPS data	[85]
2021	Cattle	AeroHawk VTOL Drone	Malaysia	Enhanced Particle Swarm Optimization	[88]

TABLE 5. Summary of the articles on cattle behavior monitoring with drones.

Year of publication	Livestock Type	UAV Type	Country	Method	Reference
2016	Cattle	3D Robotics RTF Y6 Multicopter	USA	Manually check feeding pattern of cattle from captured video	[18]
2019	Cattle	DJI Phantom 4	Canada	Measure distance among livestock using a marker-calibrated scale	[90]

Swarm Optimization (PSO) algorithm [89] called Enhanced Particle Swarm Optimization (EPSO). The algorithm utilizes mutation operators to avoid falling into local optimum, finding a globally optimal path that reduces the total path length covered. This, in turn, reduces the continuous operation time alleviating the need to replace drone batteries while on the operation.

To avoid collision among the traveling UAVs, [19] employs a collision avoidance technique by altering the altitudes of the UAVs. During traveling, if the distance between two UAVs goes under a certain threshold, the UAVs are moved towards opposite directions in altitude to avoid the collision. Table 4 presents the summary of articles written on the topic.

D. LIVESTOCK HEALTH MONITORING WITH UAVS

Monitoring the health of the livestock requires inspection of temperature, blood pressure, etc. In this regard, UAVs can be helpful. Reference [17] used UAV with a Radio Frequency Identification (RFID) repeater to capture temperature data emitted from the RFID tags attached to the ear of a cattle. They also experimented with the altitude of flight of UAVs. They found 150 feet to be the optimum altitude where they could gather data using the repeater and at the same time capture good quality images from the attached camera to the UAV operator for manual visual inspection to detect any other problems. On the other hand, [92] utilized UAVs and software to capture and analyze videos to measure feeding cattle's heat stress and respiration rate.

E. LIVESTOCK BEHAVIOR MONITORING WITH UAVS

Feeding behavior monitoring can help detect diseased livestock. To monitor this, [18] utilized UAVs to capture the feeding pattern of cattle. By counting the number of times, the muzzle of the cattle was inside the feeding bowl, the authors tried to estimate the food intake of the cattle. They found a strong positive correlation between the estimated food intake for long Alfalfa hay and long Sudangrass hay.

Cattle often exhibit complex social structures. This can be determined through their spatial proximity. To this end, [90] employed UAVs to acquire images of cattle herds. Those images were combined using photogrammetric software to create an orthomosaic of the entire herd. Using different objects in the image as reference to calibrate the scale, the distance between calves and their mothers, and the distance between calves and non-related cows were estimated. The authors estimated the distance within ± 1.96m of the actual value 95% of the time. Table 5 has presented the summary of two papers found on this topic.

F. LIVESTOCK ROUNDUP

Rounding up livestock requires gathering livestock together from a scattered position. Multiple UAVs can be employed to accomplish this task. Reference [19] simulated one such scenario where 4 coordinated UAVs are used to perform cattle roundup. From the satellite image of the pasture, GPS coordinates of the cattle are extracted. This extraction can be improved by placing GPS modules on cattle. UAVs determine the optimal flying trajectory to drive the cattle to the desired location based on the region's shape and target

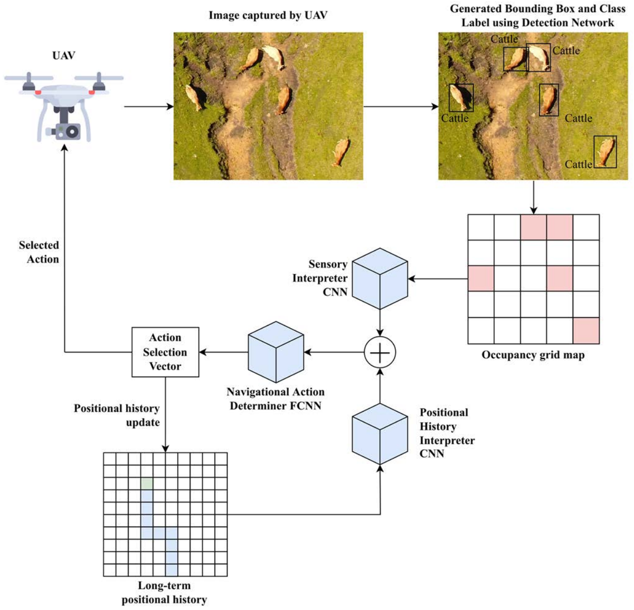

FIGURE 8. Navigation path determination using multiple CNN architectures (Adapted from [13]. Input image taken from [49]).

position. Inter-distance between the cattle and the aircraft is tracked continuously to optimize the trajectory of the UAVs. Proportional-Integral-Derivative (PID) controller is used to control the UAVs. The authors also experimented with how the UAVs can be positioned if their numbers change which can be seen in Figure 9.

G. ESTIMATION OF LIVESTOCK DISTRIBUTION

To manage the grassland ecosystem, it is crucial to understand the Spatio-temporal distribution of the livestock. In [91], the authors divided the study area into multiple grids and counted the number of detected livestock per grid from UAV images. The count was then modeled with a negative binomial distribution and logarithmic link function [93]. Reference [20] tackled this task by taking aerial photographs from UAVs flying over Yak herd. The photographs are then merged to create a georeferenced orthomosaic. It was then trimmed to only cover the yak herd and ortho-rectified. The herd was counted using software called HerdCounter to identify and count yaks. Missed and mistakenly selected yaks were manually corrected. Ten rectangles were placed randomly on the orthomosaic, and the density and dispersion were calculated with the help of ArcGIS. Table 6 has presented the summary of two papers found on this topic.

III. CHALLENGES FOR LIVESTOCK RESEARCH USING UAVS AND WAYS TO OVERCOME

Monitoring vast land mass for cattle detection, tracking, counting, health monitoring, etc., is practically infeasible without aerial surveys. Satellite image sources can be one of the ways to conduct such studies. However, the spatial information of such data is inadequate as the object of interest

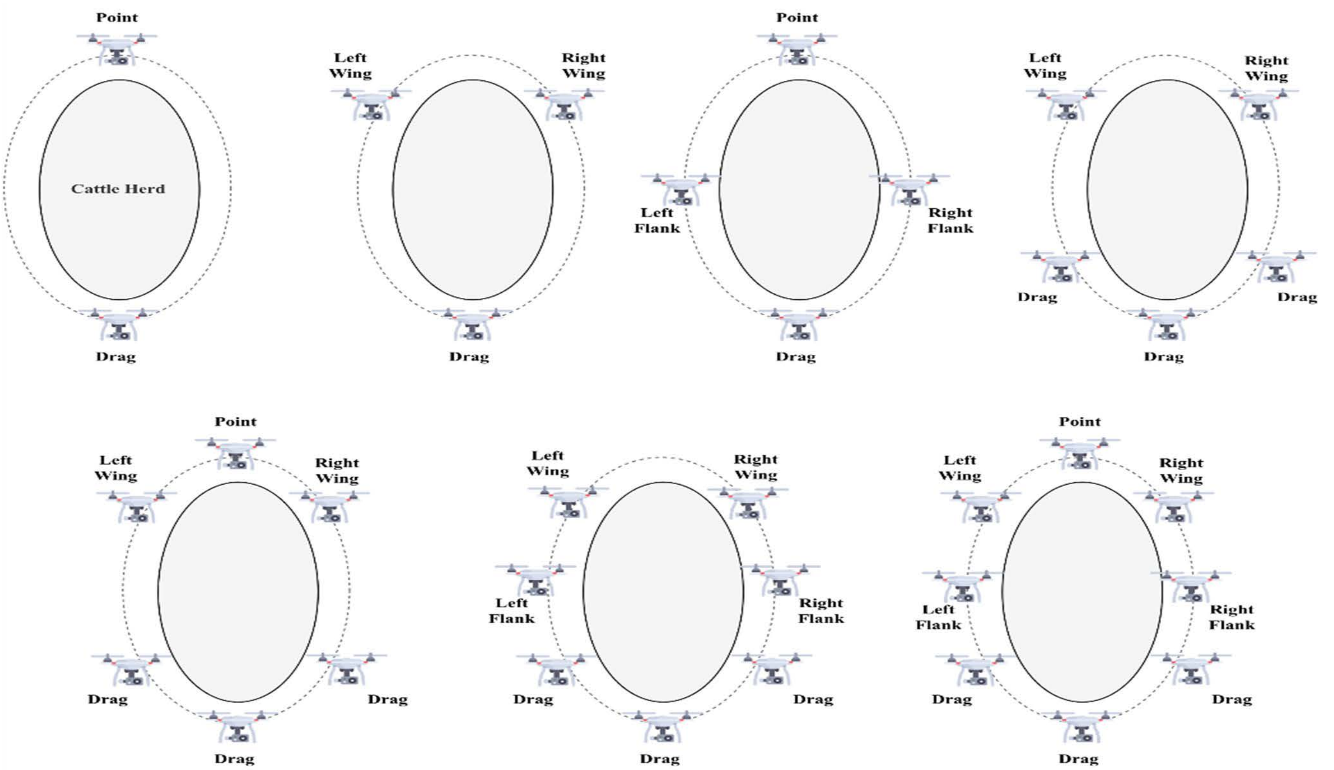

FIGURE 9. UAV positioning in livestock roundup considering the number of available UAVs (Adapted from [19]).

TABLE 6. Summary of the articles on cattle distribution estimation.

Year of publication	Livestock Type	UAV Type	Country	Method	Reference
2015	Cattle	Custom-made	Spain	Manually count livestock from the grid	[91]
2020	Yak	DJI Phantom 3	China	Manually count livestock using software	[20]

will be represented with only a few pixels. Another way to execute such surveys is using Manned Aircraft, but it is not cost-effective, and noise levels might disturb animals' normal behavior. Considering these facts, utilizing UAVs can go a long way to provide feasible solutions.

In recent times, the use of UAVs in different applications has been ever-increasing, and researchers are having trouble keeping pace with it [94]. Particularly in livestock research, people from different parts of the globe are getting more familiar with these technologies, and new doors are being opened [95]. However, despite this vast potential of UAVs, there are different technical and practical challenges which are needed to be considered while proposing any Unmanned Aerial System (UAS). This section discusses a few of such aspects.

A. SELECTING THE APPROPRIATE UAV

Selecting the proper UAV with a suitable set of sensors out of various choices is challenging and depends solely on the application. The UAV ideal for precision agriculture or wildlife monitoring might not fit in livestock research [96]. There are two types of UAVs suitable for livestock applications: rotary-wing and fixed-wing UAVs. Each type has its advantages and disadvantages.

The wing-type considerably affects the drone's maneuverability and endurance. While a fixed-wing UAV is easier to fly, it is not appropriate for hovering, where a rotary-wing UAV excels. Fixed-wing drones have flat wings that are better adapted to cover long distances quickly, spending less energy than rotary-wing drones. The flight endurance of such UAVs is higher, and they can fly at high altitudes [97]. So fixed-wing UAVs are recommended to be used for extended missions or to collect as much info as possible in one flight, such as tracking livestock for an extended period [12], [14], [47], [13], identification of misplaced livestock [15], livestock roundup from a scattered position [19].

Fixed-wing drones are an excellent choice if a big load needs to be carried due to the installation of extra equipment in the aircraft. Their wing construction provides remarkable stability, often allowing the aircraft to carry up to 50 kg loads. Such a requirement might be helpful in UAVs that are employed to serve multiple purposes. For example, UAVs can be used to capture images to detect and count livestock, collect health information, and maintain communication among each other. In this case, each of the UAVs has to carry camera equipment, microcomputer, and transceiver.

On the contrary, the flexible flying capability of rotary-wing aircraft facilitates vertical takeoffs and landings. Such aircraft can be easily flown in small grazing fields and around livestock. They can hover over fixed targets, and the modern ones can stay airborne even if one rotor is damaged. Therefore, they are suitable for inspecting cattle, hovering at a certain place for an extended amount of time. Moreover, rotary UAVs will be a better fit if the grazing field has obstacles like high trees, electric wires, etc. Additionally, hybrid constructions exist that combine the advantages of both types. They are quick and stable, have longer flying endurance, and can take off and land vertically. They are not, however, designed to hover.

Endurance is another essential factor while choosing aircraft. The fight endurance of UAVs varies from less than a quarter of an hour to even 24 hours. This mainly varies due to the wing type and weather conditions. Fixed-wing devices have higher flight endurance than rotary ones. Moreover, flying against the wind results in the consumption of a lot of energy, having a high impact on the aircraft's endurance. So depending on the geographic location and expected weather conditions of the grazing field and the span of tracking or monitoring livestock, a particular UAV can be chosen.

Finally, the UAV's payload is an important consideration. UAVs already have a fixed weight due to built-in equipment such as measuring devices, video cameras, sensors, and so on. So, if extra sensors are required to be installed in the aircraft, UAVs should be chosen with higher payload limits.

B. CHOICE OF SENSORS

After choosing the suitable aircraft, the choice of the sensors is another crucial factor to be considered. Installing more sensors increases the aircraft's capability, adding to the economic impact and payload limits. However, in this era of modern technological revolution, the size of sensors is being scaled-down and becoming a less limiting factor [98], [99].

RGB sensors offer the closest depiction like a human eye, whereas thermal sensors work with heatmaps and work well at nighttime [100]. Thermal cameras measure temperature by recording infrared light undetectable to the naked eye. Since the livestock has a higher temperature than their surroundings, thermal sensors can be used to detect livestock [11], [101]. However, they sometimes offer a lower spatial resolution, and surface emissivity and reflections may affect temperature measurements.

Images are captured using multispectral cameras at specific wavelengths, some of which are in the visible, infrared, or thermal bands. Some characteristics of the objects of interest may be more visible at specific wavelengths, which might be investigated to improve the detection process [102]. Since different species have unique spectral signatures, multispectral sensors can be used to detect and count cattle from mixed flocks [103]. On the other hand, these sensors have a lesser spatial resolution than RGB sensors [104].

Hyperspectral sensors can detect even higher spectral resolutions than multispectral ones. These sensors are more expensive, but they are excellent for detecting delicate features such as the presence of specific breeds or diseases in cattle [105]. However, such spectral resolution is not required for livestock detection and counting applications.

Video cameras are better at detecting movement and tracking specific subjects [106], [107]. On the other hand, high-resolution still photos can also be used to count livestock as an alternative. Furthermore, RFID sensors can be used for cattle health monitoring [108], and a combination of different sensors along with GPS might be helpful to guide the aircraft for intelligent monitoring applications [85]. Other sensors can include RFID transceivers for receiving data emitted from RFID tags attached to the body of the livestock [17], GPS for tracking position in order to generate georeferenced orthomosaic [20], single-board computers to establish communication and handle small processing tasks [109], etc. Careful analysis of the trade-off between the potential gain and associated cost can give further insight into which sensor to pick [110].

C. ISSUES REGARDING FLIGHT TIME AND AREA COVERAGE

Once the UAV and sensor set is chosen, several factors still need to be considered, like aircraft, environmental, operational, and image processing issues [98]. The lightweight ones often offer a limited payload, less battery life, and cannot cover large fields. Since the flight time and speed are often limited for such UAV, one solution can be to fly higher to cover large areas at once. However, this might not be feasible for certain applications since the quality of the captured image will be compromised. For example, tracking gets benefitted from pictures taken from a close proximity of the livestock as it helps the tracking model to find patterns to identify the livestock quickly [13]. This additional height might have to tackle communication failure with the operation center and several environmental factors.

Flight time and area coverage can be increased by installing bigger batteries in larger UAVs. But it becomes expensive, adds to the payload, and sometimes it may require separate pilot licenses to operate such drones. Aerial livestock monitoring in large areas can also be divided into chunks and completed step by step. But it might not be suitable for applications like cattle counting, where the target of interest is constantly moving. Multiple UAVs can be used to handle such situations. But it might not hold in cost-benefit analysis, and communication between these devices may impose different technical constraints that need to be considered [111]. However, loss of communication between the UAVs or with the Ground Control Station (GCS) can result in loss of data and cause UAVs to crash into each other or on the livestock. In case of such communication loss, the aircraft may go to some pre-specified ground stations, notify a predefined station if the network is accessible, and wait for further instructions.

Introducing solar panels can be another solution to increase flight time [112]. Although this idea is now primarily available for larger UAVs, it can be more prevalent in the nearest future. Charging stations can be placed in several places of the grazing field so that the UAVs can charge themselves in between flights.

D. OPERATIONAL ISSUES

Several challenges might be faced regarding operating the UAVs. Taking-off and landing policies for different UAV can be challenging to grasp initially. Fixed-wing drones are simple to fly, while rotor drones require sophisticated and ongoing maintenance due to their intricate design. With the rotor-wing, vertical take-off is conceivable and not with the other. Explicit licenses might be required to operate specific UAV, especially the larger ones with higher payloads.

In the case of livestock monitoring with fixed-wing UAVs, landing in rough terrain is very challenging. Uncontrolled landing in such spaces may cause damage to the aircraft sensors and even hurt the livestock. To avoid such scenarios, the payload weight is suggested to be kept well below the typical limits [98]. Paper [113] presented a path planning algorithm for rotary UAVs in environments with rough terrain. Nevertheless, UAVs are now coming with more compact designs with less strict issues regarding landing requirements.

Furthermore, there are chances of crashing due to machine failures. Recent solutions come with GPS enabled autopilots, battery health monitoring, emergency landing, etc. Moreover, UAV routes can now be remotely customized and altered in the middle of a mission using smart applications.

E. ECONOMIC FACTORS

Several factors like size of UAVs, cost regarding data storage, design of software to control process and interpret collected data, the human-hours spent setting up and conducting the surveys, as well as the training required to operate the entire system, etc. adds to the economic factors. Often agricultural applications require small UAVs, but livestock farms are usually large and require UAVs capable of covering large areas in less time. Furthermore, low-cost UAVs are more prone to mechanical failure, which could damage not only the aircraft but also the sensors and livestock. In the end, costs and benefits will be heavily influenced by these properties and intended usage; therefore, a thoroughly economic and technical review is recommended before choosing if UAVs are beneficial or not. Applications that do not require a UAV on a regular basis can use third-party services with fewer risks.

F. ENVIRONMENTAL CHALLENGES

Different environmental constraints like a strong wind, loss of signal, trees, raptors, power lines, etc., might cause the UAV to crash. Although loss can be avoided with careful planning and aviation, such occurrences are occasionally inevitable, disrupting the aircraft and sensors. Furthermore, if the grazing land contains rough terrain or high shades, it is even more difficult to prevent such losses. High winds can make the monitoring tasks of the cattle harder by deviating the UAV from its path. Different stabilization algorithms can be introduced to tackle such cases [114], but it requires additional power consumption and impacts flight time. Usage of rotary UAV is more vulnerable to wind, and it impacts the overall quality of the sensed data. UAVs with more blades are found to be more robust in unfavorable weather conditions.

G. GOVERNMENT REGULATIONS

To maintain a balance between the security of mass people and the practical usage of UAVs, different government regulations are imposed in different countries. There are separate bodies in different governments to provide the regulations regarding the usage of UAVs, such as the Federal Aviation Administration (FAA) in the United States, the European Aviation Safety Agency (EASA) in the European Union, etc.

Many of the rules are common in most countries. For example, for different applications in livestock research using UAVs, the aircraft should be registered, the pilot has to meet the minimum age criteria and pass the certification from an approved organization of govt. During the flight, the aircraft has to maintain a visual line of sight, payload limit, and maintain the maximum height limitation. It has been observed that the typical payload is below 25kg and the average allowed altitude is around 100m [115]. However, if this limit needs to be extended for specific applications, each govt has specific procedure.

Moreover, there can be requirements such as passing an aeronautical knowledge test, transportation safety security screening, etc. Based on the type of the grazing field, there are constraints regarding the maximum velocity of the aircraft. Often there are obvious clauses like flying without endangering people, keeping safety distance from urban areas, lost-link management policy, etc.

Among these regulations, keeping a Visual Line of Sight (VLOS) all the time is difficult for cattle monitoring. To conduct broad surveys in vast livestock farms, maintaining the VLOS may need multiple-person visual observers. Although waivers to this requirement are possible, the process is complicated and time-consuming. Despite this being one of the barriers, it is being normalized with the ever-increasing popularity across the globe in different practical applications [116]. As a result, it is recommended to check the most recent documentation on the matter.

H. ISSUES REGARDING IMAGE CAPTURING

Several challenges can occur while capturing and processing livestock images. Firstly, the image sensors are subject to geometric distortions which need to be corrected [90], [117]. Otherwise, such distortions can hamper the detection and tracking of livestock. One solution can be combining several overlapped images to create an orthomosaic of the entire grazing field [118]. Some of the other common issues like instrumental calibration, atmospheric correction, line-shift correction etc., can be considered depending on the application.

On the other hand, thermal imaging has been demonstrated to have great potential for livestock monitoring, but there are a few things to keep in mind. If the image is sensed with thermal cameras, collecting images when the ground temperature is lower. If the temperature of the cattle and its surroundings do not vary that much, it is challenging to differentiate these two [11], [119].

Furthermore, if the images aren't saved in the UAV, any communication failure with the ground receiver stations will result in data loss. To avoid data corruption, one method is to capture images with a 50% overlap between them, guaranteeing that every point on the ground is covered twice [115]. However, it can result in double counting of the same livestock if the images are not merged correctly. To alleviate this problem, a 3D model of the entire grazing field can be created using VisualSFM [49]. Then using SIFT features, matching feature points can be identified to combine multiple images without any overlap in order to generate an orthomosaic. A similar approach is followed in [20], [48], [90]. Then using SIFT features, matching feature points can be identified to combine multiple images without any overlap to generate an orthomosaic.

I. ANALYZING THE COLLECTED DATA

Once the image data is captured, manually identifying and counting livestock is infeasible as it requires enormous person-hours and is still prone to error, human bias, and optical illusions [120]. Designing automated algorithms can go a long way to solving this issue. But it will have to handle the change in pixel values due to different illumination and camera conditions, livestock orientations, shadows of a cattle and its contrast with surroundings, etc. [50]. Finding suitable algorithms offering high performance considering such diversified constraints is a challenging task.

In this regard, the advent of the recent deep learning algorithms can achieve high accuracy with the excellent ability to find patterns. For instance, using deep learning architecture in the detection and counting of livestock using R-CNN, UNet, and YOLO-based models have reduced the need for human input [12], [13], [49], [51], [56], [57], [121]. Long-term Recurrent Convolutional Networks have removed the need for handcrafted feature extraction and manual livestock tracking from video feed [12], [13]. Even charting a path for UAVs to traverse the entire grazing field is handled by deep neural networks [13]. However, an extensive collection of images is required to train such models, which might be challenging to obtain. Since this vast number of images might not be available for all applications, the concept of transfer learning is getting popularized where the pre-trained networks can be reused and fine-tuned with available data [8], [52], [54], [56], [57].

It can be challenging to analyze RGB images due to the lack of contrast between cattle and surroundings. Although modern Deep learning algorithms can tackle this issue to some extent, preprocessing techniques can be adopted in this regard for better performance [122]. Utilizing thermal sensors can be handy in this regard. If the livestock group together, it is also tricky for segmentation tasks to analyze them. One possible solution can be the development of software like HerdCounter that facilitates adding missed ones manually [20].

J. FACTORS REGARDING THE BEHAVIOR OF CATTLE

Since animals move over time, if the entire area can't be covered using a single image, some animals might not be considered despite several efforts. Also, in some images, cattle might be partially visible or occluded by other objects, making the task even harder. One potential solution to livestock appearing in multiple images can be flying the UAV faster so that the livestock get less time to move between adjacent images [90]. To account for the occlusion, a 'correction factor' can be used to compensate for the loss of different sensors in this regard [123].

Furthermore, animal behavior is sometimes dependent on the time of the day. If the temperature is high, cattle might rest under shade, making it an inappropriate time for counting [57], [124]. This heat issue is even more severe for thermal imagery as the system considers different-sized rocks as cattle. Shadows might be increased or decreased during sunrise or sunset, making segmentation tasks difficult [47], [56], [57], [109]. Thus based on the behavior and psychology of the livestock, the appropriate time to conduct a particular survey should be estimated [125]. To remove the influence of shadow, thresholding techniques and image adaptive correction algorithms can be employed [47], [126]. Detection models can also be trained to ignore the shadow [56], [57], [109].

Considering the ever-increasing popularity of UAVs in shepherding livestock, it is essential to monitor how UAVs flying near them impact the physical and physiological well-being of the livestock. Paper [125] investigated the physiological and behavioral responses of a few black Angus heifers to UAV flights carried out 9 meters above the ground surface. Before and after multiple UAVs flew in different patterns, the heart "rates" and movement rates were observed, which did not vary much due to UAV flights. Paper [18] trained cattle using prerecorded UAV flight sound files to make them get used to random UAV flights. In experiments conducted in [17], the cattle initially noticed the UAV flying overhead. However, it did not seem to elicit any violent or scared behavior. And eventually, the cattle got used to it. Similar research into how UAVs affect livestock behavior could be done in the future.

Table 7 has presented a summary of various challenges of using drones in this field, the reason behind those, and the probable solutions.

IV. BROADER ISSUES OF USING UAVS IN LIVESTOCK

The use of UAVs as valuable tools in farm operations is growing. Livestock herding and management are some of the areas in which UAVs have the potential to transform. As such, there is a growing research interest in the role of drones in livestock management. The different areas of this research have been discussed in the proceeding sections of this paper. However, some broader issues dominate or promise to dominate the discussion around the use of UAVs in livestock-related operations and research.

The development in sensor technology and connectivity means that IoT and related technology can be leveraged to generate more livestock management-related data. Hence, the synergy of IoT and drone technology is an area of great interest. Research attempts are being made on the Internet of Drones (IoD) [88], and further work is expected before this becomes widespread in livestock management. DL techniques are commonly employed in livestock detection from images acquired using drones or otherwise [115], [127]. ML techniques can come in handy to make sense of the resulting data. ML has also been used in animal behavior studies [128], and improvements are expected with the advent of data.

Over the years, there have been interests in the effect of UAVs on animal welfare [129]. Recently, more interest has been evident in the impact of UAVs on livestock welfare [130]. Moreover, one of the primary reasons for considering using UAVs in livestock management and research is to improve the targeted species welfare [129], [130]. However, drones may induce new forms of stress in animals due to the nature of flights [29], [131]. The behavior of animals in response to drone activities is a measure of the effects of UAVs on the welfare of different species. More so, herding livestock with UAVs requires an understanding of the behavior of various species in response to UAVs operations.

A. THE USE OF DEEP LEARNING AND OTHER MACHINE LEARNING APPROACHES

The success of most shepherding operations depends on the extraction of information from aerial images. Hence, advancements in image processing and ML techniques are essential to complement UAV technologies for improved livestock monitoring. A systematic review of the application of DL to precision cattle farming is given in [132]. The use of DL was found in two broad areas [132]: health monitoring [133], [134] and cattle identification [10], [49], [13], [135]–[138]. As evident in [132], CNN is the most adopted of the over 20 DL models employed to solve various problems in the reviewed papers. Only about 18% of the 55 papers used UAV-based images, while the remaining used ground-based images. However, all UAV based implementations focused on either counting [135], detection [135], [138], or both detection and counting applications [49], [52]. The work done in [138], for example, focused on the detection of cattle from

TABLE 7. Summary of various challenges for using drones in cattle management.

No	Name of the challenge	Reason for consideration	Probable solution
1	Selecting the appropriate UAV	Choice of UAV depends on application domain	Select UAV after proper requirement analysis of the domain and exploring the features of different UAVs such as wing-type, manoeuvrability, endurance, payload, etc.
2	Selection of sensors	Various kinds of sensors are available, but the proper selection will ease the application process	Exploit the advantages of different sensors- keeping the cost, payload, battery life etc., in mind.
3	Issues regarding flight time and area coverage	UAVs might face difficulties in area coverage due to speed and battery life limitations	Cover larger areas by increasing altitude, installing bigger batteries/ solar panels, employing multiple UAVs.
4	Operational issues	Difficulty to grasp taking-off and landing policies, operating rough terrain might be challenging, crashes might occur due to machine failures	Keep payload substantially below normal limits, explore GPS enabled autopilots, battery health monitoring system, emergency landing features
5	Economic factors	Cost of data storage, software design, person-human-hour and other risk factors.	Rigorous analysis on the potential gain vs associated cost.
6	Environmental Challenges	Heavy wind, signal loss in bad weather, obstacles in flight path	Apply different stabilization algorithms, employ UAVs with more wings,
7	Government Regulations	Govt. regulations might impose policies due to security concerns regarding licensing, payload, line of sight, speed, area coverage etc.	UAV usage is being normalized leading to less strict policies by different govts. Consider the most recent documentation of the concerned govt. May apply for special consideration in needed.
8	Issues regarding image capturing	Geometric distortions, vibrations, unfavorable weather conditions, loss of data due to communication gap with operation center	Combine multiple frames to produce a single image, apply atmospheric corrections, capturing frames by keeping overlaps with them
9	Analyzing the collected data	Manual analysis of such huge data is infeasible.	Propose advanced algorithms offering high performance with the ability to tackle diversified constraints
10	Factors regarding the behavior of cattle	Cattle are often in a group causing difficulty in segmentation, partial visibility, change of behavior in different time of the day	Algorithms may employ a correction factor. Consider the psychological and behavioral changes due to time, daylight, temperature, etc. before scheduling flights

aerial images by considering those factors that may limit detection, such as weather conditions, pasture conditions, and time of the day. The work aimed to make practical operations of drones feasible, which is a deviation from earlier works that focused on proving the concept. Most of the applications found are in cattle-related fields with minimal applications in other livestock species. Certain challenges identified are similar to those faced in other applications of DL [132]. However, there are challenges peculiar to UAV collected data.

Most UAV operations depend on the detection of objects of interest. The autonomous operation of UAVs also promises to improve their ease of use, performance, and scalability while reducing cost and enabling new applications. However, achieving full autonomous UAV operation remains a research problem that heavily relies on situational awareness, which is dependent on object detection [132]. Moreover, object detection has been extensively researched since the inception of computer vision. Excellent results are often achievable, sometimes even outperforming human performance. Hence, the natural inclination is to adopt traditional image processing and deep learning techniques in UAV based applications. However, this is not always feasible due to the unique scenery and other operating conditions associated with UAV based images. Generally, the height of UAV operation affects the nature of captured images and hence the requirements for operation. Hence, methods have been classified based on flying heights [139]. The three identified heights are eye-level view, low to medium heights and aerial images as presented in Figure 10. The eye-level corresponds to flying at 0 to 5 m above ground level. The low to medium height corresponds to flying between 5 to 120 m above ground level. The aerial imaging level corresponds to flying at heights greater than 120 m above ground level. UAV operations on at the aerial imaging level are rare and generally limited by government policies. Operations at the aerial imaging level require special permissions.

In a farm setting, UAVs generally operate either at human height or low to medium altitude, thereby having the same viewpoint as humans or wide angles of view, respectively. Because of the similarity of perspective with the humans at the eye level, classical computer vision techniques can quickly be adopted for UAV operations. However, specific computational and scientific challenges peculiar to UAV operations exist. UAVs' limited onboard computational capabilities present a challenge on the real-time detection and tracking of objects for obstacle avoidance and other operational purposes. However, there is improvement in this regard. The work presented in [140] performed on-board real-time detection and tracking of pedestrians using UAV sensor data integrated with a particle filter. Similarly, [141] used semantic segmentation to detect and track people using drones autonomously.

In real-time operations of drones at the eye-level, recent advancements in deep learning techniques could be explored in two main ways: either moving to off-board computations or developing ad-hoc architectures and adapting existing backbone networks. The former could leverage developments in the areas of cloud computing and IoT. One such application is found in [119], where R-CNN was used near real-time to detect objects using a consumer UAV. On the other hand, [142] used ResNet-18 [143] and YOLO modification for real-time on-board object detection and obstacle avoidance. The afore discussed issues present challenges and directions for research.

Other issues of interest at flight altitude of 0 to 5 m include (i) Human-drone-animal (livestock interaction) and (ii) indoor navigation. A drone operating at the eye level height interacts with humans and animals, livestock being the animals of interest in this case. Human-drone interaction (HDI) presents a wide area of research that has developed over the past decade. However, animal-drone interaction (ADI) has not been adequately studied. Typical works in this area are on dog-drone interactions [144]–[146]. Hence, the area of Human-drone-animal interaction is a virgin area requiring attention from the computer vision and ML community as it will go a long way in consolidating the benefits achievable in the autonomous coexistence of humans, drones, and animals (livestock). This interrelationship is depicted in Figure 11. Therefore, the operation of UAVs at the eye level presents a lot of research opportunities and challenges for the DL community.

Some considerations may be similar to the eye-level operation for indoor navigation and autonomous operation, even at heights slightly above 5 m. Moreover, several indoor navigational architectures have already been proposed [147]–[150]. For example, [149] demonstrated that indoor inspection of event-triggered cameras could also be exploited to detect critical events under indoor conditions.

Most current UAV operations in livestock management occur at low to medium altitudes. However, certain features

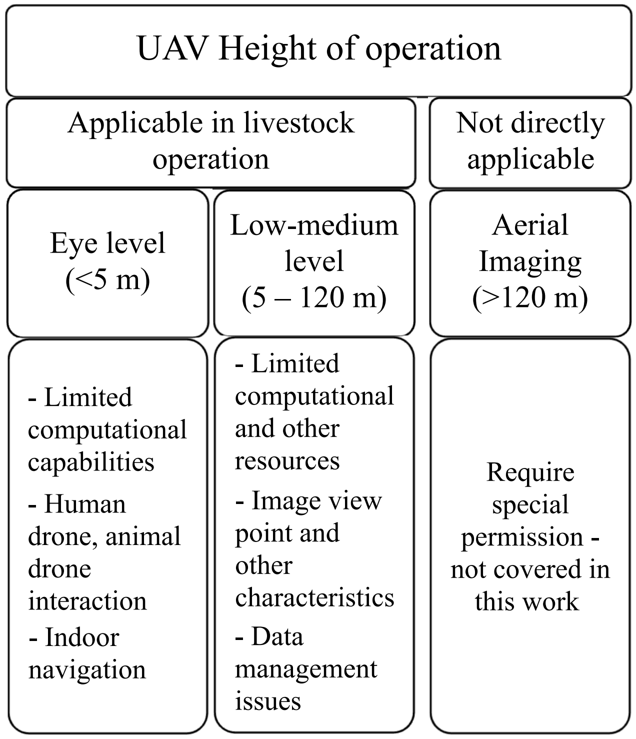

FIGURE 10. UAV operational heights.

of low altitude UAV images make object detection at this level challenging compared to standard images and often lead to a difference in mean average precision (mAP). These include small-sized objects, large image volume, inconsistent resolution, complex background and non-uniform object class [151]. There is also a noticeable object blurring due to arbitrary object orientation, the relative motion of objects, atmospheric turbulence, huge scale variation and dense distribution of objects [152]. As such low-level scene features and deep features are considered in the development of object detection techniques for low-altitude aerial images. These factors negatively affect the accuracy of object detection from low-altitude drones. A discussion on using deep learning-based object detection algorithms where the detectors were classified as two-stage, one-stage, and advanced detectors is presented in [153]. Amongst all other factors, the viewpoint variation inherent in low altitude UAV images makes object detection challenging because features are non-transferrable between images captured at different angles. Therefore, unique techniques are essential for data capture, processing and object detection [154].

Initial success in deep-learning-based object detection was achieved using two-stage detectors such as Faster R-CNN, Mask R-CNN, Cascade R-CNN, FPN and R-FCN. However, speed limitation was a significant challenge in adopting these for low altitude UAV based object detection. Therefore, the research community considered single stage detectors such as YOLO (and its improved versions YOLOv2/v3/v4), SSD, RefineDet and RetinaNet for their relatively higher efficiency. Because of their higher speed and lower memory requirements, these single-step detectors provided better results faster than single-stage detectors. As highlighted in [153], YOLOv3 achieved good results in detecting small objects with very high localization errors, while RetinaNet improves the class imbalance problem due to the extreme foreground-background ratio.

However, despite the gains with single-stage detectors, more advanced detectors may be necessary to achieve better results mainly because of the problem due to altitude variation. Hence, more advanced anchorless detectors such as CornerNet, CornerNet-lite and objects as points have also been considered. These anchorless detectors have exceptional performances when applied to the standard dataset. But for low-altitude UAV images, the performance improvement is still meagre compared to the standard dataset. Therefore, available results suggest a need for significant research efforts in deep-learning-based object detection on low-altitude UAV images. These research efforts will prove helpful for livestock-based and other applications.

Another wide dimension that is closely related to the area of machine learning is the issue of data management. The adoption of UAVs to various fields has resulted in the generation of vast data by very diverse and multi-disciplinary groups. However, issues relating to data management have not received the required attention from both the industry and academia. Hence, research groups and individuals often resort to developing ad hoc data management strategies that are costly, inefficient and non-transparent [155]. These data management related issues cut across all application areas, including livestock management research. However, the challenges present a host of opportunities for UAV data management such as the need for FAIR (Findable Accessible Interoperable Reusable) data [156]. Also, the maturation of other technologies such as developments in Big Data analytics, cloud resources and Googles' Dataset search engine need to be explored. Finally, the lack of existing accepted best practices for UAV data management minimizes the cost of adopting new practices.

Moreover, the net quantity of captured scientific data is still relatively small. This limited availability of scientific data is even more prominent for livestock-related data. Furthermore, the uniqueness of UAV data itemized in [155] underscores the need for unique data management infrastructure. Although deep-learning frameworks have been widely adopted for processing images captured with UAV, the inherent characteristics of the data mean that special considerations are necessary to derive maximum benefit from the considered data.

Another aspect of ML research can be found in animal behavior studies, where the learning abilities of ML can be explored to understand issues such as social structure, collective behavior and general welfare [128]. Humans are already able to understand the emotional state of animals based on facial cues [157], physiological cues [158], vocal cues [159] and gestures [160]. These cues could be integrated using ML for enhanced detection of emotional states [160], [161]. The data needed for the application of ML to achieve these

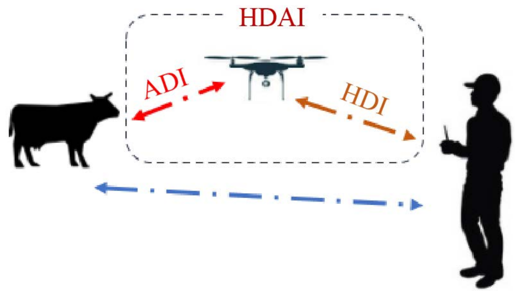

FIGURE 11. **Human-drone-animal interaction (HDAI) at the eye-level height.**

could easily be collected using drones, and some of the computations could be completed online or using edge and cloud computing resources for interconnected drones. Moreover, it is possible to collect social interaction data using passive integrated transponder tags (PIT) and proximity loggers [162]. ML applied to accelerometer readings have been successfully used in the study of Cattle behavior [163], [164]. In [115], SVM and KNN were used with accelerometer readings to study five different behaviours in lactating cows to monitor their well-being. However, techniques using accelerometer readings often lead to some misclassifications. Some misclassification examples include: resting vs ruminating, standing still vs feeding and feeding vs moving.

Therefore, additional UAVs monitoring could be explored to solve these misclassification issues. Moreover, in [126], DL techniques, implemented on an embedded system, was used to classify cattle behavior based accelerometer grazing cattle dataset. As such, the adopted techniques could be adapted for use onboard UAVs. For example, drones could use jaw and head movements to solve the misclassification problem earlier highlighted. The application of ML to livestock behavior is growing. In this line, significant work has been done in behaviour monitoring for livestock grazing [165]. Some of these could easily be adapted for use on UAVs. The behavior of sheep was classified using embedded edge devices and KNN [166]. Similarly, sheep behavior was studied using the hierarchical ML method with RF, SVM and Deep Belief Network (DBN) [167]. In [168], CART, LDA, QDA and SVM were used for *ethogram* in sheep.

Using drones to study the livestock will mean that the drones will be flying closer to the livestock. This practice may lead to a response, from the animals, to the presence of the UAVs. Hence the need to study the interaction between drones and animals. While some efforts are visible in the study of ADI, very little is available on drone-livestock interaction. Some works in dog-drone interactions include [144]–[146]. The area is generally unexplored, and the learning capabilities of ML can be explored. Hence, there are many opportunities for research and studies for proof of concept and beyond. Another area is for the drones to learn from animal and human gestures. Using reinforcement learning, drones can learn to take actions based on human emotions [169]. Future works could explore achieving the same with livestock and other animals of interest.

B. LIVESTOCK WELFARE

Over time, there have been concerns on animal welfare both in traditional and modern approaches for herding. Routine animal inspection is expected to consolidate the benefits (both welfare and otherwise) of outdoor livestock grazing over the strict rearing of animals indoors. Moreover, daily livestock inspection is a legal requirement in some jurisdictions such as Sweden [130]. Using UAVs and other digital technologies can automate sensor-based monitoring of livestock, especially in large and dispersed pastures. This automated monitoring can continuously capture environmental factors and animals' welfare and physiology. Therefore, the use of UAVs has increased the possibilities for improving animal welfare through monitoring and management. Drones allow for efficient monitoring, increasing production efficiency, lowering environmental impact, and improving animal welfare [170]. However, there are concerns that drones could lead to abnormal behavior in livestock.

Therefore, the effects of UAVs on animal welfare need to be well understood to improve livestock welfare in general. In previous studies, the presence of UAVs has been shown to lead to stress in wildlife [30]. Nevertheless, there is limited information on the effect of drone UAVs on the behavior and welfare needs of livestock and other domesticated animals. Generally, the effects of drones, for cattle herding, on animal welfare is not well researched [130]. However, some researchers believe domestication and interaction with machinery may make domestic animals less susceptible to stress from UAV activities. While some work has been done on the effect of UAVs on animal welfare, these studies are still limited and require further research.

Herders have employed sensors to monitor animal behavior and other physical and physiological indicators that guide them to take proper actions [171], [172]. However, their usage in commercial outdoor applications is somewhat limited. The limited application is partly due to data transmission requirements and energy supplies limitations, an area where drones could be explored. Moreover, real-time data transfer approaches are needed to be developed for their wide adoption. Since most existing sensor-based monitoring technology was developed for indoor use, it may not be suitable for drones in large outdoor applications. Indoor use of fixed cameras has proved helpful in small-scale settings [129].

Moreover, top-mounted cameras were particularly successful in detecting social interactions [124]. Therefore, drones could easily be harnessed to achieve the same. Different considerations may be required for indoor and outdoor operating drones. Some technological challenges associated with flying drones indoors include: (1) limited hovering due to obstacles, (2) insufficient navigation accuracy due to limited access to GPS data, (3) safety concerns due to drone failure, collision and battery explosion and integration into existing system or process. These have led to the relatively low use of drones for indoor livestock management compared to outdoor applications.

For drones operating indoors, where GPS support may be limited, advancements in computer vision, robotics mapping and localization may be explored. Some of the discussions related to computer vision have been addressed in the previous section on ML. Some indoor mapping technologies such as Light Detection and Ranging (LiDAR) and Visual Simultaneous Localization and Mapping (VSLAM) [173] have potential. The use of VSLAM for agricultural purposes is still at an early stage with very few applications [174]. In [175], a feasibility study was done to compare the performance of two VSLAM algorithms for indoor precision livestock farming. This work proved the concept of the feasibility for autonomous real-time mapping and localization of drones for indoor livestock farming. However, more work is needed to address other issues regarding energy usage, computational requirements, and the maximum area of jurisdiction for individual drones. Further work will also be required to cater for multi drone operations.

In outdoor applications, drones have been successfully used in getting landscape overviews. However, mining useful information from drone images is a challenging and laborious manual task. Therefore, the development of vision-based systems is required for automated and accurate detection and tracking of the species of interest to monitor animal welfare indicators. A comparative study on the position accuracy of images demonstrated a drone-based system's superior performance over collars with position receivers [91]. The use of multiple drones has been proposed in [176], [177]. However, more work is also needed in this area. Other camera applications in animal welfare monitoring are [178], [179].

C. LIVESTOCK BEHAVIOR TOWARDS UAVS

As discussed in the previous section, welfare concerns have generated interest in understanding the general behavior of livestock in response to the presence of UAVs. Previous works have shown that UAVs have an excellent potential for application in Livestock management [180]. However, there are concerns about the likely effects of UAVs on animal behavior, such as stress inducement [181]. Different researchers have identified the factors that elicit animals' responses to UAV activities. These include characteristics of the UAV (such as size, noise, speed, and angle of approach), the condition experience, and nature of targeted species (i.e avian or terrestrial, domesticated or wild, gender, etc.) [182], flight patterns [183].

Most of the previous studies on the effects of UAVs on animal behavior focused on wildlife [184], [185]. Nevertheless, some research attempts have concentrated on cattle [90], [115]. Therefore, it is pertinent to understand livestock behavior in response to UAV operations. Using non-invasive heart rate and movement rate measurements, it was observed that even at UAV flight height as low as 9 m above ground level, beef cattle had no negative behavioral or physiological response [29]. In this regard, [29] studied beef cattle's physiological and behavioral response to UAV flights.

This study focused on changes in the heart rate and movement rate in response to UAV operations. As with other researchers, the animals demonstrated habituation with time either to the environment or the UAV operations. This study showed no significant behavioral and physiological change in heifers responding to the grid and circular pattern flights at 9m AGL. More importantly, studies have demonstrated that low-cost sensors and UAV cameras can be used to study livestock behavior towards UAV operations [29], [186].

In general, while previous studies have investigated the links between genetics and temperament to the response of cattle to external stimulus, the influence of stimulus from UAVs has not been conclusively studied. Similarly, the possibility of using multiple UAVs in cattle health monitoring and herding has been explored [19], but its behavioral and physiological impact has not been quantified. The effects of UAV characteristics such as speed, color, approach angle on cattle behavior are also unknown. Another work [131] looked at the impact of drones, with auditory cues such as sounds of a barking dog, on sheep. Even though the initial response showed that the sheep's behavior was affected by UAVs, the animals were quick to adapt, and their heart rates did not go beyond when a herding dog was used. Also, drone maneuver, speed or height, and flock size did not significantly affect the sheep, while auditory cues improved response/alertness.

There are some preliminary results for sheep and cattle behavior. Another paper focused on the monitoring of goats [47]. However, more work is needed to understand the general response and factors that affect such responses. There is also the need to study other livestock species like camels, sheep, and goats. Future research is necessary to understand how different characteristics of flight agents (UAV) and the condition of livestock may influence response to the UAV.

D. UAV BASED SMART LIVESTOCK MANAGEMENT, MODERN COMPUTING PARADIGM AND IOT APPLICATION

Smart farming is currently receiving significant attention to solve some challenges associated with enhancing agricultural productivity. UAVs have an essential role in developing and the commercialization precision agriculture [36]. They could be employed in operations ranging from pest identification and control to asset management. Modern computing paradigms such as cloud computing, fog computing, edge computing and IoT are beginning to play a critical role in agricultural research and practices, including livestock [187]. These technologies could be explored via integration using IoT-based sensors and devices interconnected via wireless sensor networks.

Drones have been used for indoor livestock monitoring [8] and providing reliable wireless network communication for smart farming. Another recent application of drones that could benefit livestock farming is the provision of reliable and energy-efficient IoT connectivity [24], [188]. In [8], [41], drones were used to monitor and track sheep using image processing techniques. However, the application was power-hungry due to the requirement for onboard image processing algorithms. Generally, when integrated with IoT and WSN technologies, drones' role in smart farming focuses on data collection, which is significantly impacted by battery limitations. Drone path planning optimization is often adopted to optimize drone flights. This optimization typically focuses on flight time, drone speed, ''and'' flight altitude.

Cloud computing could be considered as the most advanced computing paradigm allowing for centralized computations for reduced cost, improved efficiency, scalability and reliability. However, the large amount of agricultural data which is further exasperated using drones leads to low latency, high internet bandwidth requirements, load balancing and high energy consumption, security, and privacy issues. Hence, the need for a constant high-speed network and other identified problems are bottlenecks for its widespread use of drones in livestock management. That notwithstanding, most agricultural applications of IoT use the cloud computing paradigm.

On the other hand, Fog computing allows for more distributed real-time, low-latency data processing. The Fog node serves as a bridge between the cloud and IoT sensors and devices within an IoT network. Fog computing has the advantage of more security, low latency, lower cost, and low energy usage over cloud computing. Unique characteristics of Fog computing such as low latency, real-time interaction, mobility support, improved security, efficiency, and bandwidth conservation makes it suitable for livestock and other agricultural purposes [189], [190]. Edge computing is often confused with Fog computing due to their similarity in function. However, edge computing occurs on edge devices with relatively limited computational and storage resources focusing mainly on the IoT level without support for multiple IoT applications. Also, while Fog computing collaborates with the cloud, edge computing works without the cloud. A typical architecture for smart livestock farming integrating cloud, fog and edge computing paradigms is presented in Figure 12 [187]. This architecture aims to solve the problems associated with the cloud limiting its performance for agricultural purposes. In the proposed architecture, the drone is seen to operate at the edge, and the on-board computational capabilities of the drone could be harnessed. However, the communication link between the edge and fog layers is typically implemented using ZigBee, Sigfox, LoRa and Bluetooth in the proposed architecture. The long-distance lower power communication of LoRa often makes it the preferred connectivity for IoT applications. Another edge-based architecture for improved quality of data (QoD) and latency performance, summarized in Figure 13, was proposed in [191]. Any suitable IoT connectivity technology that satisfies the requirements for a given application can be employed at the relevant layer. We adopt this architecture to propose two possible architectures for drone-based livestock management.

In the first proposed architecture shown in Figure 14, the drones will be placed at the sensing layer. This is the natural approach since drones are often equipped with sensors, and

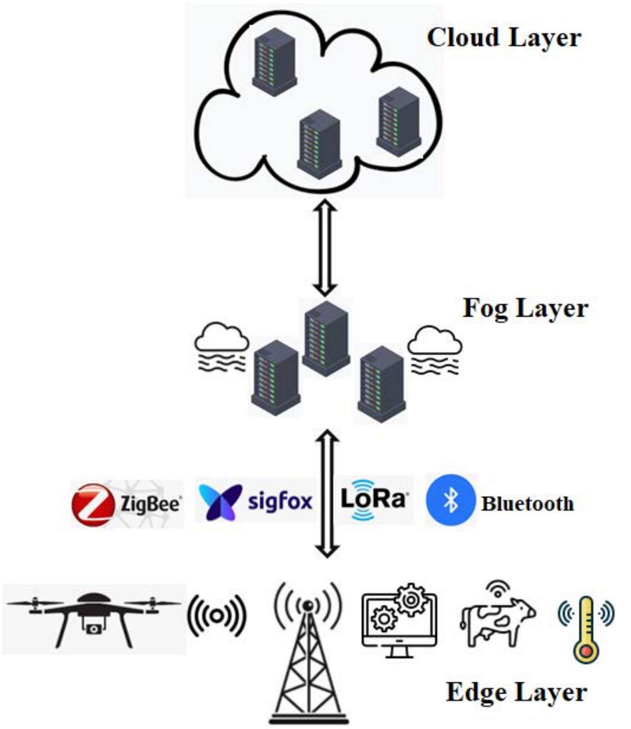

FIGURE 12. Proposed three layer architecture for smart livestock farming.

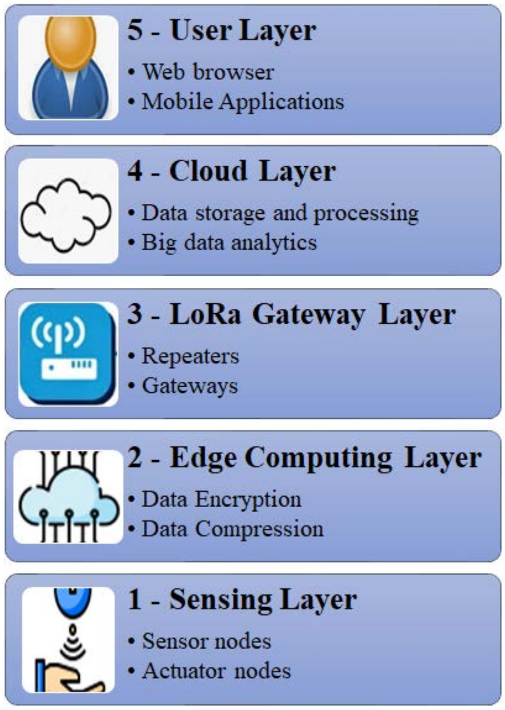

FIGURE 13. Edge based smart farming architecture.

actuators could also be integrated. The drones can coexist with other sensors and actuators at this layer, and they will send captured data to the second layer for processing and onward transmission. The drones will mainly communicate with the control center and other devices in the edge computing layer in this set-up. There will be minimum direct intercommunication between drones.

The second proposed architecture, shown in Figure 15, allows the UAV to function at the second layer. In this approach, since the UAVs have sensors onboard, the sensors will still be considered to function at the first layer. However, the UAVs will also collect data from other dispersed sensors and sensors attached to livestock for initial processing and onward transmission to upper layers. Here, the UAVs can communicate and exchange data with each other. This means that additional onboard computation and communication infrastructure may be necessary. Another problem with this approach is the power limitation of the drones. However, low power technologies such LoRa can easily be explored.

The use of IoT and WSNs has found widespread application in precision agriculture, and the same concept is extended to the application of drones. In WSNs, drones can enhance connectivity and extend wireless coverage. Drones can also be used in dynamic data collections from distributed sensor nodes, thereby reducing energy consumption, improving network coverage, and enabling efficient operation of WSNs in different environments [88]. However, the role of drones in WSNs is still limited by some technical challenges such as the availability of reliable drone-sensor node communication links, network planning, sensor placement/positioning, trajectory planning/optimization and battery limitations. One

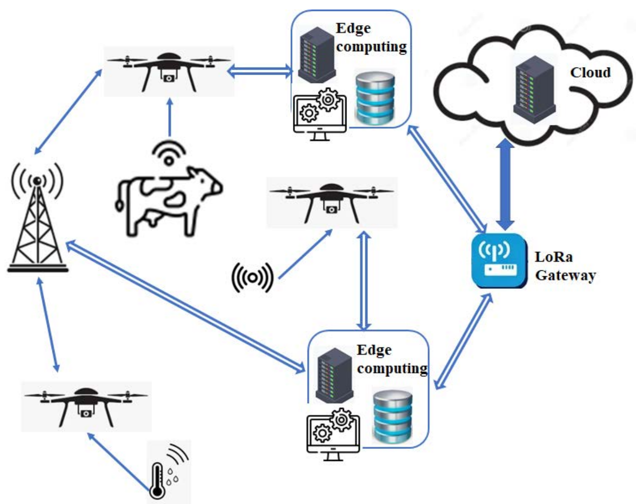

FIGURE 14. Proposed architecture with UAV function at the sensor layer.

way of tackling the highlighted challenges is by integrating IoT, LoRaWAN, and drone technologies [90].

Multi UAVs are often connected to form flying ad-hoc networks (FANET) [192], [193]. FANET is characterized by high-speed (30 to 460 km/h) and three-dimensionally-mobile nodes. UAVs' mobility and limited resources mean that FANETs have unique design and protocol requirements. Some of the challenges associated with FANET with UAV nodes and ways of addressing them are summarized in Table 8 [45]. Table 8 also gives relevant references for the respective technologies and their modifications for UAV deployment. The consolidation of these technologies and their integration could be harnessed to solve the challenges identified with

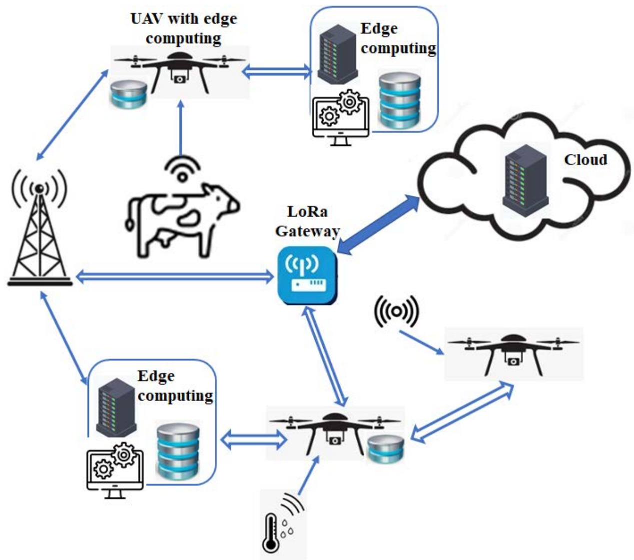

FIGURE 15. Proposed architecture with UAV functioning at the edge computing layer.

TABLE 8. Summary of challenges associated with FANET using UAV.

Brief Description of Challenge	Possible Solutions
Limited resources such as: battery and hardware (memory and computation)	Deployment of energy-aware networks low power and lossy networks (LLT) [194]–[198], [199] and other technologies such as RPL [194] and IEEE 802.15.4 [197]
Network management and hardware configuration difficulties	The use of software-defined networks (SDN) and Network function virtualization (NVF) [28], [200], [209]–[212], [201]–[208]
High node mobility leading to data loss and high network delay	The use of delay tolerant networks (DTN)[213]–[216]

FANET, which can come in handy in UAV livestock management.

Major issues that need research attention in this area include issues related to security protocols in FANET, the need for the development of new protocols in FANET [217] and the standardization of FANET bands. These developments will go a long way in improving the current performance of FANET.

Drone path planning problems could be solved online or offline depending on the nature of the operating environment. The online approach is often required for dynamic environments and requires more onboard hardware and computational power. DL and heuristics intelligent optimization methods are needed for real-time online planning. However, sensors can be pre-installed for large farms, making the environment less dynamic. Furthermore, metaheuristics can be used offline to solve the associated path planning problem. A UAV could then fly through the area of interest in an optimized way to collect data from sensors for onward transmission via a suitable gateway. Another approach will be for the drones to dynamically acquire the appropriate data using onboard sensors during the optimized flight. However, the technical challenges identified earlier in this section are equally applicable to drone-based applications.

V. CONCLUSION

UAVs are getting popular in today's world and becoming ubiquitous in many outdoor activities. Agriculture is one of such applications fields, where drones have a high potential to be used. Livestock management is an essential part of agriculture, which deals with the issue of managing cattle animals, both inside the farmhouse, or outside while grazing. The outdoor aspect of cattle farming can be eased and modernized mainly with UAVs as the farmer can readily get the birds-eye view of the whole herd, which is impossible to have with conventional methods. Therefore, lots have been talked about and researched on this issue in the recent past. This survey discusses UAV applications, opportunities, challenges, solutions to those challenges, and future research directions in livestock management. The paper has gathered all the important articles related to the topic and presented them concisely, wherever suitable. Various aspects of cattle monitoring like detection, counting the numbers, identifying the types, tracking while grazing, health issues monitoring, rounding up the cattle, behavior monitoring, estimating the herd distribution, surveilling animal's behavior, etc., are well summarized in this work. Moreover, a few broader but impactful issues like smart farming with IoT implementation, taking care of animal welfare, practicing machine learning approaches, improving inter-communication skills between drones, etc., are addressed with relevant references. The paper also highlighted the challenges in the field, the reason behind those, and the probable solution approaches.

Based on the experience of detailed literature review, some research gaps have been identified in this field, which requires intensive research to contribute more. Therefore, a list of future research directions is suggested below:

- To carry out studies on animal welfare issues while operating the UAVs around them.
- To study the benefits and challenges of ML and DL, applied to livestock farming using UAVs, to ease data processing and management, pattern recognition, real-time monitoring, etc.
- To develop DL architectures suitable for UAVs limited resources or adapt existing backbone networks.
- To develop FAIR data management processes for livestock-related operations
- To explore the automation of the process of grazing assistantship and monitoring using UAVs. Multiple layers of UAVs can be operated in such cases. The first

layer can communicate directly with the operator, and the second layer only communicates with the first.
- To investigate the synergy with other smart farming strategies under IoT and IoD concepts.
- To carry out studies to increase the run-time of the UAV by optimizing flight schedules, battery size, etc., as it will be required to operate them while grazing the animals. Here, renewable sources might be an excellent solution to this issue.
- To improve existing systems to automatically detect any abnormal behavior to safeguard the animals from any potential threat, not only the cattle identification, counting, and tracking. A possible direction is to explore artificial intelligence to train the system to recognize more patterns and situations to respond to those.
- To study the area of HDAI and develop strategies to prove existing and proposed concepts.
- To develop suitable architectures or adapt existing ones to integrate drones and other livestock resources using IoT and other modern computing paradigms such as Cloud, Fog and Edge computing.
- To address issues related to FANET such as protocols, standardization of bands
- To study and address the issues surrounding the operation of drones in different Farm environments such as the indoor operation of drones. Operation of drones at low altitudes and others discussed earlier.

Therefore, ample opportunities for contribution are present to strengthen this crucial agriculture sector. The well-summarized presentation of the research attempts and the suggestion of future research directions, done in this article, will help flourish the future world's drone revolution.

REFERENCES

[1] M. A. Mendoza, M. R. Alfonso, and S. Lhuillery, ''A battle of drones: Utilizing legitimacy strategies for the transfer and diffusion of dual-use technologies,'' *Technol. Forecasting Social Change*, vol. 166, May 2021, Art. no. 120539, doi: 10.1016/J.TECHFORE.2020.120539.

[2] X. Jiang, M. Sheng, N. Zhao, C. Xing, W. Lu, and X. Wang, ''Green UAV communications for 6G: A survey,'' *Chin. J. Aeronaut.*, May 2021, doi: 10.1016/J.CJA.2021.04.025.

[3] *The Booming Job Demand for Commercial Drone Pilots—The Atlantic*. Accessed: Nov. 13, 2021. [Online]. Available: https://www.theatlantic.com/technology/archive/2017/01/drone-pilot-school/515022/

[4] *Market Research Reports—Research and Markets—Page Gone*. Accessed: Nov. 13, 2021. [Online]. Available: https://www.researchandmarkets.com/research/nfpsbm/the_global_uav

[5] A. Carrio, J. Tordesillas, S. Vemprala, S. Saripalli, P. Campoy, and J. P. How, ''Onboard detection and localization of drones using depth maps,'' *IEEE Access*, vol. 8, pp. 30480–30490, 2020, doi: 10.1109/ACCESS.2020.2971938.

[6] B. Alzahrani, O. S. Oubbati, A. Barnawi, M. Atiquzzaman, and D. Alghazzawi, ''UAV assistance paradigm: State-of-the-art in applications and challenges,'' *J. Netw. Comput. Appl.*, vol. 166, Sep. 2020, Art. no. 102706, doi: 10.1016/J.JNCA.2020.102706.

[7] P. K. R. Maddikunta, S. Hakak, M. Alazab, S. Bhattacharya, T. R. Gadekallu, W. Z. Khan, and Q.-V. Pham, ''Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges,'' *IEEE Sensors J.*, vol. 21, no. 16, pp. 17608–17619, Aug. 2021, doi: 10.1109/JSEN.2021.3049471.

[8] N. Al-Thani, A. Albuainain, F. Alnaimi, and N. Zorba, ''Drones for sheep livestock monitoring,'' in *Proc. IEEE 20th Medit. Electrotech. Conf. (MELECON)*, Jun. 2020, pp. 672–676, doi: 10.1109/MELECON48756.2020.9140588.

[9] J. A. Goolsby, J. Jung, J. Landivar, W. McCutcheon, R. Lacewell, R. Duhaime, and A. Schwartz. (2016). *Evaluation of Unmanned Aerial Vehicles (UAVs) for detection of cattle in the Cattle Fever Tick Permanent Quarantine Zone*. [Online]. Available: http://www.subplantsci.org/wp-content/uploads/2016/05/SAE-Goolsby-et-al-2016-Galley-proofs.pdf

[10] A. Rivas, P. Chamoso, A. González-Briones, and J. M. Corchado, ''Detection of cattle using drones and convolutional neural networks,'' *Sensors*, vol. 18, no. 7, p. 2048, 2018, doi: 10.3390/s18072048.

[11] S. N. Longmore, R. P. Collins, S. Pfeifer, S. E. Fox, M. Mulero-Pázmány, F. Bezombes, A. Goodwin, M. De Juan Ovelar, J. H. Knapen, and S. A. Wich, ''Adapting astronomical source detection software to help detect animals in thermal images obtained by unmanned aerial systems,'' *Int. J. Remote Sens.*, vol. 38, nos. 8–10, pp. 2623–2638, May 2017, doi: 10.1080/01431161.2017.1280639.

[12] W. Andrew, C. Greatwood, and T. Burghardt, ''Visual localisation and individual identification of Holstein friesian cattle via deep learning,'' in *Proc. IEEE Int. Conf. Comput. Vis. Workshops (ICCVW)*, Oct. 2017, pp. 2850–2859, doi: 10.1109/ICCVW.2017.336.

[13] W. Andrew, C. Greatwood, and T. Burghardt, ''Aerial animal biometrics: Individual friesian cattle recovery and visual identification via an autonomous UAV with onboard deep inference,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Nov. 2019, pp. 237–243, doi: 10.1109/IROS40897.2019.8968555.

[14] W. Andrew, J. Gao, S. Mullan, N. Campbell, A. W. Dowsey, and T. Burghardt, ''Visual identification of individual holstein-friesian cattle via deep metric learning,'' *Comput. Electron. Agricult.*, vol. 185, Jun. 2021, Art. no. 106133, doi: 10.1016/j.compag.2021.106133.

[15] M. A. Alanezi, H. R. E. H. Bouchekara, M. S. Shahriar, Y. A. Sha'aban, M. S. Javaid, and M. Khodja, ''Motion-encoded electric charged particles optimization for moving target search using unmanned aerial vehicles,'' *Sensors*, vol. 21, no. 19, p. 6568, Sep. 2021, doi: 10.3390/s21196568.

[16] E. Pastor, J. Lopez, and P. Royo, ''UAV Payload and Mission Control Hardware/Software Architecture,'' *IEEE Aerosp. Electron. Syst. Mag.*, vol. 22, no. 6, pp. 3–8, Jun. 2007, doi: 10.1109/MAES.2007.384074.

[17] P. Webb, S. A. Mehlhorn, and P. Smartt, ''Developing protocols for using a UAV to monitor herd health,'' Tech. Rep., 2017, doi: 10.13031/aim.201700865.

[18] S. Nyamuryekung'e, A. F. Cibils, R. E. Estell, and A. L. Gonzalez, ''Use of an unmanned aerial vehicle-mounted video camera to assess feeding behavior of raramuri criollo cows,'' *Rangeland Ecol. Manage.*, vol. 69, no. 5, pp. 386–389, Sep. 2016, doi: 10.1016/j.rama.2016.04.005.

[19] S. Jung and K. B. Ariyur, ''Strategic cattle roundup using multiple quadrotor UAVs,'' *Int. J. Aeronaut. Space Sci.*, vol. 18, no. 2, pp. 315–326, Jun. 2017, doi: 10.5139/IJASS.2017.18.2.315.

[20] Y. Sun, S. Yi, F. Hou, D. Luo, J. Hu, and Z. Zhou, ''Quantifying the dynamics of livestock distribution by unmanned aerial vehicles (UAVs): A case study of yak grazing at the household scale,'' *Rangeland Ecology Manage.*, vol. 73, no. 5, pp. 642–648, Sep. 2020, doi: 10.1016/j.rama.2020.05.004.

[21] T. Zin, I. Kobayashi, P. Tin, and H. Hama, (2016). *A General Video Surveillance Framework for Animal Behavior Analysis*. Accessed: Nov. 13, 2021. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8008657/

[22] R. Umega and M. A. Raja. (2017). *Design and Implementation of Livestock Barn Monitoring System*. Accessed: Nov. 13, 2021. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8094063/

[23] M. Gharibi, R. Boutaba, and S. L. Waslander, ''Internet of Drones,'' *IEEE Access*, vol. 4, pp. 1148–1162, 2016, doi: 10.1109/ACCESS.2016.2537208.

[24] P. Boccadoro, D. Striccoli, and L. A. Grieco, ''An extensive survey on the Internet of Drones,'' *Ad Hoc Netw.*, vol. 122, Nov. 2021, Art. no. 102600, doi: 10.1016/J.ADHOC.2021.102600.

[25] M. S. Mahmud, A. Zahid, A. K. Das, M. Muzammil, and M. U. Khan, ''A systematic literature review on deep learning applications for precision cattle farming,'' *Comput. Electron. Agricult.*, vol. 187, Aug. 2021, Art. no. 106313, doi: 10.1016/j.compag.2021.106313.

[26] M. Razaak, *An Integrated Precision Farming Application Based on 5G, UAV and Deep Learning Technologies*, vol. 1089. Cham, Switzerland: Springer, 2019, doi: 10.1007/978-3-030-29930-9_11.

[27] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine learning applications for precision agriculture: A comprehensive review," *IEEE Access*, vol. 9, pp. 4843–4873, 2021, doi: 10.1109/ACCESS.2020.3048415.

[28] O. S. Oubbati, M. Atiquzzaman, T. A. Ahanger, and A. Ibrahim, "Softwarization of UAV networks: A survey of applications and future trends," *IEEE Access*, vol. 8, pp. 98073–98125, 2020, doi: 10.1109/ACCESS.2020.2994494.

[29] G. Abdulai, M. Sama, and J. Jackson, "A preliminary study of the physiological and behavioral response of beef cattle to unmanned aerial vehicles (UAVs)," *Appl. Animal Behav. Sci.*, vol. 241, Aug. 2021, Art. no. 105355, doi: 10.1016/j.applanim.2021.105355.

[30] N. M. Schroeder, A. Panebianco, R. G. Musso, and P. Carmanchahi, "An experimental approach to evaluate the potential of drones in terrestrial mammal research: A gregarious ungulate as a study model," *Roy. Soc. Open Sci.*, vol. 7, no. 1, Jan. 2020, Art. no. 191482, doi: 10.1098/rsos.191482.

[31] F. Nex and F. Remondino, "UAV for 3D mapping applications: A review," *Appl. Geomatics*, vol. 6, no. 1, pp. 1–15, Mar. 2014, doi: 10.1007/s12518-013-0120-x.

[32] C. Torresan, A. Berton, F. Carotenuto, S. F. Di Gennaro, B. Gioli, A. Matese, F. Miglietta, C. Vagnoli, A. Zaldei, and L. Wallace, "Forestry applications of UAVs in Europe: A review," *Int. J. Remote Sens.*, vol. 38, nos. 8–10, pp. 2427–2447, May 2017, doi: 10.1080/01431161.2016.1252477.

[33] J. Seo, L. Duque, and J. Wacker, "Drone-enabled bridge inspection methodology and application," *Autom. Construct.*, vol. 94, pp. 112–126, Oct. 2018, doi: 10.1016/j.autcon.2018.06.006.

[34] M. Kaamin, S. N. M. Razali, N. F. A. Ahmad, S. M. Bukari, N. Ngadiman, A. A. Kadir, and N. B. Hamid, "The application of micro UAV in construction project," in *Proc. AIP Conf.*, 2017, Art. no. 020070, doi: 10.1063/1.5005403.

[35] I. Colomina and P. Molina, "Unmanned aerial systems for photogrammetry and remote sensing: A review," *ISPRS J. Photogram. Remote Sens.*, vol. 92, pp. 79–97, Jun. 2014, doi: 10.1016/j.isprsjprs.2014.02.013.

[36] D. C. Tsouros, S. Bibi, and P. G. Sarigiannidis, "A review on UAV-based applications for precision agriculture," *Information*, vol. 10, no. 11, p. 349, Nov. 2019, doi: 10.3390/INFO10110349.

[37] T. Adão, J. Hruška, L. Pádua, J. Bessa, E. Peres, R. Morais, and J. J. Sousa, "Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry," *Remote Sens.*, vol. 9, no. 11, p. 1110, Oct. 2017, doi: 10.3390/rs9111110.

[38] H. Ren, Y. Zhao, W. Xiao, and Z. Hu, "A review of UAV monitoring in mining areas: Current status and future perspectives," *Int. J. Coal Sci. Technol.*, vol. 6, no. 3, pp. 320–333, Sep. 2019, doi: 10.1007/s40789-019-00264-5.

[39] N. Kerle, F. Nex, M. Gerke, D. Duarte, and A. Vetrivel, "UAV-based structural damage mapping: A review," *ISPRS Int. J. Geo-Inf.*, vol. 9, no. 1, p. 14, Dec. 2019, doi: 10.3390/ijgi9010014.

[40] H. Nawaz, H. M. Ali, and A. A. Laghari, "UAV communication networks issues: A review," *Arch. Comput. Methods Eng.*, vol. 28, no. 3, pp. 1349–1369, May 2021, doi: 10.1007/s11831-020-09418-0.

[41] A. B. Alhassan, X. Zhang, H. Shen, and H. Xu, "Power transmission line inspection robots: A review, trends and challenges for future research," *Int. J. Electr. Power Energy Syst.*, vol. 118, Jun. 2020, Art. no. 105862, doi: 10.1016/j.ijepes.2020.105862.

[42] M. Esposito, M. Crimaldi, V. Cirillo, F. Sarghini, and A. Maggio, "Drone and sensor technology for sustainable weed management: A review," *Chem. Biol. Technol. Agricult.*, vol. 8, no. 1, p. 18, Dec. 2021, doi: 10.1186/s40538-021-00217-8.

[43] S. Oleksyn, L. Tosetto, V. Raoult, K. E. Joyce, and J. E. Williamson, "Going batty: The challenges and opportunities of using drones to monitor the behaviour and habitat use of rays," *Drones*, vol. 5, no. 1, p. 12, Feb. 2021, doi: 10.3390/DRONES5010012.

[44] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A survey on the role of IoT in agriculture for the implementation of smart farming," *IEEE Access*, vol. 7, pp. 156237–156271, 2019, doi: 10.1109/ACCESS.2019.2949703.

[45] H. Shakhatreh, A. H. Sawalmeh, A. Al-Fuqaha, Z. Dou, E. Almaita, I. Khalil, N. S. Othman, A. Khreishah, and M. Guizani, "Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges," *IEEE Access*, vol. 7, pp. 48572–48634, 2019, doi: 10.1109/ACCESS.2019.2909530.

[46] F. Sarwar, A. Griffin, P. Periasamy, K. Portas, and J. Law, "Detecting and counting sheep with a convolutional neural network," in *Proc. 15th IEEE Int. Conf. Adv. Video Signal Based Surveill. (AVSS)*, Nov. 2018, pp. 1–6, doi: 10.1109/AVSS.2018.8639306.

[47] J.-A. Vayssade, R. Arquet, and M. Bonneau, "Automatic activity tracking of goats using drone camera," *Comput. Electron. Agricult.*, vol. 162, pp. 767–772, Jul. 2019, doi: 10.1016/J.COMPAG.2019.05.021.

[48] M. Rahnemoonfar, D. Dobbs, M. Yari, and M. J. Starek, "DisCountNet: Discriminating and counting network for real-time counting and localization of sparse objects in high-resolution UAV imagery," *Remote Sens.*, vol. 11, no. 9, p. 1128, May 2019, doi: 10.3390/rs11091128.

[49] W. Shao, R. Kawakami, R. Yoshihashi, S. You, H. Kawase, and T. Naemura, "Cattle detection and counting in UAV images based on convolutional neural networks," *Int. J. Remote Sens.*, vol. 41, no. 1, pp. 31–52, Jan. 2020, doi: 10.1080/01431161.2019.1624858.

[50] J. G. A. Barbedo, L. V. Koenigkan, T. T. Santos, and P. M. Santos, "A study on the detection of cattle in UAV images using deep learning," *Sensors*, vol. 19, no. 24, pp. 1–14, 2019, doi: 10.3390/s19245436.

[51] L. Han, P. Tao, and R. R. Martin, "Livestock detection in aerial images using a fully convolutional network," *Comput. Vis. Media*, vol. 5, no. 2, pp. 221–228, Jun. 2019, doi: 10.1007/s41095-019-0132-5.

[52] B. Xu, W. Wang, G. Falzon, P. Kwan, L. Guo, G. Chen, A. Tait, and D. Schneider, "Automated cattle counting using mask R-CNN in quadcopter vision system," *Comput. Electron. Agricult.*, vol. 171, Apr. 2020, Art. no. 105300, doi: 10.1016/J.COMPAG.2020.105300.

[53] B. Xu, W. Wang, G. Falzon, P. Kwan, L. Guo, Z. Sun, and C. Li, "Livestock classification and counting in quadcopter aerial images using mask R-CNN," *Int. J. Remote Sens.*, vol. 41, no. 21, pp. 8121–8142, Nov. 2020, doi: 10.1080/01431161.2020.1734245.

[54] J. G. A. Barbedo, L. V. Koenigkan, P. M. Santos, and A. R. B. Ribeiro, "Counting cattle in UAV images—Dealing with clustered animals and animal/background contrast changes," *Sensors*, vol. 20, no. 7, p. 2126, Apr. 2020, doi: 10.3390/s20072126.

[55] J. G. A. Barbedo, L. V. Koenigkan, and P. M. Santos, "Cattle detection using oblique UAV images," *Drones*, vol. 4, no. 4, p. 75, Dec. 2020, doi: 10.3390/drones4040075.

[56] F. Sarwar, A. Griffin, S. U. Rehman, and T. Pasang, "Detecting sheep in UAV images," *Comput. Electron. Agricult.*, vol. 187, Aug. 2021, Art. no. 106219, doi: 10.1016/j.compag.2021.106219.

[57] V. H. A. Soares, M. A. Ponti, R. A. Gonçalves, and R. J. G. B. Campello, "Cattle counting in the wild with geolocated aerial images in large pasture areas," *Comput. Electron. Agricult.*, vol. 189, Oct. 2021, Art. no. 106354, doi: 10.1016/j.compag.2021.106354.

[58] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, doi: 10.1109/CVPR.2014.81.

[59] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017, doi: 10.1109/TPAMI.2016.2577031.

[60] K. Chatfield, K. Simonyan, A. Vedaldi, and A. Zisserman, "Return of the devil in the details: Delving deep into convolutional nets," in *Proc. Brit. Mach. Vis. Conf.*, 2014, pp. 1–11, doi: 10.5244/C.28.6.

[61] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-ResNet and the impact of residual connections on learning," in *Proc. AAAI Conf. Artif. Intell.*, 2017, pp. 4278–4284, doi: 10.48550/arXiv.1602.07261.

[62] R. Girshick, "Fast R-CNN," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2015, pp. 1440–1448, doi: 10.1109/ICCV.2015.169.

[63] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention* (Lecture Notes in Computer Science), vol. 9351. Cham, Switzerland: Springer, 2015, pp. 234–241, doi: 10.1007/978-3-319-24574-4_28.

[64] K. He, G. Gkioxari, P. Dollár, and R. B. Girshick, "Mask R-CNN," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2017, pp. 2980–2988, doi: 10.1109/ICCV.2017.322.

[65] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 779–788, doi: 10.1109/CVPR.2016.91.

[66] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, ''SSD: Single shot multibox detector,'' in *Computer Vision* (Lecture Notes in Computer Science), vol. 9905. Cham, Switzerland: Springer, 2016, pp. 21–37, doi: 10.1007/978-3-319-46448-0_2.

[67] K. Simonyan and A. Zisserman, ''Very deep convolutional networks for large-scale image recognition,'' in *Proc. 3rd Int. Conf. Learn. Represent. (ICLR)*, 2015, pp. 1–14.

[68] J. Redmon and A. Farhadi, ''YOLO9000: Better, faster, stronger,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 6517–6525, doi: 10.1109/CVPR.2017.690.

[69] G. A. Miller, R. Beckwith, C. Fellbaum, D. Gross, and K. J. Miller, ''Introduction to WordNet: An on-line lexical database,'' *Int. J. Lexicography*, vol. 3, no. 4, pp. 235–244, 1990, doi: 10.1093/ijl/3.4.235.

[70] C. Wu, S. Agarwal, B. Curless, and S. M. Seitz, ''Multicore bundle adjustment,'' in *Proc. CVPR*, Jun. 2011, pp. 3057–3064, doi: 10.1109/CVPR.2011.5995552.

[71] C. Wu, ''Towards linear-time incremental structure from motion,'' in *Proc. Int. Conf. 3D Vis.*, Jun. 2013, pp. 127–134, doi: 10.1109/3DV.2013.25.

[72] Y. Furukawa, B. Curless, S. M. Seitz, and R. Szeliski, ''Towards internet-scale multi-view stereo,'' in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, Jun. 2010, pp. 1434–1441, doi: 10.1109/CVPR.2010.5539802.

[73] Y. Furukawa and J. Ponce, ''Accurate, dense, and robust multiview stereopsis,'' *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 8, pp. 1362–1376, Aug. 2010, doi: 10.1109/TPAMI.2009.161.

[74] M. Kazhdan and H. Hoppe, ''Screened Poisson surface reconstruction,'' *ACM Trans. Graph.*, vol. 32, no. 3, pp. 1–13, Jun. 2013, doi: 10.1145/2487228.2487237.

[75] H. W. Kuhn, ''The Hungarian method for the assignment problem,'' *Nav. Res. Logist. Q.*, vol. 2, nos. 1–2, pp. 83–97, Mar. 1955, doi: 10.1002/nav.3800020109.

[76] M. J. Starek, T. Davis, D. Prouty, and J. Berryhill, ''Small-scale UAS for geoinformatics applications on an island campus,'' in *Proc. Ubiquitous Positioning Indoor Navigat. Location Based Service (UPINLBS)*, Nov. 2014, pp. 120–127, doi: 10.1109/UPINLBS.2014.7033718.

[77] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, ''Speeded-up robust features (SURF),'' *Comput. Vis. Image Understand.*, vol. 110, no. 3, pp. 346–359, Jun. 2008, doi: 10.1016/j.cviu.2007.09.014.

[78] S. Leutenegger, M. Chli, and R. Y. Siegwart, ''BRISK: Binary robust invariant scalable keypoints,'' in *Proc. Int. Conf. Comput. Vis.*, Nov. 2011, pp. 2548–2555, doi: 10.1109/ICCV.2011.6126542.

[79] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and F. Li, ''ImageNet large scale visual recognition challenge,'' *Int. J. Comput. Vis.*, vol. 115, no. 3, pp. 211–252, Dec. 2015, doi: 10.1007/s11263-015-0816-y.

[80] B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le, ''Learning transferable architectures for scalable image recognition,'' in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 8697–8710, doi: 10.1109/CVPR.2018.00907.

[81] B. Zoph and Q. V. Le, ''Neural architecture search with reinforcement learning,'' Tech. Rep., 2017.

[82] F. Chollet, ''Xception: Deep learning with depthwise separable convolutions,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 1800–1807, doi: 10.1109/CVPR.2017.195.

[83] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, ''Rethinking the inception architecture for computer vision,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 2818–2826, doi: 10.1109/CVPR.2016.308.

[84] H. R. E. H. Bouchekara, ''Electric charged particles optimization and its application to the optimal design of a circular antenna array,'' *Artif. Intell. Rev.*, vol. 54, no. 3, pp. 1767–1802, Mar. 2021, doi: 10.1007/s10462-020-09890-x.

[85] X. Li and L. Xing, ''Use of unmanned aerial vehicles for livestock monitoring based on streaming K-Means clustering,'' *IFAC-PapersOnLine*, vol. 52, no. 30, pp. 324–329, 2019, doi: 10.1016/j.ifacol.2019.12.560.

[86] J. F. Araujo, P. B. Sujit, and J. B. Sousa, ''Multiple UAV area decomposition and coverage,'' in *Proc. IEEE Symp. Comput. Intell. Secur. Defense Appl. (CISDA)*, Apr. 2013, pp. 30–37, doi: 10.1109/CISDA.2013.6595424.

[87] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ''ImageNet classification with deep convolutional neural networks,'' *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[88] M. Behjati, A. B. Mohd Noh, H. A. H. Alobaidy, M. A. Zulkifley, R. Nordin, and N. F. Abdullah, ''LoRa communications as an enabler for Internet of Drones towards large-scale livestock monitoring in rural farms,'' *Sensors*, vol. 21, no. 15, p. 5044, Jul. 2021, doi: 10.3390/s21155044.

[89] M. R. Bonyadi and Z. Michalewicz, ''Particle swarm optimization for single objective continuous space problems: A review,'' *Evol. Comput.*, vol. 25, no. 1, pp. 1–54, Mar. 2017, doi: 10.1162/EVCO_r_00180.

[90] J. T. Mufford, D. J. Hill, N. J. Flood, and J. S. Church, ''Use of unmanned aerial vehicles (UAVs) and photogrammetric image analysis to quantify spatial proximity in beef cattle,'' *J. Unmanned Vehicle Syst.*, vol. 7, no. 3, pp. 194–206, Sep. 2019, doi: 10.1139/juvs-2018-0025.

[91] M. Mulero-Pázmány, J. Á. Barasona, P. Acevedo, J. Vicente, and J. J. Negro, ''Unmanned aircraft systems complement biologging in spatial ecology studies,'' *Ecol. Evol.*, vol. 5, no. 21, pp. 4808–4818, Nov. 2015, doi: 10.1002/ece3.1744.

[92] J. T. Mufford, M. W. Reudink, M. Rakobowchuk, C. N. Carlyle, and J. S. Church, ''Using unmanned aerial vehicles to record behavioral and physiological indicators of heat stress in cattle on feedlot and pasture,'' *Can. J. Animal Sci.*, vol. 102, no. 1, pp. 1–8, Mar. 2022, doi: 10.1139/cjas-2020-0125.

[93] C. A. Colin and T. Pravin, *Regression Analysis of Count Data*, 2nd ed. Cambridge, U.K.: Cambridge Univ. Press, 2013, doi: 10.1017/CBO9781139013567.

[94] S. D. Hogan, M. Kelly, B. Stark, and Y. Chen, ''Unmanned aerial systems for agriculture and natural resources,'' *California Agricult.*, vol. 71, no. 1, pp. 5–14, Feb. 2017, doi: 10.3733/ca.2017a0002.

[95] L. D. Allmon, ''Will cattle producers be willing to adopt electronic cattle monitoring systems?'' Tech. Rep., 2014.

[96] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, ''A compilation of UAV applications for precision agriculture,'' *Comput. Netw.*, vol. 172, May 2020, Art. no. 107148, doi: 10.1016/j.comnet.2020.107148.

[97] S. M. Adams, M. L. Levitan, and C. J. Friedland, ''High resolution imagery collection utilizing unmanned aerial vehicles (UAVs) for post-disaster studies,'' Tech. Rep., 2013, doi: 10.1061/9780784412626.067.

[98] K. Anderson and K. J. Gaston, ''Lightweight unmanned aerial vehicles will revolutionize spatial ecology,'' *Frontiers Ecol. Environ.*, vol. 11, no. 3, pp. 138–146, Apr. 2013, doi: 10.1890/120150.

[99] A. Pisciotta, G. Vitale, S. Scudero, R. Martorana, P. Capizzi, and A. D'Alessandro, ''A lightweight prototype of a magnetometric system for unmanned aerial vehicles,'' *Sensors*, vol. 21, no. 14, p. 4691, Jul. 2021, doi: 10.3390/s21144691.

[100] D. Lovarelli, J. Bacenetti, and M. Guarino, ''A review on dairy cattle farming: Is precision livestock farming the compromise for an environmental, economic and social sustainable production?'' *J. Cleaner Prod.*, vol. 262, Jul. 2020, Art. no. 121409, doi: 10.1016/j.jclepro.2020.121409.

[101] M. F. F. Rahman, S. Fan, Y. Zhang, and L. Chen, ''A comparative study on application of unmanned aerial vehicle systems in agriculture,'' *Agriculture*, vol. 11, no. 1, p. 22, Jan. 2021, doi: 10.3390/AGRICULTURE11010022.

[102] P. S. Alvarez-Hess, A. L. Thomson, S. B. Karunaratne, M. L. Douglas, M. M. Wright, J. W. Heard, J. L. Jacobs, E. M. Morse-McNabb, W. J. Wales, and M. J. Auldist, ''Using multispectral data from an unmanned aerial system to estimate pasture depletion during grazing,'' *Animal Feed Sci. Technol.*, vol. 275, May 2021, Art. no. 114880, doi: 10.1016/j.anifeedsci.2021.114880.

[103] T. Hollings, M. Burgman, M. van Andel, M. Gilbert, T. Robinson, and A. Robinson, ''How do you find the green sheep? A critical review of the use of remotely sensed imagery to detect and count animals,'' *Methods Ecol. Evol.*, vol. 9, no. 4, pp. 881–892, Apr. 2018, doi: 10.1111/2041-210X.12973.

[104] D. Chabot and D. M. Bird, ''Wildlife research and management methods in the 21st century: Where do unmanned aircraft fit in?'' *J. Unmanned Vehicle Syst.*, vol. 3, no. 4, pp. 137–155, Dec. 2015, doi: 10.1139/juvs-2015-0021.

[105] S. Weng, B. Guo, Y. Du, M. Wang, P. Tang, and J. Zhao, ''Feasibility of authenticating mutton geographical origin and breed via hyperspectral imaging with effective variables of multiple features,'' *Food Anal. Methods*, vol. 14, no. 4, pp. 834–844, Apr. 2021, doi: 10.1007/s12161-020-01940-y.

[106] Y. Fang, S. Du, R. Abdoola, K. Djouani, and C. Richards, ''Motion based animal detection in aerial videos,'' *Proc. Comput. Sci.*, vol. 92, pp. 13–17, Jan. 2016, doi: 10.1016/j.procs.2016.07.316.

[107] B. G. Marcot, T. J. Lorenz, P. Fischer, B. G. Weinstein, and S. Cowell, "Efficacy of automated detection of motion in wildlife monitoring videos," *Wildlife Soc. Bull.*, vol. 43, no. 4, pp. 726–736, Dec. 2019, doi: 10.1002/wsb.1016.

[108] B. Achour, M. Belkadi, I. Filali, M. Laghrouche, and M. Lahdir, "Image analysis for individual identification and feeding behaviour monitoring of dairy cows based on convolutional neural networks (CNN)," *Biosyst. Eng.*, vol. 198, pp. 31–49, Oct. 2020, doi: 10.1016/j.biosystemseng.2020.07.019.

[109] A. Rivas, P. Chamoso, A. González-Briones, and J. M. Corchado, "Detection of cattle using drones and convolutional neural networks," *Sensors*, vol. 18, no. 7, p. 2048, Jun. 2018, doi: 10.3390/s18072048.

[110] G. Jang, J. Kim, J.-K. Yu, H.-J. Kim, Y. Kim, D.-W. Kim, K.-H. Kim, C. W. Lee, and Y. S. Chung, "Review: Cost-effective unmanned aerial vehicle (UAV) platform for field plant breeding application," *Remote Sens.*, vol. 12, no. 6, p. 998, Mar. 2020, doi: 10.3390/rs12060998.

[111] J.-J. Wang, C.-X. Jiang, Z. Han, Y. Ren, R. G. Maunder, and L. Hanzo, "Taking drones to the next level: Cooperative distributed unmanned-aerial-vehicular networks for small and mini drones," *IEEE Veh. Technol. Mag.*, vol. 12, no. 3, pp. 73–82, Sep. 2017, doi: 10.1109/MVT.2016.2645481.

[112] K. R. B. Sri, P. Aneesh, K. Bhanu, and M. Natarajan, "Design analysis of solar-powered unmanned aerial vehicle," *J. Aerosp. Technol. Manage.*, vol. 8, no. 4, pp. 397–407, Oct. 2016, doi: 10.5028/jatm.v8i4.666.

[113] Z. Xu, E. Zhang, and Q. Chen, "Rotary unmanned aerial vehicles path planning in rough terrain based on multi-objective particle swarm optimization," *J. Syst. Eng. Electron.*, pp. 130–141, Jan. 2020, doi: 10.21629/JSEE.2020.01.14.

[114] J. Zhang and J. Yan, "A novel control approach for flight-stability of fixed-wing UAV formation with wind field," *IEEE Syst. J.*, vol. 15, no. 2, pp. 2098–2108, Jun. 2021, doi: 10.1109/JSYST.2020.3002809.

[115] J. G. A. Barbedo and L. V. Koenigkan, "Perspectives on the use of unmanned aerial systems to monitor cattle," *Outlook Agricult.*, vol. 47, no. 3, pp. 214–222, Sep. 2018, doi: 10.1177/0030727018781876.

[116] P. K. Freeman and R. S. Freeland, "Agricultural UAVs in the U.S.: Potential, policy, and hype," *Remote Sens. Appl., Soc. Environ.*, vol. 2, pp. 35–43, Dec. 2015, doi: 10.1016/j.rsase.2015.10.002.

[117] K. Kawamura, J. Lim, Y. Kurokawa, T. Obitsu, M. Yayota, and S. Ogura, "Monitoring spatial heterogeneity of pasture within Paddock scale using a small unmanned aerial vehicle (sUAV)," *J. Integr. Field Sci.*, vol. 14, pp. 61–66, Mar. 2017. [Online]. Available: https://tohoku.repo.nii.ac.jp/?action=repository_action_common_download&item_id=123813&item_no=1&attribute_id=18&file_no=1

[118] D. Gómez-Candón, A. De Castro, and F. Lopez-Granados, "Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat," *Precis. Agricult.*, vol. 15, no. 1, pp. 44–56, Feb. 2014, doi: 10.1007/s11119-013-9335-4.

[119] C. Burke, M. Rashman, S. Wich, A. Symons, C. Theron, and S. Longmore, "Optimizing observing strategies for monitoring animals using drone-mounted thermal infrared cameras," *Int. J. Remote Sens.*, vol. 40, no. 2, pp. 439–467, Jan. 2019, doi: 10.1080/01431161.2018.1558372.

[120] J. G. A. Barbedo, "A review on the main challenges in automatic plant disease identification based on visible range images," *Biosyst. Eng.*, vol. 144, pp. 52–60, Apr. 2016, doi: 10.1016/j.biosystemseng.2016.01.017.

[121] B. Xu, W. Wang, G. Falzon, P. Kwan, L. Guo, G. Chen, A. Tait, and D. Schneider, "Automated cattle counting using mask R-CNN in quadcopter vision system," *Comput. Electron. Agricult.*, vol. 171, Apr. 2020, Art. no. 105300, doi: 10.1016/j.compag.2020.105300.

[122] J. Linchant, J. Lisein, J. Semeki, P. Lejeune, and C. Vermeulen, "Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges," *Mammal Rev.*, vol. 45, no. 4, pp. 239–252, Oct. 2015, doi: 10.1111/mam.12046.

[123] L.-P. Chrétien, J. Théau, and P. Ménard, "Wildlife multispecies remote sensing using visible and thermal infrared imagery acquired from an unmanned aerial vehicle (UAV)," *Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.*, vol 1, pp. 241–248, Aug. 2015, doi: 10.5194/isprsarchives-XL-1-W4-241-2015.

[124] O. Guzhva, H. Ardö, A. Herlin, M. Nilsson, K. Åström, and C. Bergsten, "Feasibility study for the implementation of an automatic system for the detection of social interactions in the waiting area of automatic milking stations by using a video surveillance system," *Comput. Electron. Agricult.*, vol. 127, pp. 506–509, Sep. 2016, doi: 10.1016/j.compag.2016.07.010.

[125] G. Abdulai, M. Sama, and J. Jackson, "A preliminary study of the physiological and behavioral response of beef cattle to unmanned aerial vehicles (UAVs)," *Appl. Animal Behav. Sci.*, vol. 241, Aug. 2021, Art. no. 105355, doi: 10.1016/j.applanim.2021.105355.

[126] Y. Qiao, M. Truman, and S. Sukkarieh, "Cattle segmentation and contour extraction based on mask R-CNN for precision livestock farming," *Comput. Electron. Agricult.*, vol. 165, Oct. 2019, Art. no. 104958, doi: 10.1016/j.compag.2019.104958.

[127] A. Zakeri, M. Saberi, O. K. Hussain, and E. Chang, "An early detection system for proactive management of raw milk quality: An Australian case study," *IEEE Access*, vol. 6, pp. 64333–64349, 2018, doi: 10.1109/ACCESS.2018.2877970.

[128] J. J. Valletta, C. Torney, M. Kings, A. Thornton, and J. Madden, "Applications of machine learning in animal behaviour studies," *Animal Behaviour*, vol. 124, pp. 203–220, Feb. 2017, doi: 10.1016/J.ANBEHAV.2016.12.005.

[129] A. Jukan, X. Masip-Bruin, and N. Amla, "Smart computing and sensing technologies for animal welfare: A systematic review," *ACM Comput. Surv.*, vol. 50, no. 1, pp. 1–27, Jan. 2018, doi: 10.1145/3041960.

[130] A. Herlin, E. Brunberg, J. Hultgren, N. Högberg, A. Rydberg, and A. Skarin, "Animal welfare implications of digital tools for monitoring and management of cattle and sheep on pasture," *Animals*, vol. 11, no. 3, p. 829, Mar. 2021, doi: 10.3390/ani11030829.

[131] K. J. Yaxley, K. F. Joiner, and H. Abbass, "Drone approach parameters leading to lower stress sheep flocking and movement: Sky shepherding," *Sci. Rep.*, vol. 11, no. 1, pp. 1–9, Dec. 2021, doi: 10.1038/s41598-021-87453-y.

[132] M. S. Mahmud, A. Zahid, A. K. Das, M. Muzammil, and M. U. Khan, "A systematic literature review on deep learning applications for precision cattle farming," *Comput. Electron. Agricult.*, vol. 187, Aug. 2021, Art. no. 106313, doi: 10.1016/J.COMPAG.2021.106313.

[133] E. T. Psota, E. K. Luc, G. M. Pighetti, L. G. Schneider, R. T. Trout Fryxell, J. W. Keele, and L. A. Kuehn, "Development and validation of a neural network for the automated detection of horn flies on cattle," *Comput. Electron. Agricult.*, vol. 180, Jan. 2021, Art. no. 105927, doi: 10.1016/J.COMPAG.2020.105927.

[134] Y.-C. Tsai, J.-T. Hsu, S.-T. Ding, D. J. A. Rustia, and T.-T. Lin, "Assessment of dairy cow heat stress by monitoring drinking behaviour using an embedded imaging system," *Biosyst. Eng.*, vol. 199, pp. 97–108, Nov. 2020, doi: 10.1016/J.BIOSYSTEMSENG.2020.03.013.

[135] J. G. A. Barbedo, L. V. Koenigkan, and P. M. Santos, "Cattle detection using oblique UAV images," *Drones*, vol. 4, no. 4, p. 75, Dec. 2020, doi: 10.3390/DRONES4040075.

[136] J. G. A. Barbedo, L. V. Koenigkan, P. M. Santos, and A. R. B. Ribeiro, "Counting cattle in UAV images—Dealing with clustered animals and animal/background contrast changes," *Sensors*, vol. 20, no. 7, p. 2126, Apr. 2020, doi: 10.3390/S20072126.

[137] M. Bacco, A. Berton, E. Ferro, C. Gennaro, A. Gotta, S. Matteoli, F. Paonessa, M. Ruggeri, G. Virone, and A. Zanella, "Smart farming: Opportunities, challenges and technology enablers," in *Proc. IoT Vert. Top. Summit Agric. Tuscany, IoT Tuscany*, Jun. 2018, pp. 1–6, doi: 10.1109/IoT-TUSCANY.2018.8373043.

[138] J. G. A. Barbedo, L. V. Koenigkan, T. T. Santos, and P. M. Santos, "A study on the detection of cattle in UAV images using deep learning," *Sensors*, vol. 19, no. 24, p. 5436, Dec. 2019, doi: 10.3390/S19245436.

[139] D. Cazzato, C. Cimarelli, J. L. Sanchez-Lopez, H. Voos, and M. Leo, "A survey of computer vision methods for 2D object detection from unmanned aerial vehicles," *J. Imag.*, vol. 6, no. 8, p. 78, Aug. 2020, doi: 10.3390/JIMAGING6080078.

[140] F. De Smedt, D. Hulens, and T. Goedeme, "On-board real-time tracking of pedestrians on a UAV," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2015, pp. 1–8, doi: 10.1109/CVPRW.2015.7301359.

[141] C. Cifuentes-García, D. González-Medina, and I. García-Varea, "People detection and tracking using an on-board drone camera," in *Advances in Intelligent Systems and Computing*. Cham, Switzerland: Springer, 2020, pp. 668–680, doi: 10.1007/978-3-030-36150-1_55.

[142] N. Smolyanskiy, A. Kamenev, J. Smith, and S. Birchfield, "Toward low-flying autonomous MAV trail navigation using deep neural networks for environmental awareness," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Sep. 2017, pp. 4241–4247, doi: 10.1109/IROS.2017.8206285.

[143] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[144] A. Zamansky, D. van der Linden, and S. Baskin, "Teaching animal-computer interaction," in *Proc. 4th Int. Conf. Animal-Comput. Interact.*, Nov. 2017, pp. 1–7, doi: 10.1145/3152130.3152136.

[145] M. Foster, T. Agcayazi, T. Agcayazi, T. Wu, M. Gruen, D. L. Roberts, and A. Bozkurt, "Preliminary evaluation of dog-drone technological interfaces," in *Proc. 6th Int. Conf. Animal-Comput. Interact.*, Nov. 2019, pp. 1–5, doi: 10.1145/3371049.3371065.

[146] A. Zamansky, "Dog-drone interactions," in *Proc. 3rd Int. Conf. Animal-Comput. Interact.*, Nov. 2016, pp. 1–4, doi: 10.1145/2995257.3012021.

[147] Y. Li, M. Scanavino, E. Capello, F. Dabbene, G. Guglieri, and A. Vilardi, "A novel distributed architecture for UAV indoor navigation," *Transp. Res. Proc.*, vol. 35, pp. 13–22, Jan. 2018, doi: 10.1016/j.trpro.2018.12.003.

[148] T. Mori and S. Scherer, "First results in detecting and avoiding frontal obstacles from a monocular camera for micro unmanned aerial vehicles," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2013, pp. 1750–1757, doi: 10.1109/ICRA.2013.6630807.

[149] H. Hamledari, B. Mccabe, and S. Davari, "Automated computer vision-based detection of components of under-construction indoor partitions," *Autom. Construct.*, vol. 74, pp. 78–94, Feb. 2017, doi: 10.1016/j.autcon.2016.11.009.

[150] A. Loquercio, E. Kaufmann, R. Ranftl, A. Dosovitskiy, V. Koltun, and D. Scaramuzza, "Deep drone racing: From simulation to reality with domain randomization," *IEEE Trans. Robot.*, vol. 36, no. 1, pp. 1–14, Feb. 2020, doi: 10.1109/TRO.2019.2942989.

[151] P. Zhu, L. Wen, X. Bian, H. Ling, and Q. Hu, "Vision meets drones: A challenge," 2018, *arXiv:1804.07437*.

[152] J. Zhou, C.-M. Vong, Q. Liu, and Z. Wang, "Scale adaptive image cropping for UAV object detection," *Neurocomputing*, vol. 366, pp. 305–313, Nov. 2019, doi: 10.1016/j.neucom.2019.07.073.

[153] P. Mittal, R. Singh, and A. Sharma, "Deep learning-based object detection in low-altitude UAV datasets: A survey," *Image Vis. Comput.*, vol. 104, Dec. 2020, Art. no. 104046, doi: 10.1016/J.IMAVIS.2020.104046.

[154] D. van der Merwe, D. R. Burchfield, T. D. Witt, K. P. Price, and A. Sharda, "Drones in agriculture," 2020, pp. 1–30, doi: 10.1016/bs.agron.2020.03.001.

[155] J. Wyngaard, L. Barbieri, A. Thomer, J. Adams, D. Sullivan, C. Crosby, C. Parr, J. Klump, S. Raj Shrestha, and T. Bell, "Emergent challenges for science sUAS data management: Fairness through community engagement and best practices development," *Remote Sens.*, vol. 11, no. 15, p. 1797, Jul. 2019, doi: 10.3390/RS11151797.

[156] M. D. Wilkinson *et al.*, "The FAIR guiding principles for scientific data management and stewardship," *Sci. Data*, vol. 3, no. 1, Dec. 2016, Art. no. 160018, doi: 10.1038/sdata.2016.18.

[157] P. Michel and R. El Kaliouby, "Real time facial expression recognition in video using support vector machines," in *Proc. 5th Int. Conf. Multimodal Interfaces (ICMI)*, 2003, p. 258, doi: 10.1145/958468.958479.

[158] M. S. Bin, O. O. Khalifa, and R. A. Saeed, "Real-time personalized stress detection from physiological signals," in *Proc. Int. Conf. Comput., Control, Netw., Electron. Embedded Syst. Eng. (ICCNEEE)*, Sep. 2015, pp. 28–29.

[159] M. Shami and W. Verhelst, "An evaluation of the robustness of existing supervised machine learning approaches to the classification of emotions in speech," *Speech Commun.*, vol. 49, no. 3, pp. 201–212, Mar. 2007, doi: 10.1016/j.specom.2007.01.006.

[160] G. Castellano, S. D. Villalba, and A. Camurri, "Recognising human emotions from body movement and gesture dynamics," in *Affective Computing and Intelligent Interaction*. Berlin, Germany: Springer, 2007, pp. 71–82, doi: 10.1007/978-3-540-74889-2_7.

[161] M. Machado and I. J. O. Silva, "Does farm animals experience emotions and feelings?" *J. Animal Behav. Biometeorol.*, vol. 7, no. 4, pp. 170–175, 2019, doi: 10.31893/2318-1265jabb.v7n4p170-175.

[162] J. Krause, A. D. M. Wilson, and D. P. Croft, "New technology facilitates the study of social networks," *Trends Ecol. Evol.*, vol. 26, no. 1, pp. 5–6, Jan. 2011, doi: 10.1016/j.tree.2010.10.004.

[163] R. Arablouei, L. Wang, L. Currie, F. A. P. Alvarenga, and G. J. Bishop-Hurley, "Animal behavior classification via deep learning on embedded systems," 2021, *arXiv:2111.12295*.

[164] P. Balasso, G. Marchesini, N. Ughelini, L. Serva, and I. Andrighetto, "Machine learning to detect posture and behavior in dairy cows: Information from an accelerometer on the animal's left flank," *Animals*, vol. 11, no. 10, p. 2972, Oct. 2021, doi: 10.3390/ani11102972.

[165] R. García, J. Aguilar, M. Toro, A. Pinto, and P. Rodríguez, "A systematic literature review on the use of machine learning in precision livestock farming," *Comput. Electron. Agricult.*, vol. 179, Dec. 2020, Art. no. 105826, doi: 10.1016/j.compag.2020.105826.

[166] J. A. Vázquez-Diosdado, V. Paul, K. A. Ellis, D. Coates, R. Loomba, and J. Kaler, "A combined offline and online algorithm for real-time and long-term classification of sheep behaviour: Novel approach for precision livestock farming," *Sensors*, vol. 19, no. 14, p. 3201, Jul. 2019, doi: 10.3390/s19143201.

[167] H. Suparwito, K. W. Wong, H. Xie, S. Rai, and D. Thomas, "A hierarchical classification method used to classify livestock behaviour from sensor data," Tech. Rep., 2019, pp. 204–215, doi: 10.1007/978-3-030-33709-4_18.

[168] E. S. Fogarty, D. L. Swain, G. M. Cronin, L. E. Moraes, and M. Trotter, "Behaviour classification of extensively grazed sheep using machine learning," *Comput. Electron. Agricult.*, vol. 169, Feb. 2020, Art. no. 105175, doi: 10.1016/j.compag.2019.105175.

[169] M. Pollak, A. Salfinger, and K. A. Hummel, "Teaching drones on the fly: Can emotional feedback serve as learning signal for training artificial agents?" 2022, *arXiv:2202.09634*.

[170] D. Lovarelli, J. Bacenetti, and M. Guarino, "A review on dairy cattle farming: Is precision livestock farming the compromise for an environmental, economic and social sustainable production?" *J. Cleaner Prod.*, vol. 262, Jul. 2020, Art. no. 121409, doi: 10.1016/j.jclepro.2020.121409.

[171] C. J. Rutten, A. G. J. Velthuis, W. Steeneveld, and H. Hogeveen, "Invited review: Sensors to support health management on dairy farms," *J. Dairy Sci.*, vol. 96, no. 4, pp. 1928–1952, Apr. 2013, doi: 10.3168/jds.2012-6107.

[172] A. Helwatkar, D. Riordan, and J. Walsh, "Sensor technology for animal health monitoring," *Int. J. Smart Sens. Intell. Syst.*, vol. 7, no. 5, pp. 1–6, Jan. 2014, doi: 10.21307/IJSSIS-2019-057.

[173] T. Taketomi, H. Uchiyama, and S. Ikeda, "Visual SLAM algorithms: A survey from 2010 to 2016," *IPSJ Trans. Comput. Vis. Appl.*, vol. 9, no. 1, p. 16, Dec. 2017, doi: 10.1186/s41074-017-0027-2.

[174] F. Shu, P. Lesur, Y. Xie, A. Pagani, and D. Stricker, "SLAM in the field: An evaluation of monocular mapping and localization on challenging dynamic agricultural environment," in *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, Jan. 2021, pp. 1760–1770, doi: 10.1109/WACV48630.2021.00180.

[175] S. Krul, C. Pantos, M. Frangulea, and J. Valente, "Visual SLAM for indoor livestock and farming using a small drone with a monocular camera: A feasibility study," *Drones*, vol. 5, no. 2, p. 41, May 2021, doi: 10.3390/drones5020041.

[176] T. Elmokadem and A. V. Savkin, "Computationally-efficient distributed algorithms of navigation of teams of autonomous UAVs for 3D coverage and flocking," *Drones*, vol. 5, no. 4, p. 124, Oct. 2021, doi: 10.3390/drones5040124.

[177] C. Ju and H. Son, "Multiple UAV systems for agricultural applications: Control, implementation, and evaluation," *Electronics*, vol. 7, no. 9, p. 162, Aug. 2018, doi: 10.3390/electronics7090162.

[178] K. Ren, J. Karlsson, M. Liuska, M. Hartikainen, I. Hansen, and G. H. Jørgensen, "A sensor-fusion-system for tracking sheep location and behaviour," *Int. J. Distrib. Sensor Netw.*, vol. 16, no. 5, May 2020, Art. no. 155014772092177, doi: 10.1177/1550147720921776.

[179] S. M. C. Porto, C. Arcidiacono, A. Giummarra, U. Anguzza, and G. Cascone, "Localisation and identification performances of a real-time location system based on ultra wide band technology for monitoring and tracking dairy cow behaviour in a semi-open free-stall barn," *Comput. Electron. Agricult.*, vol. 108, pp. 221–229, Oct. 2014, doi: 10.1016/j.compag.2014.08.001.

[180] H. Brady, "Watch a drone 'herd' cattle across open fields," Nationalgeographic, Nat. Geography, Tech. Rep., 2017.

[181] M. A. Ditmer, J. B. Vincent, L. K. Werden, J. C. Tanner, T. G. Laske, P. A. Iaizzo, D. L. Garshelis, and J. R. Fieberg, "Bears show a physiological but limited behavioral response to unmanned aerial vehicles," *Current Biol.*, vol. 25, no. 17, pp. 2278–2283, Aug. 2015, doi: 10.1016/j.cub.2015.07.024.

[182] C. E. Smith, S. T. Sykora-Bodie, B. Bloodworth, S. M. Pack, T. R. Spradlin, and N. R. LeBoeuf, ''Assessment of known impacts of unmanned aerial systems (UAS) on marine mammals: Data gaps and recommendations for researchers in the united states,'' *J. Unmanned Vehicle Syst.*, vol. 4, no. 1, pp. 31–44, Mar. 2016, doi: 10.1139/juvs-2015-0017.

[183] M. Mulero-Pázmány, S. Jenni-Eiermann, N. Strebel, T. Sattler, J. J. Negro, and Z. Tablado, ''Unmanned aircraft systems as a new source of disturbance for wildlife: A systematic review,'' *PLoS ONE*, vol. 12, no. 6, Jun. 2017, Art. no. e0178448, doi: 10.1371/journal.pone.0178448.

[184] F. Christiansen, L. Rojano-Doñate, P. T. Madsen, and L. Bejder, ''Noise levels of multi-rotor unmanned aerial vehicles with implications for potential underwater impacts on marine mammals,'' *Frontiers Mar. Sci.*, vol. 3, Dec. 2016, doi: 10.3389/fmars.2016.00277.

[185] D. J. Krause, J. T. Hinke, W. L. Perryman, M. E. Goebel, and D. J. LeRoi, ''An accurate and adaptable photogrammetric approach for estimating the mass and body condition of pinnipeds using an unmanned aerial system,'' *PLoS ONE*, vol. 12, no. 11, Nov. 2017, Art. no. e0187465, doi: 10.1371/journal.pone.0187465.

[186] G. Abdulai, ''The response of beef cattle to disturbances from unmanned aerial vehicles (UAVs),'' Univ. Kentucky, Lexington, Kentucky, Tech. Rep. 87, 2022, doi: 10.13023/etd.2022.013.

[187] Y. Kalyani and R. Collier, ''A systematic survey on the role of cloud, fog, and edge computing combination in smart agriculture,'' *Sensors*, vol. 21, no. 17, p. 5922, Sep. 2021, doi: 10.3390/s21175922.

[188] S. Zaidi, M. Atiquzzaman, and C. T. Calafate, ''Internet of flying things (IoFT): A survey,'' *Comput. Commun.*, vol. 165, pp. 53–74, Jan. 2021, doi: 10.1016/J.COMCOM.2020.10.023.

[189] M. R. Anawar, S. Wang, M. Azam Zia, A. K. Jadoon, U. Akram, and S. Raza, ''Fog computing: An overview of big IoT data analytics,'' *Wirel. Commun. Mob. Comput.*, vol. 2018, May 2018, Art. no. 7157192, doi: 10.1155/2018/7157192.

[190] A. Ometov, O. L. Molua, M. Komarov, and J. Nurmi, ''A survey of security in cloud, edge, and fog computing,'' *Sensors*, vol. 22, no. 3, p. 927, Jan. 2022, doi: 10.3390/s22030927.

[191] S. R. Gopal and V. S. V. Prabhakar, ''Intelligent edge based smart farming with Lora and IoT,'' *Int. J. Syst. Assurance Eng. Manage.*, Jan. 2022, pp. 1–7, doi: 10.1007/s13198-021-01576-z.

[192] G. A. Kakamoukas, P. G. Sarigiannidis, and A. A. Economides, ''FANETs in agriculture—A routing protocol survey,'' *Internet Things*, vol. 2020, Mar. 2020, Art. no. 100183, doi: 10.1016/j.iot.2020.100183.

[193] A. Chriki, H. Touati, H. Snoussi, and F. Kamoun, ''FANET: Communication, mobility models and security issues,'' *Comput. Netw.*, vol. 163, Nov. 2019, Art. no. 106877, doi: 10.1016/j.comnet.2019.106877.

[194] T. Winter, P. Thubert, A. Brandt, J. Hui, R. Kelsey, P. Levis, K. Pister, R. Struik, J.-P. Vasseur, and R. Alexander, ''RPL: IPv6 routing protocol for low-power and lossy networks,'' Tech. Rep., 2012.

[195] W. Zafar and B. M. Khan, ''A reliable, delay bounded and less complex communication protocol for multicluster FANETs,'' *Digit. Commun. Netw.*, vol. 3, no. 1, pp. 30–38, Feb. 2017, doi: 10.1016/j.dcan.2016.06.001.

[196] L. Atzori, A. Iera, and G. Morabito, ''The Internet of Things: A survey,'' *Comput. Netw.*, vol. 54, no. 15, pp. 2787–2805, Oct. 2010, doi: 10.1016/j.comnet.2010.05.010.

[197] M. C. Domingo, ''An overview of the Internet of Things for people with disabilities,'' *J. Netw. Comput. Appl.*, vol. 35, no. 2, pp. 584–596, Mar. 2012, doi: 10.1016/j.jnca.2011.10.015.

[198] Y. Zeng, R. Zhang, and T. J. Lim, ''Wireless communications with unmanned aerial vehicles: Opportunities and challenges,'' *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 36–42, May 2016, doi: 10.1109/MCOM.2016.7470933.

[199] J. Zhang, G. Chuai, and W. Gao, ''Energy-efficient optimization for energy-harvesting-enabled mmWave-UAV heterogeneous networks,'' *Entropy*, vol. 24, no. 2, p. 300, Feb. 2022, doi: 10.3390/e24020300.

[200] K. Kaur, V. Mangat, and K. Kumar, ''An eagle's eye view of software defined network function virtualisation,'' *Int. J. Internet Technol. Secured Trans.*, vol. 12, no. 2, p. 161, 2022, doi: 10.1504/IJITST.2022.121421.

[201] B. Han, V. Gopalakrishnan, L. Ji, and S. Lee, ''Network function virtualization: Challenges and opportunities for innovations,'' *IEEE Commun. Mag.*, vol. 53, no. 2, pp. 90–97, Feb. 2015, doi: 10.1109/MCOM.2015.7045396.

[202] R. Jain and S. Paul, ''Network virtualization and software defined networking for cloud computing: A survey,'' *IEEE Commun. Mag.*, vol. 51, no. 11, pp. 24–31, Nov. 2013, doi: 10.1109/MCOM.2013.6658648.

[203] S. Khorsandroo, A. G. Sánchez, A. S. Tosun, J. Arco, and R. Doriguzzi-Corin, ''Hybrid SDN evolution: A comprehensive survey of the state-of-the-art,'' *Comput. Netw.*, vol. 192, Jun. 2021, Art. no. 107981, doi: 10.1016/j.comnet.2021.107981.

[204] M. Alharthi, A.-E.-M. Taha, and H. S. Hassanein, ''Evaluating softwarization gains in drone networks,'' in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2021, pp. 1–6, doi: 10.1109/GLOBECOM46510.2021.9685722.

[205] C. Rametta and G. Schembra, ''Designing a softwarized network deployed on a fleet of drones for rural zone monitoring,'' *Future Internet*, vol. 9, no. 1, p. 8, Mar. 2017, doi: 10.3390/fi9010008.

[206] F. Al-Turjman, M. Abujubbeh, A. Malekloo, and L. Mostarda, ''UAVs assessment in software-defined IoT networks: An overview,'' *Comput. Commun.*, vol. 150, pp. 519–536, Jan. 2020, doi: 10.1016/j.comcom.2019.12.004.

[207] V. Sanchez-Aguero, L. F. Gonzalez, F. Valera, I. Vidal, and R. A. L. da Silva, ''Cellular and virtualization technologies for UAVs: An experimental perspective,'' *Sensors*, vol. 21, no. 9, p. 3093, Apr. 2021, doi: 10.3390/s21093093.

[208] N. Zhang, S. Zhang, P. Yang, O. Alhussein, W. Zhuang, and X. Shen, ''Software defined space-air-ground integrated vehicular networks: Challenges and solutions,'' *IEEE Commun. Mag.*, vol. 55, no. 7, pp. 101–109, Jul. 2017, doi: 10.1109/MCOM.2017.1601156.

[209] N. M. Yungaicela-Naula, C. Vargas-Rosales, J. A. Pérez-Díaz, and M. Zareei, ''Towards security automation in software defined networks,'' *Comput. Commun.*, vol. 183, pp. 64–82, Feb. 2022, doi: 10.1016/j.comcom.2021.11.014.

[210] N. Aljeri and A. Boukerche, ''An efficient heuristic switch migration scheme for software-defined vehicular networks,'' *J. Parallel Distrib. Comput.*, vol. 164, pp. 96–105, Jun. 2022, doi: 10.1016/j.jpdc.2022.01.011.

[211] N. McKeown, T. Anderson, H. Balakrishnan, G. Parulkar, L. Peterson, J. Rexford, S. Shenker, and J. Turner, ''OpenFlow,'' *ACM SIGCOMM Comput. Commun. Rev.*, vol. 38, no. 2, pp. 69–74, Mar. 2008, doi: 10.1145/1355734.1355746.

[212] L. Gupta, R. Jain, and G. Vaszkun, ''Survey of important issues in UAV communication networks,'' *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1123–1152, Nov. 2016, doi: 10.1109/COMST.2015.2495297.

[213] M. Le, J. Park, and M. Gerla, ''UAV assisted disruption tolerant routing,'' in *Proc. MILCOM*, 2006, Oct. 2006, pp. 1–5, doi: 10.1109/MILCOM.2006.302310.

[214] S. Burleigh, A. Hooke, L. Torgerson, K. Fall, V. Cerf, B. Durst, K. Scott, and H. Weiss, ''Delay-tolerant networking: An approach to interplanetary Internet,'' *IEEE Commun. Mag.*, vol. 41, no. 6, pp. 128–136, Jun. 2003, doi: 10.1109/MCOM.2003.1204759.

[215] J. Loo, J. L. Mauri, and J. H. Ortiz, *Mobile Ad Hoc Networks*. Boca Raton, FL, USA: CRC Press, 2016, doi: 10.1201/b11447.

[216] A. M. Deaconu, R. Udroiu, and C.-Ş. Nanau, ''Algorithms for delivery of data by drones in an isolated area divided into squares,'' *Sensors*, vol. 21, no. 16, p. 5472, Aug. 2021, doi: 10.3390/s21165472.

[217] B. O. Sadiq, A. E. Adedokun, M. B. Mu'azu, and Y. A. Sha'aban, ''A specific routing protocol for flying adhoc network,'' *Telecommun. Comput. Electron. Control*, vol. 16, no. 2, p. 606, Apr. 2018, doi: 10.12928/telkomnika.v16i2.8444.

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