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Short Communication

A Remote Surveillance System for the Detection of Farmland Invasion by Cattle in Sub-Saharan African Country

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ABSTRACT

Farmer-herder conflict in Nigeria mainly involves disputes over land between agrarian communities and nomadic Fulani herdsmen resulting to loss of farmlands and crops, which consequently affects the nation's economy. Engagement of local security operatives in stopping this menace of the herders have proved abortive. Hence, this work proposes a farmland surveillance-alert system using unmanned aerial vehicles for the detection of cattle presence on farmlands as a solution to curbing the problem of farm invasion and destruction. The technique modifies CNN-YOLOV2 architecture, the outcome was accessed with DJI phantom 4 captured 656 images for the detection of cattle invasion. The system on detecting cattle presence above a threshold level sends SMS to farmer’s designated number. The system achieved an average confidence score of 0.92 for the test dataset and 0.72 on real-life data. Hence, it can be employed to mitigate incessant farm invasion and destruction problem and in other surveillance systems.

Keywords: convolutional neural network, unmanned aerial vehicles, surveillance, mean average confidence score, yolov2, short messaging service

1. INTRODUCTION

Technological innovations have impacted significantly on all sectors of economy of which agriculture is very notable. One example of these is the use of Unmanned Aerial Vehicle (UAV) for agricultural purposes ranging from application of herbicides and pesticides to general farmland surveillance against all forms of prejudice to crop plants. Farmland invasion by cattle is a great concern to agrarian communities in developing countries, Nigeria in particular, where open grazing and nomadic cattle rearing are not yet outlawed. This in many cases has often led to conflicts between farmers and herder resulting into loss of lives and properties.

Nigeria as a case study, conflicts between farmers and herders is perceived as a problem of access to grazing land for cattle from the herder's point of view. Whereas, from the farmer's point of view, it is a problem of farmers not being able to prevent arable crop farmland against cattle invasion proactively. Physical monitoring of a large area of farmland tends to be a tedious work for farmers, it is associated with high degree of risk and can be very time consuming and costly. Aerial photos obtained by unmanned aerial vehicle (UAV) show special potential for wildlife monitoring over broad and difficult-to-reach areas on the ground.

Therefore, remote monitoring of farmland against livestock invasion using computer vision technique and short messaging service (SMS) to minimize risk and cost for farmers is proposed in this work. High resolution spatial images of farmland captured by UAV were preprocessed and used as the image dataset split into train and test dataset. A trained model for cattle detection and localization was developed by feeding part of the image dataset to a modified pretrained You-Only-Look-Once Version2 (YOLOV2) deep learning framework. The trained model was tested with test images drawn from the dataset and performance was validated using several cattle grazing images sourced from the internet using Mean Average Confidence Score (MACS) metric.

Real time images captured by the UAV during each scheduled flight were analyzed for possible presence of cattle on the farmland. A threshold is set that triggers an alert system when the number of cattle detected equals or exceeds the set threshold. The alert system was designed to integrate with a database of farmers phone number in the area to be surveyed and send bulk SMS to the farmers and security operatives to warn against the invasion.

2. LITERATURE REVIEW

Unmanned aerial vehicles (UAVs) are remotely controlled flying robots that outperform conventional remote sensing technologies with the use of low power to achieve easy data collection, high spatial resolution image capture and less risk. The benefits listed above makes UAV an excellent choice in task such as mapping, surveillance and precision agriculture (Chika and Olasupo, 2019).

Several works have identified some specific application of UAV in agriculture, some of which are presented here. It has been reported that the use of UAV for crop planting has made it possible for farmers to cover larger farmland area in short time with high accuracy. A decrease of planting cost by 85% has also been reported (Chika Yinka-Banjo *et al.*, 2019). Ahirwar, et al reported that the use of UAV has eased the task of crop spraying for farmers resulting in improved spraying accuracy and optimization of resources. The authors also reported the use of UAV for farm irrigation.

The major challenge farmers encounter in monitoring large farmland against invasion is low efficient real time monitoring device with access to real time information (Ahirwar et al.,2019). UAV with thermal sensor has been used to capture and detect cattle images on the farmland, this is done by getting the position of cattle on a spot at a particular temperature that brought about the emission of electromagnetic wave with light intensity emitted by the object at a given distance (Alberto Rivas et. Al, 2018.). The images captured are analysed and processed using a suitable model developed.

In order to make Agricultural information available to farmers in rural areas. Tegegnie A.K. et. Al, 2019 developed an SMS based system where rural farmers can get agricultural knowledge service. The system helps farmers to access agricultural information and delivers such to the users via mobile phones. Their work solves the problem of inappropriate agricultural information where internet access is limited or unavailable.

Le Cun et. al., 1998 laid down the essential foundations of the capability of CNNs in the process of image recognition but an alternative to the CNN network has been introduced in image recognition process. YOLOV (You Only Look Once) is a newly develop technological base system for image processing. It is a state-of-the-art real-time detector that can detect thousands of different object images (Joseph Redmon et. al. 2017). The outline of YOLOv2 network is shown in Fig. 1. It comprises of the input stage, convolution layer, pooling layer for the purpose of feature abstraction and the output stage where bounding box is placed on the detected image.

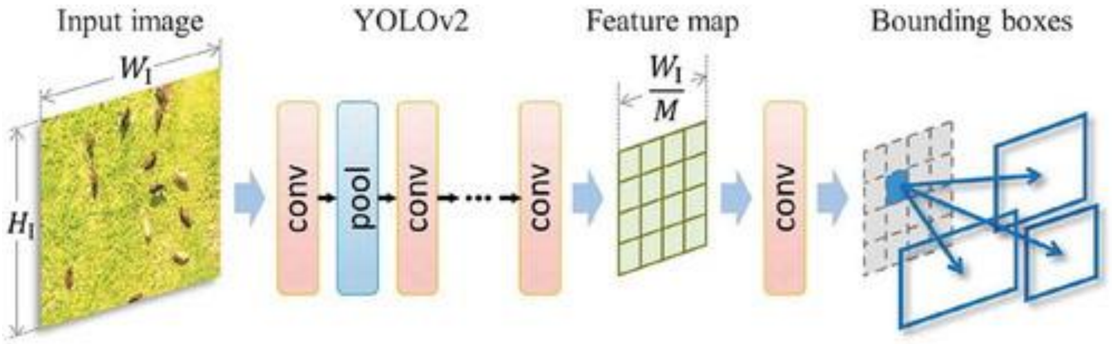

Fig. 1. YOLOv2 network Outline (Redmon et. Al. 2017).

If the network down samples a picture by M, we adjust the original training image ahead of time to make the target object size equal to $M \times M$, as shown in Fig 2. When the target size in a $WO \times HO$ original training image is $WC \times HC$, the ideal input resolution $Wi \times Hi$ can be computed as:

$$W_I = \frac{W_O M}{W_c} \quad 1$$

$$H_I = \frac{H_O M}{H_c} \quad 2$$

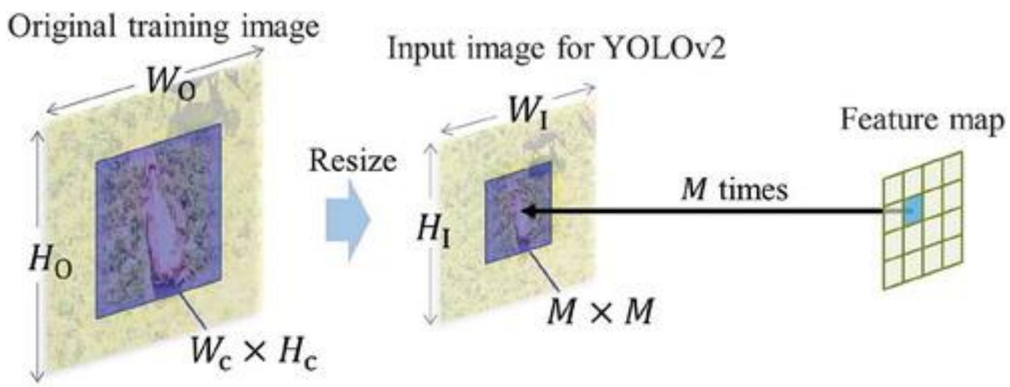

Fig. 2. Optimization of resolution.

Accordingly, when an input image for YOLOv2 is down-sampled to a $C \times D$ feature map, $CM \times DM$ closest to $W_I \times H_I$ is the optimized resolution.

3. METHODOLOGY

3.1. Image Detection with CNN Using YOLOV2 with Existing Datasets

After image collection, the collected images are pre-processed and classified for feature extraction. Image pre-processing includes accurate georeferencing, ortho-rectification, image selection and mosaicking (aligning images using image control points, point cloud and ground control point). The image pre-processing is done by structure from motion (SFM) technique and image classification for feature extraction is done by convolutional neural network with YOLOV2 base platform. SFM is a technique from computer vision and photogrammetry that uses overlapping images for 3D surface model reconstruction. The input sequence is an existing data set images, and the output is the number of individual targets that appear in that sequence. At the output, a candidate bounding box was produced, which is utilized to count the number of cows detected.

The images were supplied into the YOLOV2 input, and the feature map computations were done once for all of the images. Because cattle represent only a small portion of the entire image, this strategy is deemed efficient. On the images, convolution and max pooling procedures (where rectification is conducted) are performed, followed by down sampling for extraction. YOLOV2 architecture predicts bounding box position with the use of a regression function which is processed on individual output feature map cell. Better detection is expected when the object size is equal to cell size, this implies that, adjusting the cell to the target size should result in a more efficient regression.

The output sequence of the detected cows from SFM is fed into the convolutional neural network with a YOLOV2 based platform for optimization of resolution. YOLOV2 is a convolutional neural network consist 24 convolutional layers, trailed by two fully connected layers. It can be built with arbitrary detectors for cattle but YOLOV2 was purposely selected because of its suitability for real-world application system building. YOLOV2 has a detection accuracy that is close to middle-scale state-of-the-art benchmark and it runs with near real-time speed on single GPU.

After calculating all of the three-dimensional coordinates of the detection result, the result was merged, a Hungarian approach was used to match each frame's detection results to the existing cattle lists, and the result is regarded to be the same target. Each target's coordinate is replaced with the coordinate in the new one, and unassigned detection results are added to the list.

3.2. Scheduled Flights for UAV Aerial Image Capturing

A UAV scheduling system is needed to assign task to UAVs for efficient task execution, putting into consideration the timestamps of each action in a logical manner. Hence, scheduling system is an important segment of UAV operation system. In the scheduling system, scheduler components interact with trajectory, task and UAV databases. The databases are storage of detailed information (e.g., start and end positions, processing time and precedence relationship) of the yet to be executed tasks.

The UAV is scheduled for farmland surveillance flight of 25 minutes duration every 3hours and cover a particular area of land within that time-stamp. Followed by inspection task for another 5 minutes. The tasks execution and actions are calculated and designed in a manner that reduces the overall make span. Therefore, this schedule assists to detect farm invasion ahead of time, scheduling an UAV for flights at specific time intervals is important not just for early detection but also to converse the resources used.

3.3. The model detection of cattle and triggering of an alarm when the number of cattle passes the set threshold

The detection result is blended for an accurate order of livestock counting on a field site. Because some fields are frequently located in mountainous locations, recognizing the same cattle showing in several overlapped images is a necessary task. As a result, the cattle are assumed to be motionless and they are reconstructed in a three-dimensional model per area of the field by structure from motion. All the detection result positions are calculated in the coordinate system of the three-dimensional reconstructed model and merged as the same target following the photographic time sequence. Once the number of cattle exceeds the set threshold (one cattle for this work), it triggers an alarm system and send SMS alert to the registered mobile numbers of the farmer and security operatives.

4. RESULTS

The model was tested with two sets of test images, one is the set of test images pulled from the main data-set while the other set were similar images sourced online. A blue bounding box with confidence level was created around each detected cow in an image and an average confidence score is returned for each test image. The results are presented in Tables 1 and 2, indicating mean confidence score of 0.92 and 0.72 for the data-set test images and internet sourced test images respectively.

Table 1. Average confidence score results from the data set test images.

Test Images	Number of Cattle Detected	Average Confidence Score
a.	0	1.00
b.	0	1.00
c.	0	1.00
d.	0	1.00
e.	3	0.89
f.	1	0.95
g.	7	0.60
h.	2	0.91
i.	11	0.63
j.	4	0.88
k.	5	0.66
l.	11	0.61
m.	3	0.82
n.	1	0.94
o.	2	0.95

Table 2. Average confidence score results from sourced internet test images.

Test Images	Number of Cattle Detected	Average Confidence Score
a.	6	0.83
b.	14	0.70
c.	0	1.00
d.	19	0.58
e.	15	0.50
f.	17	0.50
g.	19	0.65
h.	19	0.65
i.	41	0.58
j.	74	0.59
k.	87	0.86
l.	5	0.56
m.	16	0.77
n.	10	0.83
o.	32	0.84
p.	43	0.87
q.	26	0.80
r.	47	0.84

The high mean confidence score obtained when the model was tested with test image drawn from the main data-set can be attributed to the fact that all images were taken at the same altitude. However, the reduction in average confidence score recorded when the model was tested with similar images sourced online is attributed to the wide variability in altitude at which the images were captured. It is observed that for cases where the altitude is high, the average confidence score is high while for low altitudes, the average confidence score is low. It was also observed that in images where cattle are clustered, the confidence is low as opposed to cases where the cattle are scattered.

5. CONCLUSION AND RECOMMENDATION

The joint use of modern technologies such as Unmanned Aerial Vehicles for capturing farmland images, Convolution Neural Network for cattle detection, and SMS for sending alert to farmers is a potential solution to the problem of farm invasion caused by herdsmen.

It is recommended that images taken at varying altitude be used to train the model so that built model can detect cattle efficiently in real life scenarios. We recommend future research in areas of inclusion of additional monitoring systems that use physical sensors to detect farm invasion.

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