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Behavior Recognition of Group-ranched Cattle from Video Sequences using Deep Learning

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ABSTRACT

Background: One important indicator for the wellbeing status of livestock is their daily behavior. More often than not, daily behavior recognition involves detecting the heads or body gestures of the livestock using conventional methods or tools. To prevail over such limitations, an effective approach using deep learning is proposed in this study for cattle behavior recognition.

Methods: The approach for detecting the behavior of individual cows was designed in terms of their eating, drinking, active, and inactive behaviors captured from video sequences and based on the investigation of the attributes and practicality of the state-of-the-art deep learning methods.

Result: Among the four models employed, Mask R-CNN achieved average recognition accuracies of 93.34%, 88.03%, 93.51% and 93.38% for eating, drinking, active and inactive behaviors. This implied that Mask R-CNN achieved higher cow detection accuracy and speed than the remaining models with 20 fps, making the proposed approach competes favorably well with other approaches and suitable for behavior recognition of group-ranched cattle in real-time.

Key words: Behavior recognition, Deep learning, Group-ranched cattle, Mask R-CNN.

INTRODUCTION

Recently, the demand for cow meat has increased dramatically (Pedersen, 2018; Nasirahmadi *et al.*, 2017; Velarde *et al.*, 2015). Continuous growth in the human population and increase per capita incomes are the keys that drive this development. Consequently, outcomes that are germane to research on immune response and control of disease in cattle are being attained in genomics contrary to the manual observation employed in the past (Chauhan *et al.*, 2021; Chouhan *et al.*, 2021; Dohare *et al.,* 2021; Thorat *et al.*, 2021; Zaborski and Grzesiak, 2021; Zheng *et al.*, 2018) which greatly relied on the experience of farmers with so many limitations (Yang *et al.*, 2020). Hence, there is a need to devise a recognition method automatic enough to overcome these limitations.

So many attempts have been made using machine vision techniques and deep learning models to provide lasting solutions to these limitations (Bello *et al.*, 2021a; Bello *et al.*, 2021b; Bello *et al.*, 2020b; Bello *et al.*, 2020a; Zheng *et al.*, 2018; Kim *et al.,* 2017; Lao *et al.,* 2016; Saberioon and Cisar, 2016; Stavrakakis *et al.*, 2015; Kashiha *et al.*, 2014). Some of these techniques are the Faster R-CNN (Ren *et al.*, 2017; Simonyan and Zisserman, 2015), improved Filter Layer-based YOLOv3 (Jiang *et al.,* 2019; Redmon and Farhadi, 2018), YOLOv4 (Bochkovskiy *et al.*, 2020). However, none of the above techniques could accurately recognize cattle in terms of their eating, drinking, active, and inactive behaviors, thereby motivating this study to devise a technique for studying the behavior recognition of group-ranched cattle from video sequences using deep learning.

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MATERIALS AND METHODS

Acquisition of datasets

Six cows (Keteku and Muturu breeds) in a ranch were acquired for this study in September 2020. They are the trypanotolerant breeds that are common among the Fulanis in Nigeria and mostly reared for their meat and sometimes as farm tools. Each cow possesses body length and body height of 86.6 cm and 95.0 cm respectively. The laboratory experiment on the acquired data was carried out in the Laboratory of the School of Computer Sciences, Universiti Sains Malaysia, in the year 2021. While Fig 1 shows the system for acquiring datasets in the cattle ranch, Fig 2 shows the video image of the individual cows engaging in feeding and drinking.

Process-flow of cattle behavior recognition

Fig 3 shows the four steps that are involved in this study. The first step comprises the video sequences of group-ranched cattle that were extracted from the camera that was placed on the pole as shown in Fig 1. Data labeling and augmentation implementation were involved in the second step. Afterward, using the principle of transfer learning, and by pre-training some models, and comparing their detection accuracy, the most suitable model was chosen for individual cows detection. Behavior analysis of individual cows takes the final step with the investigation of individual cows' behavior generating statistical results.

Labeling and augmentation of data

One thousand (1000) keyframes were selected and labeled using LabelMe (Russell *et al.,* 2008), from which 800 frames were used as training datasets, and 200 frames were used as testing datasets. Data augmentation was applied to our little annotated data to meet the large annotated data required for training the deep learning models. The augmentation generated multiple folds of both training and

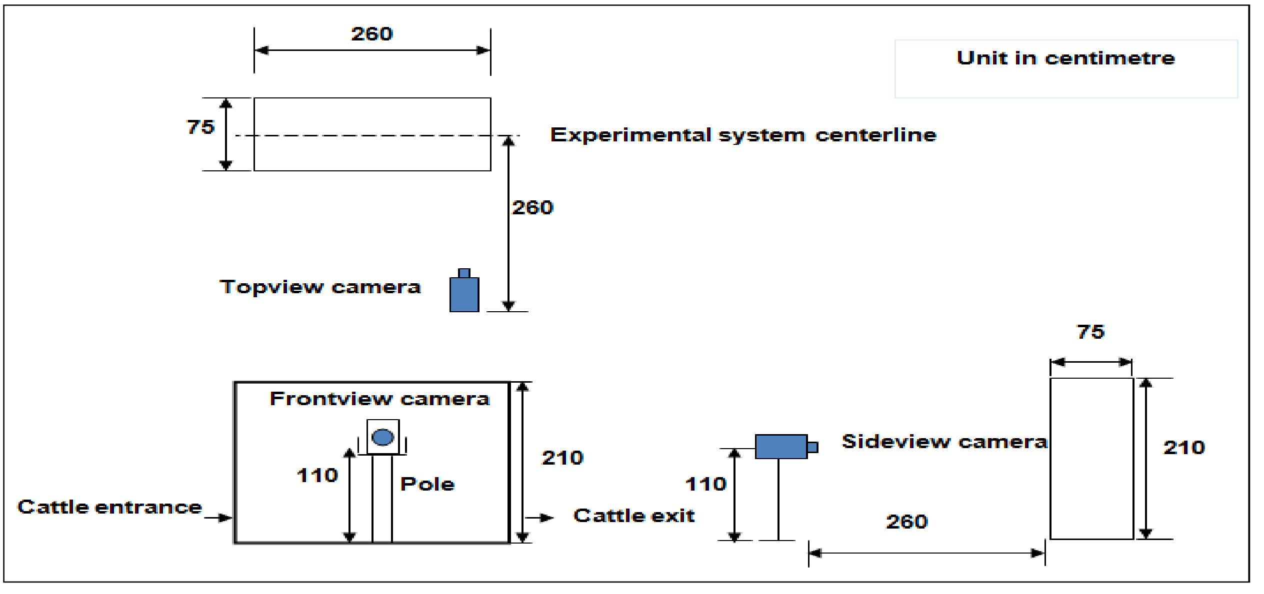


Fig 1: System for acquiring datasets in the cattle ranch.

Fig 2: Video image of cattle in the ranch.

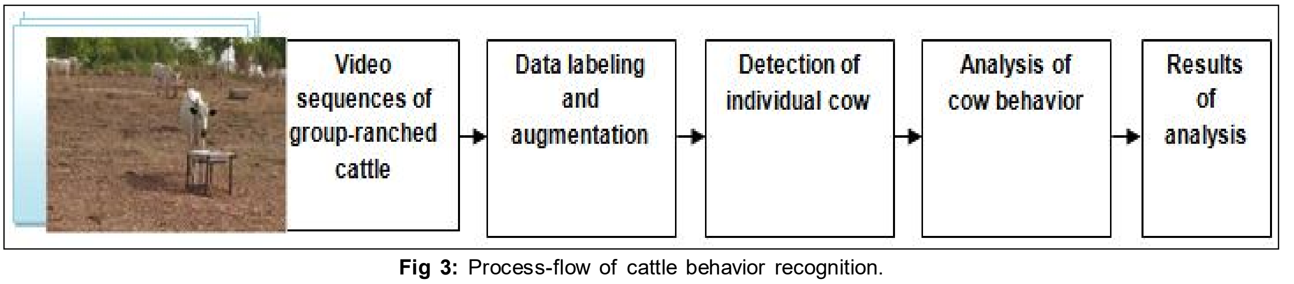


Fig 3: Process-flow of cattle behavior recognition.

testing datasets from which 4000 frames were used as training datasets and 1000 frames as testing datasets.

Detection of individual cows

Four pre-trained object detection models, namely Mask R-CNN, Faster R-CNN, YOLOv3 and YOLOv4 were employed as potential detection models. Mask R-CNN (He *et al.*, 2020; He *et al.*, 2017), an extension of Faster R-CNN added mask generator to the model of Faster R-CNN for better object detection. Using the Mask R-CNN as cow detection model, the generated outputs included bounding box, object class, confidence score and mask. With the other models, the generated outputs included all the aforementioned outputs except the masks.

Eq. (1) is the intersection over union (IoU) for determining the accuracy of the bounding box and the remaining outputs, the equation extends to Eq. (4).

$$\text{IoU} = \frac{\text{Area of intersection}}{\text{Area of union}} \tag{1}$$

The IoU values from 0.5 to 0.95 with mAP@X notation are considered in this study, where X is the value of the threshold employed to compute the metric. Only after all the matches for the image are established can the precision-recall be computed. Precision is the total number of correct objects that the model produces and it is computed as follows:

$$P = \frac{\text{False positive}}{\text{True positive + True positive}} \tag{2}$$

A recall measures the total positive objects that the model can produce and it is computed as follows:

$$R = \frac{\text{False positive}}{\text{True positive + True positive}} \tag{3}$$

Where

True-positive predicted as positive as was correct, false-positive predicted as positive but was incorrect and false-negative failed to predict an object that was there. AP is calculated by taking the area under the PR curve and by segmenting the recalls evenly to different parts. AP is calculated as follows:

$$AP = \sum_{n=1}^{N} [R(n) - R(n-1)].\max P(n) \tag{4}$$

Where

N is the calculated number of PR points.

Cow behavior recognition

The following equations calculate both the cow recognition accuracy and the ratio of misidentification:

$$A_b = \frac{C_b}{G_b} \times 100 \tag{5}$$

$$M_b = \frac{T_b - C_b}{G_b} \times 100 \tag{6}$$

Where

b is one type of the behaviors, A_b is behavior recognition accuracy, M_b is the ratio of the number of misidentified behavior to the number of real behavior. G_b is the ground-truth observation of a cow. C_b is the correctly identified behavior. T_b is the total number of one type of behavior that could also represent misidentified behaviors in addition to the correctly identified behaviors.

Analysis of cow behavior recognition

Fig 4 shows the framework for recognizing cattle behaviors. The following steps described the recognition process of the cow's behavior.

Step 1: Individual cows in the current frame were detected by using the preferred model for cow detection. After validating both the previous and current frames, implementation of Step 2 was performed for cow behavior recognition. If not, the action was carried out on the next frame, thenceforth; the implementation of cow detection was performed from Step 1.

Step 2: Analysis of the relationship of spatial location between the bounding boxes and the ground-truth was

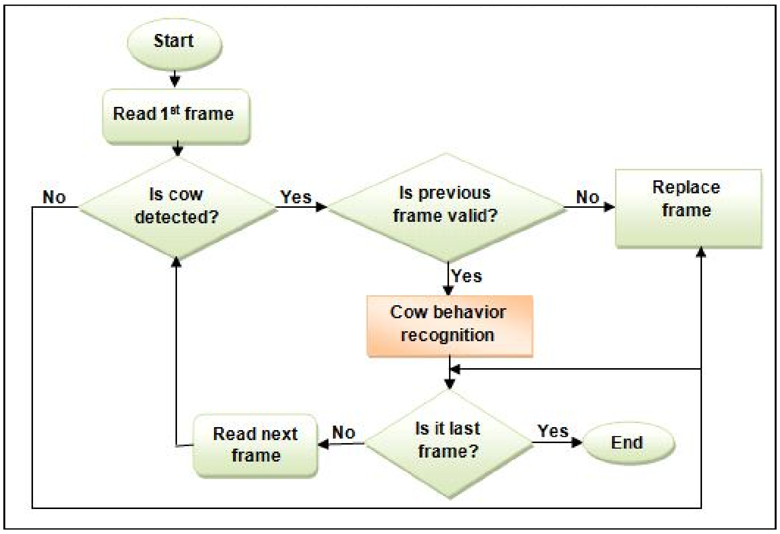


Fig 4: Framework for recognizing cattle behavior.

performed, and using Eq. (1) through Eq. (4), the IoU was calculated and compared with IoU threshold values from 0.5 to 0.80 with mAP@X notation. In Step 2.1, based on the partial bounding box area ratio, the cow eating and drinking behaviors were established. If not, the emphasis was laid on differentiating between behaviors of the cattle's activeness and inactiveness as iterated in Step 2.2. The action was carried out on the next frame after recognition of cow in the current frame has been ended, thenceforth; the implementation of cow detection was performed from Step 1.

Step 2.1: Eating and drinking behaviors recognition.

(1) Eating behavior recognition

A comparison was made between the IoU of the bounding box and the threshold value of 0.55 if and only if the bounding box's horizontal length was greater than its vertical length. Or else, the comparison was made between IoU of the bounding box and a threshold value of 0.60. Afterward, if IoU> threshold value of 0.55 or IoU> threshold value of 0.60, the current behavior was recognized as eating. If not, the emphasis was laid on differentiating between behaviors of the cattle's activeness and inactiveness as iterated in Step 2.2.

(2) Drinking behavior recognition

A comparison was made between the IoU of the bounding box and the threshold value of 0.65 if and only if the bounding box's horizontal length was greater than its vertical length. Or else, the comparison was made between the IoU of the bounding box and the threshold value of 0.70. Afterward, if IoU> threshold value of 0.65 or IoU> threshold value of 0.70, the current behavior was recognized as drinking. If not, the emphasis was laid on differentiating between behaviors of the cattle's activeness and inactiveness as iterated in Step 2.2.

Step 2.2: Activeness and inactiveness of cow behaviors recognition.

Activeness and inactiveness of cow behavior recognition were measured using Eq. (7). This is necessary where the intersection between the bounding box and the troughs was not established or the Step 2.1 conditions were not satisfied.

$$d(x,y) = \sum_{n=1}^{n} (X_i - Y_i)^2 \quad (7)$$

Where

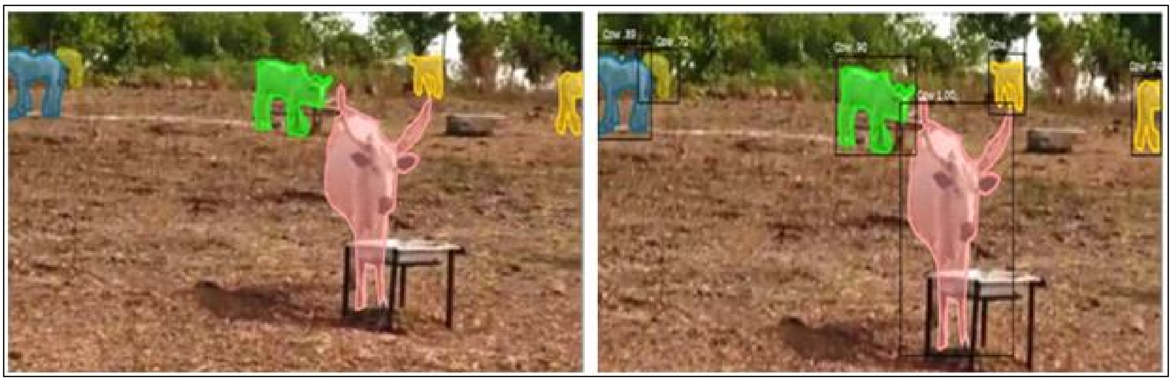
d was the amount of cow movement which was compared with the threshold value of 0.80 and the activeness of cow behavior was established if *d* is greater than the threshold value of 0.80, if not, inactiveness behavior was established. The aforementioned thresholds, that is, 0.5 to 0.80 with mAP@X notation were essential for the cow behavior recognition output. In general, the features of bounding boxes and cow behaviors determine the thresholds and these thresholds were of different values due to different sizes of cow body and the way and manner in which the cow images were captured. All invalid frames were not considered in the experiment as they were all replaced with valid frames.

Intersection over union

Fig 5(a) shows the mask-based position distribution. To ease detection accuracy, the IoU was established as shown in Fig 5(b), where the confidence scores were assigned to individual cows in the frame and the precision-recall was computed only after all the matches for the image were established.

Table 1: Description of experimental video clips.

Scenarios	Video clips	Duration	Number of frames	Frame rate (fps)	File size (MB)
Feeding	Video 1	3.56	963	25	39
	Video 2	3.58	965	25	40
	Video 3	3.55	962	25	38
Non-feeding	Video 4	3.50	960	25	36
	Video 5	3.52	961	25	37
	Video 6	3.59	957	25	34



(a) (b)

Fig 5: (a) Mask-based position distribution, (b) Mask-based coordinate system.

Table 2: Experimental software and hardware.

Software	Type/version	Hardware	Type/version
Operating system	64-bit Windows 10	CPU	Intel core i5-84002.81GHz
IDE	Visual studio 2019	RAM	16 Gigabytes
Mask R-CNN	Tensor flow 1.9.0 and Darknet	Graphics card	NVIDIA GeForce GTX 1080 Ti GPU
Faster R-CNN	Tensor flow with CUDA-9.0 and CUDNN-7.1	Graphics card	NVIDIA GeForce GTX 1080 Ti GPU
YOLOv3 and YOLOv4	Darknet with CUDA-10.0 and CUDNN-7.6	Graphics card	NVIDIA GeForce GTX 1080 Ti GPU
MATLAB	R2019b	Hard-disk	2 Terabytes
		Camera module	Vision datum LEO 640H-200gc High -Speed 200fps Sharp RJ33 CCD Gigabit ethernet 3d
		Monitor	10.1 inch IPS HD Portable LCD Gaming monitor PC display VGA HDMI interface for PS3/PS4/XBOx 360/CCTV/Camera

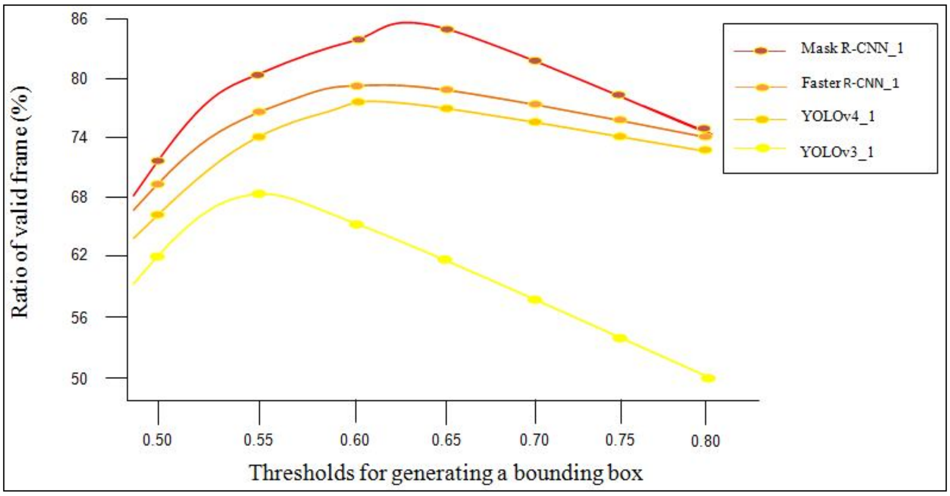


Fig 6: Ratio of valid frame under different thresholds for generating a bounding box in feeding scenario.

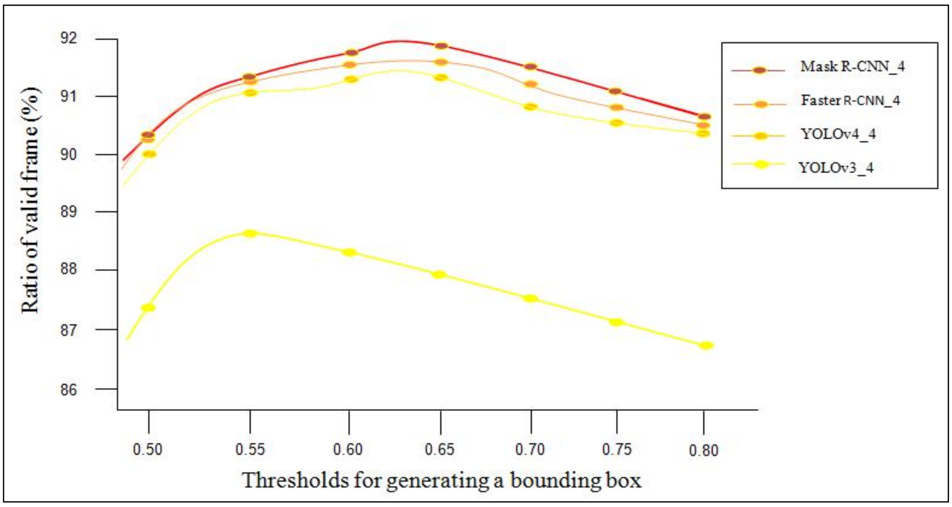


Fig 7: Ratio of valid frame under different thresholds for generating a bounding box in non-feeding scenario.

RESULTS AND DISCUSSION

Table 1 shows the description of the experimental video clips. Table 2 shows both the software and hardware employed for the four models. Table 3 shows the training parameters for the four models with one category. The preliminary experiments confirmed the suitability of the models for cow behavior recognition considering the threshold values.

Fig 6 and Fig 7 show the ratio of the valid frame in the four models employed for this study. When Mask R-CNN, Faster R-CNN, YOLOv3 and YOLOv4 were used for cow detection respectively, Mask R-CNN_1, Faster R-CNN_1, YOLOv3_1 and YOLOv4_1 symbolized the ratio of valid frames to entire frames in video 1. Likewise, when Mask R-CNN, Faster R-CNN, YOLOv3 and YOLOv4 were used for cow detection respectively, Mask R-CNN_4, Faster_4, YOLOv3_4 and YOLOv4_4 symbolized the ratio of valid frames to entire frames in video 4.

Fig 6 and Fig 7 show the upward and downward movement of the four models. As presented in Table 4-7, comparing the models' performance on cow detection in feeding and non-feeding scenarios, the results achieved in the non-feeding scenario were fairly equal to the results achieved in the feeding scenario due to the continuous morphological change in postures and behaviors exhibited by the cattle in the feeding scenario.

Table 3: Model hyper-parameters.

Models	Specifications	Amount in number
Model	Specification	Amount in number
Mask R-CNN	Initial learning rate	0.001
	Initial steps	40000
	Subsequent learning rate	0.0001
	Subsequent steps	20000
	Size of batch	16
	Iterations per epoch	60000
	Sub-divisions	20
	Mask shape	28×28
Faster R-CNN	Initial learning rate	0.001
	Initial steps	80000
	Subsequent learning rate	0.0001
	Subsequent steps	40000
	Training iterations	120000
	Sub-divisions	10
	Size of batch	16
YOLOv3 and YOLOv4	Initial learning rate	0.001
	Initial steps	20000
	Subsequent learning rate	0.0001
	Subsequent step	10000
	Size of batch	16
	Training iterations	7000
	Sub-divisions	4

Precision and speed of the cow detection

The experiment for detecting cows was carried out on the feeding scenario video clips (video 1 and video 2) and non-feeding scenario video clips (video 4 and video 5). The ratio of valid frame of the six video clips of both feeding and non-feeding scenarios handled by the four models for cow detection is shown in Fig 6 and Fig 7 respectively, with Mask R-CNN and YOLOv4 achieving higher detection accuracies. The detection speed of Mask R-CNN, Faster R-CNN, YOLOv3 and YOLOv4 were 20 fps, 15 fps, 6 fps and 10 fps respectively. Therefore, Mask R-CNN was selected for the cow detection problem with a threshold value of 0.80 for bounding box generation.

Cow behavior recognition

Table 4-7 show the detailed results of the several cow behavior recognition experiments performed in this study using Eq. (5) and Eq. (6) with average recognition accuracies of 93.34%, 88.03%, 93.51% and 93.38% achieved by Mask R-CNN for eating, drinking, active and inactive behaviors recognition respectively, making our approach competes

Table 4: Analysis of eating behavior recognition.

Video clips	Ground-truth	Correct recognition	A_b (%)	Misidentified	M_b (%)
Video 1	3987	3901	97.84	57	1.43
Video 2	2475	2270	91.72	35	1.41
Video 3	2352	2247	95.56	37	1.57
Video 4	1234	1124	91.09	9	0.73
Video 5	998	925	92.69	10	1.00
Video 6	1254	1143	91.15	6	0.48

Table 5: Analysis of drinking behavior recognition.

Video clips	Ground-truth	Correct recognition	A_b (%)	Misidentified	M_b (%)
Video 1	196	178	90.82	18	9.18
Video 2	153	134	87.58	10	6.54
Video 3	112	99	88.39	2	1.79
Video 4	98	84	85.71	5	5.10
Video 5	57	49	85.96	4	7.02
Video 6	78	70	89.74	3	3.85

Table 6: Analysis of active behavior recognition.

Video clips	Ground-truth	Correct recognition	A_b (%)	Misidentified	M_b (%)
Video 1	1100	1000	90.91	47	4.27
Video 2	1001	978	97.70	25	2.50
Video 3	999	887	88.79	17	1.70
Video 4	1023	989	96.68	4	0.39
Video 5	1006	985	97.91	5	0.50
Video 6	998	889	89.08	3	0.30

Table 7: Analysis of inactive behavior recognition.

Video clips	Ground-truth	Correct recognition	A_b (%)	Misidentified	M_b (%)
Video 1	186	172	92.47	23	12.37
Video 2	164	153	93.29	19	11.59
Video 3	113	101	89.38	11	9.73
Video 4	3987	3901	97.84	57	1.43
Video 5	2475	2270	91.72	35	1.41
Video 6	2352	2247	95.56	37	1.57

favorably well with the works of (Fuentes *et al.,* 2020), (Jiang *et al*., 2020), (Jingqui *et al.,* 2017), (Yang *et al*., 2018b), (Shen *et al*., 2020) and (Zhu *et al*., 2017).

However, due to the uncontrollable contributory factors such as invalid frames, cattle overlapping and instability in the cattle feeding scenario, lots of cattle feeding and non-feeding behavior scenarios were misidentified.

CONCLUSION

Deep learning has been proposed in this study for recognizing group-ranched cattle behaviors from video sequences. Mask R-CNN and three other models, namely Faster R-CNN, YOLOv3 and YOLOv4 were employed as models to experiment with different behavior recognition scenarios such as eating, drinking, active and inactive behaviors. Mask R-CNN showed higher behavior recognition accuracy than other models under the behavior recognition scenarios with 20 fps. Future work includes mitigating the uncontrollable contributory factors that led to the misidentification of some behavior recognition scenarios.

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