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Full Paper

Detection of standing estrus behaviour of beef cow using video images and deep machine learning

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Abstract: A deep machine learning model, YOLOv8, was developed to detect cow estrus behaviour using video images. The model was trained using Google-Colab on 130 original images from a mobile phone camera based on original images from various scenes. The performance was compared between two models with two different annotation patterns: 1) the mounting cow model (M), involving drawing bounding boxes around cows showing signs of mounting other cows, and 2) the standing cow model (S), involving drawing bounding boxes around cows showing signs of standing estrus and cows showing signs of mounting other cows. The final trained weight of each model was used with the Python program to test the estrus behaviour video data set, using for the first time daytime and night-time videos recorded with an internet-protocol camera installed inside the cow stable area. Results revealed superior performance of the M model, exhibiting higher precision, recall, and F1-score across the YOLOv8n, YOLOv8s and YOLOv8m models when compared to the S model. Notably, the inference speed of the models ranged from 36 to 48 frames per sec., meeting the crucial requirements for fast and accurate detection of cow estrus events through video surveillance by internet-protocol cameras. A computer vision program was developed to detect cow estrus by analysing instances where a cow remained still for over 3 sec. while others attempted mounting. The system, which uses an internet-protocol camera, sends data remotely and allows farmers to monitor their cows online. Real-time notifications are sent via the LINE platform, delivering messages and images to their mobile devices.

Keywords: standing estrus, beef cow, YOLOv8, internet-protocol camera

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INTRODUCTION

Commercial beef cow-calf production is economically important and prevalent throughout Thailand. The goal of cow-calf production is to obtain one calf per cow per year. Therefore, cows must become pregnant within 90 days after calving [1]. Detecting the signs of estrus is very important for the reproductive success of a herd as it can determine an optimum artificial insemination time and thus results in increased conception rates for the herd [1]. A cow standing to be mounted is the most accurate sign of estrus. Standing estrus results from a series of hormonal changes that occur at the end of each estrus cycle [2]. Standing estrus is when a cow/heifer stands still and allows other cattle to mount, with the cow that stands still being in standing estrus and suitable for the next stage of artificial insemination [2].

Failure to detect estrus or an erroneous diagnosis of estrus is common in beef farms because beef cows have a short estrus period and present unclear estrus behaviour, resulting in missed and untimely insemination, with consequent economic losses [3]. Traditional estrus detection relies on close observation by humans. Recently, however, the visual detection method has become more difficult as the duration and intensity of estrus expression have decreased [4, 5]. In addition, cows tend to show standing estrus in the early morning and late at night [5]. A human cannot manually observe every cow on a farm all the time because of cost and time limitations. There are several methods of automatic estrus detection in cows, including methods based on the cow activity level using electonic sensors in direct contact with cows [6]. The parameters are measured by sensors and data are then processed and classified to analyse cow behaviour and detect the estrus [7]. Sometimes, sensors can record false readings when they are bumped on fences or other cows or when cows are sick. In addition, the sensing devices are expensive for farmers [1].

In recent years, with the rapid development of deep learning technology, computer vision technology has developed using non-contact and real-time technology [8]. Object detection as an important part of computer vision has been widely used in many fields [9, 10]. Object detection based on image processing extracts the features from images and then obtains and analyses the object information such as category, position and direction [11]. Object detection has been successfully used for target detection and behaviour recognition in livestock [1, 12, 13].

A convolutional neural network (CNN) is an algorithm that has become the standard used for object detection. During its development, several other algorithms based on CNN have emerged, some of which are region-based-CNN (R-CNN), fast R-CNN, faster R-CNN, Single-Shot Multi-Box Detector (SSD) and You-Only-Look-Once (YOLO) [14, 15]. In terms of object detection speed, the YOLO method performed better than the region proposal methods [16]. The YOLO series is an object detection algorithm that is very simple in preparation, has very high precision and is fast in image processing [11]. The Ultralytics YOLOv8 model, developed by Ultralytics, is a cutting-edge, state-of-the-art model that builds upon the success of previous YOLO versions and introduces new features and improvements to further boost performance and flexibility [17]. YOLOv8 is trained on the COCO data set and comes in various sizes as follows: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l and YOLOv8x (nano, small, medium, large, extra large) to cater to different needs [17]. YOLOv8 is fast, accurate and easy to use, making it a good choice for detecting the estrus of cows in images and videos.

The objective of this study is to develop an algorithm to detect estrus behaviour of cows based on the YOLOv8 model by focusing on the mounting and standing behaviour of cows. The modified model will be further developed into an automatic estrus detection system for on-farm use.

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MATERIALS AND METHODS

Animals

The study was carried out on a beef cattle farm at Tubkwang Research Station, Department of Animal Science, Faculty of Agriculture, Kasetsart University, Saraburi, Thailand. The breed used was Kamphaeng Saen, which is a crossbred-cattle bloodline containing 25% native Thai cattle, 25% Brahman and 50% Charolais. The study involved 50 cyclic cows aged between 4 and 12 years in the postpartum period (90 days) with a body condition score of 6.31 ± 0.74, where 1 represents emaciated and 9 represents fat. All cows were housed in a dirt lot with an indoor feeding area under good care conditions at a temperature of 29.67 ± 2.45 °C and a temperature-humidity index of 80.66 ± 2.97. All cows were fed on Ruzigrass (*Brachiaria ruziziensis*) and Napier grass (*Pennisetum purpureum*) and had free access to water.

Data Collection

Standing estrus detection in cows was carried out intensively twice daily (06.00-07.00 am and 06.00-07.00 pm) by experienced persons. In total, 130 images of cows showing standing estrus behaviour from different scenes were photographed from side view of the animal at a distance of 3-5 metres using a mobile phone camera (Galaxy A42, Samsung®) with an image aspect ratio of 16:9 (width:height) to produce the data set for the experiment. All images were captured at a resolution of 72 dots per in. and colour representation was based on the standard RGB (red, green, blue) format.

Data Annotation

All images were uploaded to the Roboflow® framework [18] and divided into the training data set (80%) and validation data set (20%). In the image data set, each image was manually annotated by drawing bounding boxes around the area of interest. The bounding boxes represented a potential region of interest. This experiment tested and compared 2 models with different bounding boxes patterns: 1) mounting cow model (M), involving drawing bounding boxes around cows showing signs of mounting other cows and images in the data set were labelled to describe the mounting behaviour (Figure 1) and 2) standing cow model (S), involving drawing bounding boxes around cows showing signs of standing estrus and cows showing signs of mounting other cows, and images in the data set were labelled to describe the standing behaviour (Figure 2).

Data Pre-processing and Augmentation

To obtain a more generalised model, the training data should have fine diversity as the objects vary in size, lighting conditions and poses. All the images were pre-processed by resizing to 800×800 pixels (Fit (black edges)) and the image colour was adjusted to grayscale. Image augmentation techniques were applied to increase the number of images and diversity on the training data set without acquiring new images [19]. The following augmentation was applied to generate new images of each source image: 1) 50% probability of horizontal flip, 2) brightness adjustment of between -10% and +10%, 3) exposure adjustment of between -10% and +10%, and 4) gaussian blur of between 0 and 1 pixels. Finally, of the 338 images, 312 were used for the training data set and the remaining 26 were used for the validation data set.

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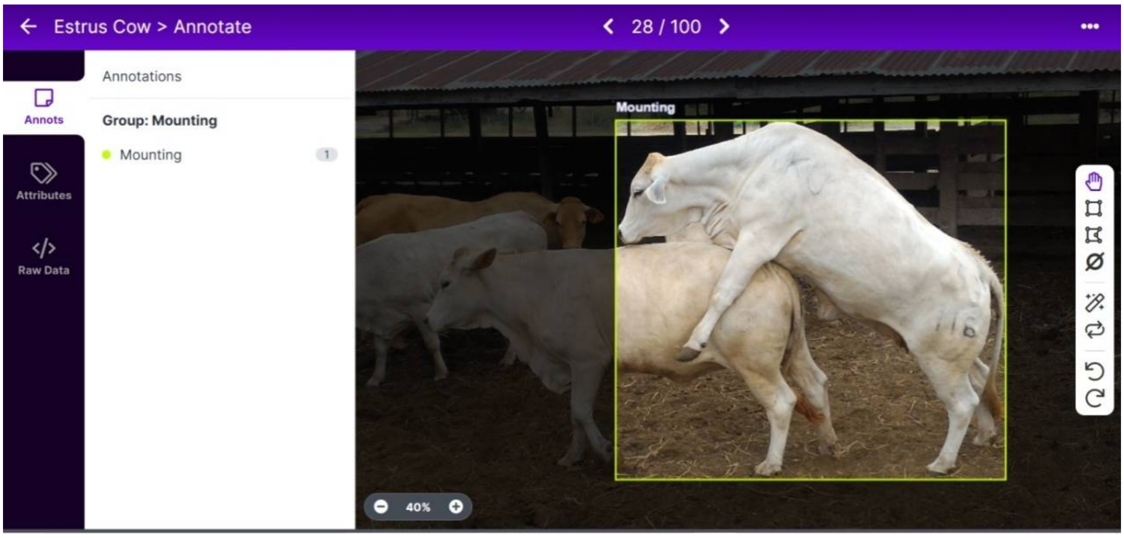

Figure 1. Mounting cow model (M) with bounding box around cow showing signs of mounting another cow

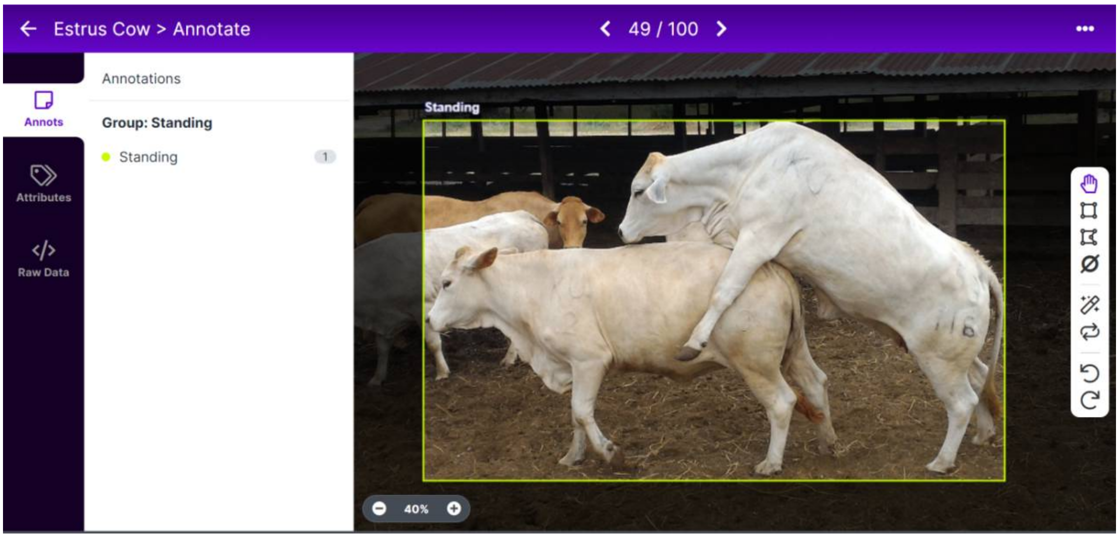

Figure 2. Standing cow model (S) with bounding box around cow showing signs of standing estrus and cow showing signs of mounting another cow

Training Machine Learning Model

The data set was converted to YOLOv5 PyTorch format for the Roboflow® framework and exported for training using Google-Colab, which provides free access to cloud-based GPU (Google CoLaboratory Pro, Google LLC, Mountain View, CA, US; Tesla V100) based on the YOLOv8 model with pre-trained COCO weights. A YOLO v8 model was trained on the data set using transfer learning, where we initialised the model with pre-trained weights on the COCO data set and fine-tuned it on our data set. This experiment tests the performance of YOLOv8 models at different sizes, which are divided into 3 sizes: 1) nano-sized model (YOLOv8n), 2) small-sized model (YOLOv8s), and 3) medium-sized model (YOLOv8m). The configured model is as follows: model = yolov8n.pt or yolov8s.pt or yolov8m.pt, batch size =16, epochs = 100, learning rate = 0.01 and imgsz = 800. The instruction code used for processing the model training was based on the Python language, which is an open source [20].

Model Performance Evaluation

After the model training was completed, models were generated as graphs of changes in mean average precision (mAP) and average loss during the training of the model; these were used for model performance evaluation [21]. In this article we developed a program for standing estrus detection in a video feed using the OpenCV and Ultralytics libraries in Python. OpenCV and Ultralytics are huge open-source libraries for computer vision, machine learning and image processing [22]. The final trained weight of each model was applied to the Python program to test the estrus behaviour shown in the data set videos (based on videos that had never been used in model training). These videos were recorded from an internet-protocol camera (VStarcam® C18S, China) with a video resolution of 1,920×1,080 pixels, a frame rate of 25 frames per sec. and the operation of the infrared function. The cameras installed in the cow barn recorded multiple video data sets under various lighting conditions (daytime and night-time) (Figure 3).

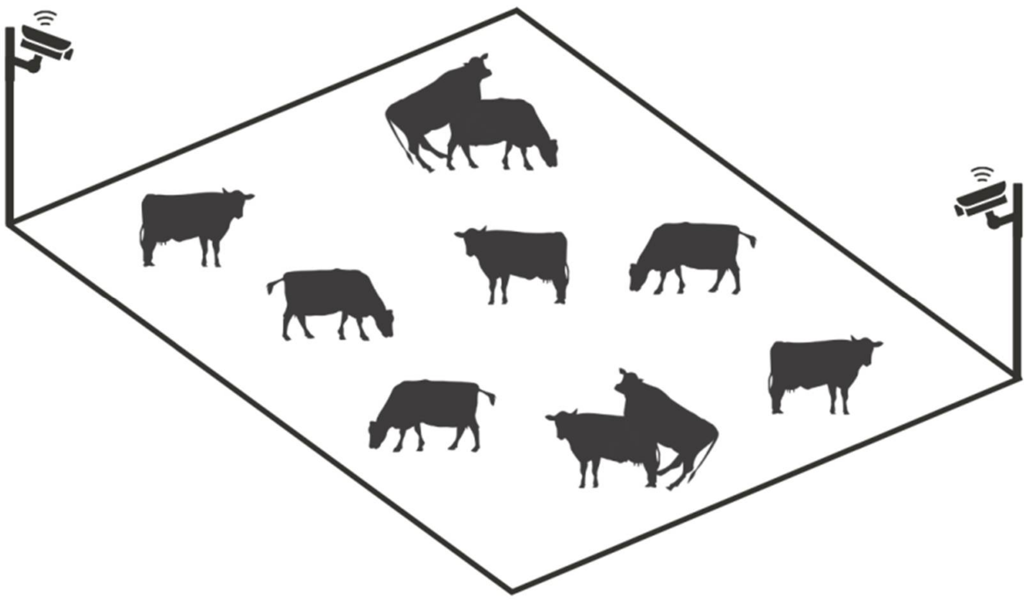

Figure 3. Structure of cattle barn and location of installed internet-protocol cameras

A teaser bull with surgical displacement of the penis was used to help in the detection of estrus cows among the herd. The estrus behaviour video data were extracted as images every 1 sec. for the testing of object detection. The extracted image data were saved in the form of a JPG file with a 960×540 resolution using the Free Video to JPG Converter® program (Digital Wave Ltd., UK) on a computer. The length of each estrus behaviour video is 10 sec. (mounting or standing behaviour with an average time of approximately 3 sec.). In total, 400 estrus behaviour images were acquired from 40 estrus behaviour videos (20 videos during day-time and 20 videos during night-time) and used for testing all models by checks involving the detection capability by creating a box around the detected object and setting the minimum confidence threshold of detection to 0.50 and 50% Intersection over Union (IoU).

A sample video data set, model and Python program for our fieldwork are available at the GitHub repository [23]. The precision, recall and F1-score, which were used to analyse the performance of the model, were calculated from the confusion matrix in the Pascal VOC Challenge using the following equations [21]:

$$\text{Precision (\%)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \times 100 \tag{1}$$

$$\text{Recall (\%)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100 \tag{2}$$

$$\text{F1 (\%)} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100 \tag{3}$$

Precision (1) is the ability of the model to identify only the relevant objects. Recall (2) is the ability of the model to detect all the relevant objects. F1-score (3) is the first harmonic mean between recall and precision. The detections are normally validated using IoU metric considering only detections with IoU $\geq$ 50% [24].

A true positive indicates an instance when the estrus posture is properly determined and the mounting or standing behaviour is marked with a bounding box, i.e. a detection for which IoU $\geq$ 50%. A false positive indicates any case where a bounding box is displayed in the wrong place, a detection for which IoU < 50%. A false negative indicates a case in which the estrus posture image data are determined as normal image data. A true negative indicates a case in which normal image data are determined to be abnormal image data. In object detection this metric does not apply because there are many possible predictions that are not detected in an image. Thus, true negative includes all possible wrong detections that are not detected [21].

Ethics Statements

This study was approved by Kasetsart University's Institutional Animal Care and Use Committee (Approval no. ACKU65-AGR-015).

RESULTS AND DISCUSSION

Comparison of Model Performance

Following the utilisation of YOLOv8 models for training, a graph depicting the mounting cow model (M) was generated as illustrated in Figure 4. The YOLOv8n-trained model achieved mAP at IoU 0.5 of 97.60%, loss of 0.17% and model size of 6.2 MB, whereas the values for the YOLOv8s-trained model were mAP at IoU 0.5 of 98.50%, loss of 0.14% and model size of 22.5 MB. The results for the YOLOv8m-trained model were values for mAP at IoU 0.5 of 99.10%, loss of 0.15% and model size of 52.0 MB.

A graph was generated for the training of the standing cow model (S) as illustrated in Figure 5. The YOLOv8n-trained model achieved mAP at IoU 0.5 of 97.70%, loss of 0.18% and model size of 6.2 MB, whereas the values for the YOLOv8s-trained model were mAP at IoU 0.5 of 98.60%, loss of 0.14% and model size of 22.5 MB. The results for the YOLOv8m-trained model gave mAP at IoU 0.5 of 98.90%, loss of 0.16% and model size of 52.0 MB.

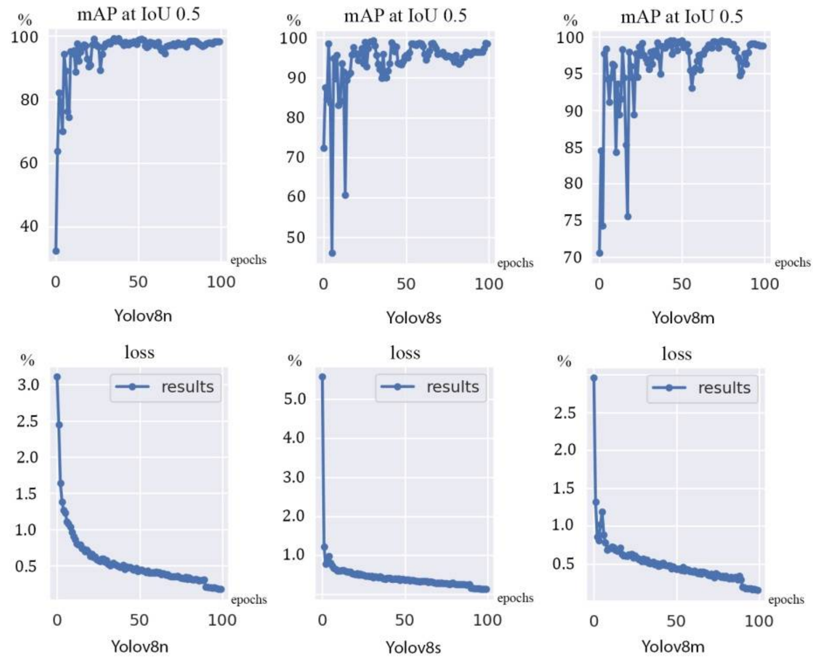

Figure 4. Graphs of performance during training of mounting cow model (M) based on YOLOv8n, YOLOv8s and YOLOv8m models

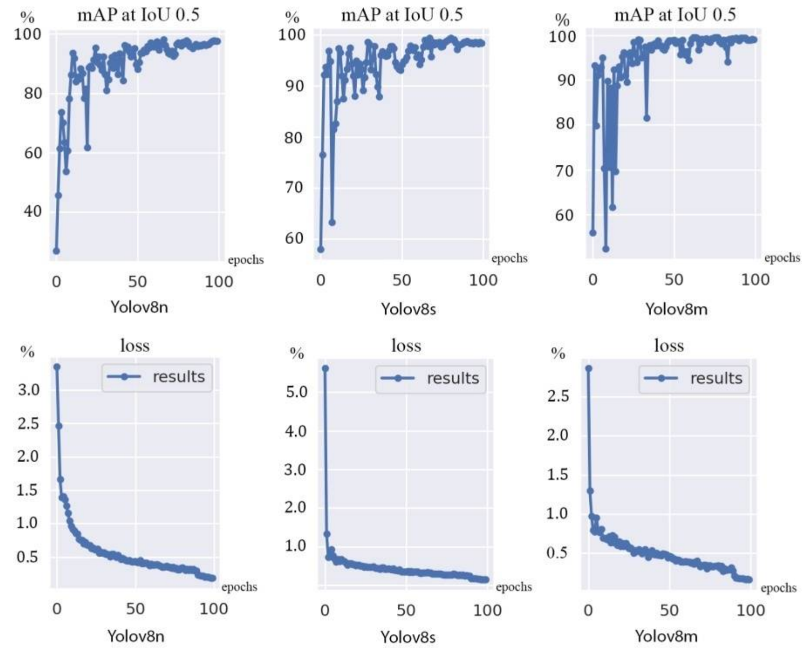

Figure 5. Graphs of performance during training of standing cow model (S) based on YOLOv8n, YOLOv8s and YOLOv8m models

Mounting is a typical behaviour of cows during estrus. Studies have shown that a typical dairy cow will mount other cows or be mounted 2-10 times during an estrus period. Therefore, accurate detection of mounting behaviour can allow the identification of cows in estrus. One popular state-of-the-art, CNN-based model for the real-time detection of objects in an image is "You-Only-Look-Once version 8" or YOLOv8, which has a larger feature map and substantially improved convolutional network than its previous versions in terms of both speed and accuracy

[17]. The YOLOv8 network utilises the Darknet-53 backbone network, which is faster and more precise than the previous YOLOv7 network [25]. The architecture consists of a backbone, head and neck. It has a new architecture, improved convolutional layers (backbone) and a more advanced detection head, making it a top choice for real-time object detection [26]. YOLOv8 also offers support for the latest computer vision algorithms such as instance segmentation, which enables multiple object detection in an image or video. Therefore, we decided to use the YOLOv8 model to train the model for detecting the estrus behaviour of cows.

The model evaluation process utilised mAP and average loss. In general, mAP is defined as the mean average of the ratios of true positives to all positives and for all recall values [27]. The YOLOv8 model adopts object detection and classification loss functions to measure the category error between the predicted box and the ground-truth box [28]. Thus, this metric is more often used as a target metric for evaluating the performance of the model during training and also in decision-making for choosing the best model among YOLOv8 models. From the results of model training in the current experiment, as more iterations were completed, the model continued to learn more, resulting in reduced training loss in subsequent iterations. From 90 epochs onwards, there was a relatively constant loss, indicating that the network learning was becoming more accurate [29] and therefore the training loss was probably slight, as shown graphically in Figures 4 and 5. Loss is a value that represents the sum of errors in our model. It measures how well (or badly) our model is doing. If the model's prediction is perfect, the loss will be close to zero [30].

While the loss function was greatly decreased, on the other hand, the mAP value continued to increase and eventually remained constant. In the current study, we found that the medium-sized model (YOLOv8m) had higher mAP and lower loss than the small-sized model (YOLOv8s) and the nano-sized model (YOLOv8n) in both the mounting cow model (M) and the standing cow model (S). The mAP measures performance in terms of both the classification ability (type of object in image) and the localisation ability (position of object in image). The mAP is calculated as the mean of the average precision over all classes for a range of thresholds defining the minimum overlap between the predicted and ground-truth bounding boxes (IoU) [31]. Note that since our models only trained mounting behaviour, the mounting behaviour AP is equivalent to the mean average precision (mAP), which is a widely used object detection metric [27]. The higher the value of mAP is the better the detection capability of cows' standing estrus becomes [32]. For object detection, a detector needs to both locate and correctly classify objects. Intersection over Union (IoU) is the proportion of overlapping area and combined area of the bounding boxes of the prediction and the ground-truth objects [33]. A correct classification is only counted as a true positive detection if the predicted mask or bounding box has an IoU higher than 50% [16, 33]. In the current study the detection from YOLOv8n, YOLOv8s and YOLOv8m models had good localisation based on the mean IoU metric at an IoU threshold of 0.5, which is more than 80% for the mounting cow model (M) and the standing cow model (S), indicating that both models were suitable for further use.

The trained weights of each model, i.e. the M model and S model, were used to process input video recordings of cows showing standing estrus from the internet-protocol camera with a frame resolution of 1,920×1,080 pixels at an average of 25 frames per sec. using the Python computer program (based on videos that had never been used in model training). All models were tested on the same machine. The computer runs on Windows 11 and has a GeForceRTX3070 GPU, an Intel(R) Core (TM) i7-11800H CPU@2.3GHz, and 32 GB of running RAM. Model creation and validation were carried out in Python, utilising the PyTorch deep learning framework, Visual Studio Code development tools, and a computational framework based on the CUDA 11.5 version

(NVIDIA Developer, Santa Clara, CA, USA). Results revealed superior performance of the M model, exhibiting higher precision, recall and F1-score across the YOLOv8n, YOLOv8s and YOLOv8m models when compared to the S model (Tables 1, 2). A higher F1-score shows that the model is more effective [34]. In addition, both models were able to detect standing estrus behaviour effectively in night-time video images that had low contrast, blurred visual effects, and unclear details (Figures 6, 7). However, we used image augmentation techniques that adjusted the image in the data set for brightness, exposure and blur consistent with the night-time image. Typically, data augmentation is performed as a part of data set preprocessing for training an image detection and classification model such as the CNN-based model and this allows the model to learn more, resulting in high performance [19].

Table 1. Comparison of testing performance for each model of mounting cow (M)

Model	Precision	Recall	F1-score	FPS[a]	Model size
YOLOv8n	98.50 %	82.30%	89.80%	48	6.2 MB
YOLOv8s	99.00 %	83.70%	90.70%	46	22.5 MB
YOLOv8m	98.80 %	99.20%	98.90%	37	52.0 MB

[a] Frames per sec.

Table 2. Comparison of testing performance for each model of standing cow (S)

Model	Precision	Recall	F1-score	FPS[a]	Model size
YOLOv8n	90.30%	88.70%	89.50%	48	6.2 MB
YOLOv8s	90.90%	89.40%	90.10%	46	22.5 MB
YOLOv8m	91.00%	89.60%	90.30%	37	52.0 MB

[a] Frames per sec.

However, a detection error was identified when attempting to capture cows in estrus during night-time videos (Figure 7). This challenge arises due to the presence of complex shadows generated by the animals themselves and their environment, particularly when the model needs to discern two cows exhibiting estrus behaviour together. The increased complexity of detecting dual instances of cows in estrus may lead to more confusion for the model compared to the situation where it is detecting a single mounting cow.

Accurately detecting the mounting behaviour in beef cattle is critical to estrus detection. Computer vision technology, which has the advantages of being non-contact and real-time, has been used to study cow mounting behaviour [1, 12]. The results of the current study suggest that computer vision technology has promise as an automated and accurate technique for estrus detection in beef cattle. Similarly, Chae and Cho [35] demonstrated that employing deep learning based on YOLOv3 algorithm for the identification of mating posture images of cattle from mating behaviours in the CCTV video data attained 97.90% precision, 97.30% recall, and 97.60% F1-score. Wang et al. [36] discovered that the cow estrus behaviour detection method in natural breeding scene images, derived from captured videos of cows mounting, was based on the improved YOLOv5 model. The average accuracy of the enhanced model reached 94.30%, with precision at 97.00% and recall at 89.50%. Wang et al. [37] enhanced the monitoring of cow estrus by utilising the YOLOv8n model, which was referred to as Estrus-YOLO (E-YOLO), and demonstrated that the suggested model achieved an average precision of 95.70% and an F1-score of 93.70% in detecting mounting behaviour.

Figure 6. Cow mounting behaviour detection results using M model from video data set using internet-protocol camera

Figure 7. Cow mounting and standing behaviour detection results using S model from video data set using internet-protocol camera

Nevertheless, there have been a limited number of studies researching on the efficiency and speed of detecting cows' estrus behaviour using direct video surveillance, particularly in practical farm applications. In this paper the video plays a role in verifying the real-time performance of the algorithm. Frames per sec. is an important parameter for measuring the speed of detection and is commonly employed to describe the real-time capabilities of the model. A higher frame rate leads to improved real-time performance [38].

In fact, the findings of the experiments demonstrate that smaller models are faster than their larger counterparts at detecting estrus from video captured by internet-protocol cameras (Tables 1, 2). This speed advantage is attributed to the reduced complexity of image processing in smaller models [17]. Wang et al. [37] utilised the YOLOv8n model on the Ubuntu 18.04.6 LTS operating system with an Intel(R) Core(TM) i7-10700 K CPU @ 3.80 GHz and an Nvidia GeForce RTX 3080Ti GPU to monitor cow estrus. The system achieved a detection speed of 8.1 frames per sec. for detecting mounting behaviour. Nevertheless, it is important to understand that this increase in efficiency is accompanied by a decrease in accuracy in comparison to larger models. Smaller models possess the inherent property of involving less complex image processing, resulting in faster outcomes [17, 39]. Based on these findings, it is important to select a model that is compatible with the processing device's capabilities.

Utilisation in Practical Applications

Previous studies and research on cow estrus behaviour detection have mostly emphasised the accuracy of detection. Indeed, in the farm field, cows will exhibit various symptoms prior to estrus. The most prominent indications of estrus activity in cows are closely associated with mounting or standing behaviour. A cow at estrus will stand still for several sec. when mounted by another cow [40, 41]. Consistent with this study, which collected video data on the estrus behaviour of beef cows, it was observed that standing estrus cows would remain motionless for a duration of 3 sec. or more to allow mounting by other cows (Figure 8). Normally, cows that are not in a state of standing estrus promptly evade being mounted by other cows (Figure 9). Most cows that stand to be mounted are in their estrus cycle [40]. Mounting activity often occurs in the middle of the estrus cycle, while standing to be mounted behaviour occurs in the later phases of the estrus. Therefore, the best time for insemination is usually chosen by observing the standing behaviour [40].

Figure 8. Cows with estrus behaviour remain standing still for more than 3 sec. while other cows attempted mounting

Figure 9. Cows not exhibiting estrus behaviour quickly avoid being mounted by other cows. The duration of standing time is shorter than 3 sec.

The duration of estrus in cows is short, with ovulation occurring 10-12 hr after the end of estrus or 24-30 hr after the onset of estrus. The ideal timing for inseminating a cow is 12-18 hr following the onset of estrus [40, 42]. This strategic timing aligns with the physiological stages of the estrus cycle, increasing the chances of successful insemination. Consequentially, we were interested in the duration of standing to be mounted by another cow as a potential means of identifying true estrus in a group of cows. A customised program utilising computer vision techniques (OpenCV and Ultralytics libraries in Python) was developed for this purpose. The analysis targeted instances where a cow remained standing still for more than 3 sec. while others attempted mounting, signalling the onset of estrus. The cow estrus alert system, designed to identify such behaviour through the internet-protocol camera, transmitted the data remotely, and the video stream could be obtained online at the workstation to monitor cows on the farm. It triggered real-time notifications via the LINE platform, delivering messages and images of cows on the farm to farmers' mobile devices. A video data set, model and Python program for our fieldwork can be accessed in the GitHub repository [23]. This system aims to provide farmers with immediate alerts, facilitating timely and informed decisions on reproductive management for enhanced herd health and productivity.

CONCLUSIONS

A deep machine learning model has been developed to detect cow estrus behaviour using video images. The YOLOv8 algorithm can be used for real-time detection, and this can be further developed into an automated monitoring system for cattle. The system can be monitored using low-cost internet-protocol cameras and personal computers, allowing real-time detection of estrus events in cattle without contact or intrusive devices.

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