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Automated Cow Estrus Detection Using YOLOv8s Model

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ABSTRACT: The detection of cow estrus plays a vital role in reproductive management and maximizing breeding efficiency in dairy and livestock industries. Traditional methods for estrus detection rely on visual observation and physical examination, which are time-consuming, labour-intensive, and prone to human error. Therefore, this research proposed an automated cow estrus detection system using the You Only Look Once version 8 (YOLOv8) object detection algorithm, which falls under the category of Convolutional Neural Networks (CNNs), a subset of deep learning algorithms. The chosen model is YOLOv8s and it is trained on a pre-processed dataset, aiming for precise estrus identification. The outcomes of the chosen YOLOv8s model records the best parameters which are 99.1 percent of mAP, 97.8 percent of precision, 98.0 percent of recall and 97.9 percent of f1-score.

KEYWORDS: *Cow estrus detection, breeding efficiency, YOLOv8, convolutional neural network, deep learning algorithm.*

1. INTRODUCTION

The accurate identification of cow estrus is crucial for efficient reproductive management in dairy farming but, conventional visual observation methods often lead to misinterpretations as noted in [1], resulting in missed opportunities, reduced breeding efficiency, and decreased profitability, exacerbated by the challenges of monitoring large-scale farms and the drawbacks of invasive detection methods causing discomfort and stress to the animals.

The primary objectives of this research project are to develop a non-invasive and automated cow estrus detector using deep learning algorithms that ensures the comfort of the cows and detect cow estrus precisely by using advanced object detection algorithm which is You Only Look Once version 8 (YOLOv8) for the efficiency of reproduction.

Cow estrus, also known as heat, is a period of time when a female cow is receptive to mating and can become pregnant. This is typically a 12–24-hour period that occurs every 21 days, although it can vary depending on the individual cow and breed. Reference [2] stated that cows may exhibit certain behaviors such as increased vocalization, mounting other cows, and restlessness during estrus. They may also show physical signs such as a swollen vulva and increased vaginal discharge. Detecting when a cow is in estrus is important for dairy farmers because it allows them to time breeding and maximize reproductive efficiency. This can be done through visual observation, but there are also automated systems available that use sensors to detect changes in behavior, physiology, or body temperature that indicate estrus [16].

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2. COW ESTRUS DETECTION

Cow estrus detection is vital for maintaining dairy herd health, optimizing resource utilization, and ensuring animal welfare. Timely detection of estrus is crucial for successful reproduction, leading to higher pregnancy rates, reduced calving difficulties, and improved overall herd health. This process is equally essential for milk production, as aligning breeding cycles correctly is directly linked to optimal milk output. In terms of financial implications, the economic impact of missed estrus detection is substantial, involving the loss of resources such as semen, labor, and time. Additionally, it can lead to decreased milk production, elevated veterinary costs, and extended calving intervals, negatively affecting farm profitability. Furthermore, the welfare of cows is at stake, as cows in estrus may experience discomfort and stress. Timely estrus detection and proper breeding can mitigate the risk of reproductive health issues, promoting better overall welfare and ensuring the health and productivity of the dairy herd.

2.1 Behavioral signs of estrus

Estrus behaviour is categorised into primary and secondary signs. The direct physical and behavioural changes that occur in cows throughout the estrus cycle are referred to as primary signs. Secondary signs, on the other hand, are deviations from the primary signs.

2.1.1. Primary sign of estrus

Among the previous studies, [2] stated that standing to be mounted was considered as the primary sign to show a cow is in estrus and AI considered it as a sexually receptive. However, the number of cows showing standing estrus decreased significantly due to the daily milk production. Reference [3] stated that approximately 50% of the cows in several earlier experiments stood to be mounted on the day of estrus. According to [4], the average estrus lasted 7.6 mounts per cow on average, lasting 4 seconds on average, and [5] noted that 8 to 9 hours on average, but it might last as little as 6 hours in some dairy herds [6].

2.1.2. Secondary sign of estrus

The secondary sign of estrus can be found in mounting behaviour, cow's activity, rumination time, agonistic interactions and social interactions.

Cow's mounting behaviour. During estrus, cows may mount other cows more frequently or may stand still and allow other cows to mount them. This behavior is an indication that the cow is ready to be bred and can be a helpful indicator for farmers and other workers in identifying the onset of estrus. According to [4], between 1 to 6 hours before and 3 hours after standing estrus, there was a discernible increase in the frequency of mounting. 80 percent of the cows exhibited mounting behaviour, with an average of 2.9 mounts per cow [7]. According to a recent study, increasing estrus lasted an average of 12.9 hours [4].

Moreover, *cow's activity*. Cows in estrus tend to be more active, often pacing back and forth or roaming around its environment more than usual. The cows may also be more vocal, calling out to other cows or responding to calls from bulls. Increased activity can be detected using sensors such as accelerometers or activity monitors, which are attached to the cow and measure movement and other indicators of activity [2]. By monitoring cow activity, farmers can identify when cows are in estrus and take appropriate action to breed them. Reference [8] stated that compared with the day before estrus, the time spent walking increased by 342% with a range from 21% to 913% on the estrus day for each cow, lasting from 8 hours before to 5 hours after the onset of estrus.

Other than that, *cow's rumination time.* During estrus, cows may have decreased rumination time, which refers to the amount of time spent chewing its cud. This is because cows in estrus are more focused on seeking out a mate and are therefore less interested in eating and ruminating. By monitoring rumination time using sensors such as rumination collars, farmers can identify changes in cow behavior that may be indicative of estrus. This can help to ensure that cows are bred at the optimal time for successful conception and pregnancy.

Furthermore, *cow's agonistic interactions*. Cows in estrus may be more aggressive towards other cows, especially those of the same sex, as competing for access to a bull. This aggression can manifest in behaviors such as head-butting, mounting, or blocking other cows from accessing food or water. Reference [2] shared that with an incidence of 73.4% the most frequent agonistic behavior was head-to-head butting. By monitoring for signs of aggression, farmers can identify when cows are in estrus and take appropriate action to breed them.

Lastly, *cow's social interactions.* During estrus, cows may be more interested in interacting with other cows, especially males, as seeking out a mate. This can manifest in behaviors such as vocalizations, sniffing, licking, and grooming [2]. Chin-resting and sniffing/licking represented 48.0% and 21.7%, respectively, of all sexual interactions on the day of estrus [8]. By monitoring social interactions using video cameras or other sensors, farmers can identify when cows are in estrus and take appropriate action to breed them.

2.2 Previous works on cow estrus detection system

Table 1 shows the summary of the previous works done by other researchers in improving the accuracy of cow estrus detection using different types of algorithms.

Table 1: Comparison framework from previous works on cow estrus detection

No.	Algorithm	Sensors Used	Accuracy in object (cattle) detection	Accuracy in estrus detection	F1-score	Limitations
1	Motion Detection, Region Segmentation, Foreground Segmentation, and Blob Analysis [9]	IP Dome Camera	-	100% (True Positive) 0.333% (False Positive)	-	Only at daytime, Indoor setup
2	R-CNN Localization, and Tracking [10]	UAV integrated camera	98.13%	-	-	Only at daytime, Not suitable for marker-less cattle
3	Motion Detection, Region Segmentation, Foreground Segmentation [11]	Infrared Camera	-	-	-	Shadow appearances

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4	Motion Analysis [12]	Pedometer and reader	-	91.86%	-	Indoor setup, Lack of cattle identification
5	BSCTF, SVM, Geometric and Optical Flow Feature extraction [13]	Fixed IP Camera	98.3%	90.9% (True Positive) 4.2% (False Positive)	-	Indoor setup, Lack of cattle identification
6	Faster R-CNN and SSD Localization and Tracking [1]	PTZ Camera	94% (SSD) 50% (FRCNN)	50% (True Positive) 50% (False Positive)	-	Indoor setup, Not suitable for marker-less cattle
7	YOLOv3 and RetinaNet [14]	Camera	99%	82%	-	Sensitivity of the new features to body part locations
8	YOLOv8n [15]	Camera	93.9%	93.50%	93.74%	Missed detection of tiny target

3. SYSTEM DEVELOPMENT

3.1 Prototype

The prototype of the proposed cow estrus detection system is shown in Figure 1. The webcam module is connected to the laptop using USB connecter cable to receive the power source from the laptop. The webcam module is mounted on tripod and being clipped to the farm's pole by using cable tie to achieve a suitable and stable position to capture the image of cows' activity.

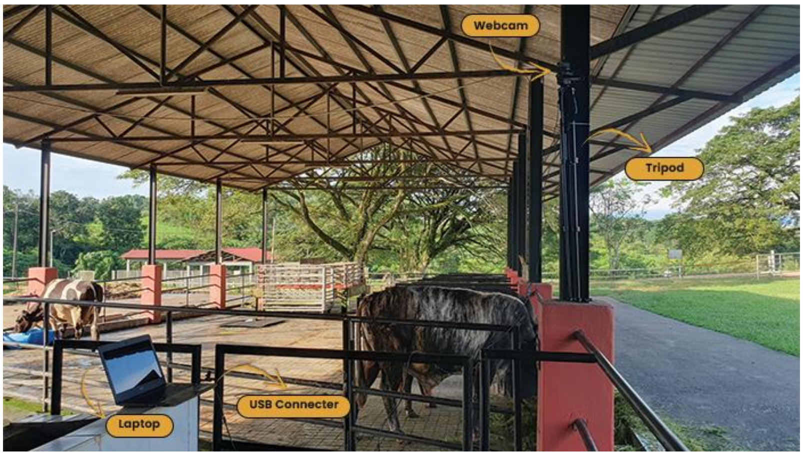

Fig. 1. Prototype of proposed cow estrus detection system

3.2 Dataset preparation

In preparing the dataset, the cows' dataset have been obtained manually in Research Farm, Universiti Putra Malaysia (UPM). A video of cows' activity is recorded for 20 minutes and converted into 3 frames per second for labelling process. Therefore, there are about 3600 images dataset. However, only 400 images are used for labelling process for time saving. The process of labelling the dataset are fully done by using Roboflow. All the 400 images are uploaded into Roboflow project and labelled into two classes which are *Estrus* indicated by yellow colour bounding box and *Normal* with green colour bounding box as depicted in Figure 4. For exporting the dataset for training purposes, all of the images are resized into 640 pixels x 640 pixels to reduce the time consuming in training process. Then, the dataset are exported into YOLOv8 format and trained using Google Colab with the GPU provided to improve the training time.

Fig. 2. Labelling cow images into two classes

3.3 System architecture

Referring Figure 3, the cow estrus detection system divided into four process state. Firstly, the webcam or camera work as an input that would capturing image of cows. Then, the images being processed by YOLOv8 model to extract the features from the image within the bounding box. After that, the extracted features being compared with the trained data in the database that consists of the estrus images and normal images. The system calculates the similarity or accuracy of the input image with the trained images. If the input image matched, the message "Estrus" being displayed in the monitor. Otherwise, the output "Normal" displayed that indicates there is no estrus events occurred.

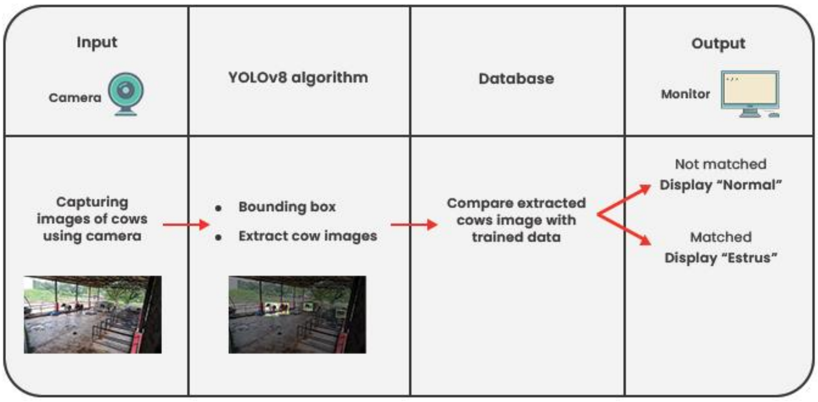

Fig. 3. Cow estrus detection system flowchart

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3.4 Workflow of the proposed cow estrus detection

Figure 4 illustrates the workflow of the proposed cow estrus detection system. The system initially begins with the loading the YOLOv8 trained model in the input section to perform image classification and object detection. If the camera is not turning on, the system will be terminated. Otherwise, the image frames will be processed by the camera and continues to visualize *Estrus* and *Normal* predictions and identify object overlapping inside the image frames. Then, if there is more than one detection (number of cows) in the data frames and it is overlapping, the message of *Estrus* and the image of estrus activity will be displayed as the output. Otherwise, the output message of *Normal* being displayed. The detection system also shows the accuracy percentage of cow detection in the output image of estrus activity and normal activity. The cycle of object detection continues to be performed with the visualize state process until it being shut down by the farmers.

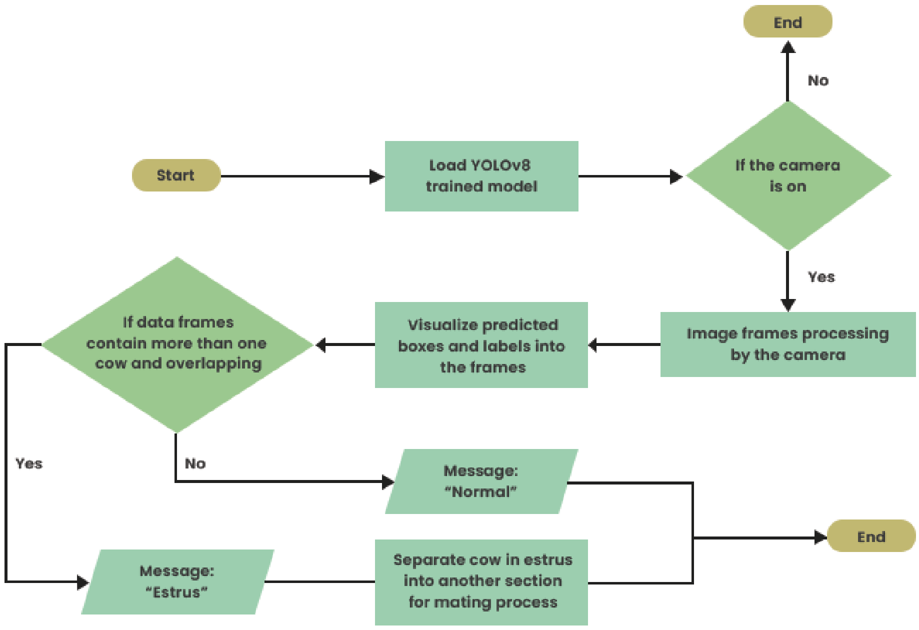

Fig. 4. Flowchart of the proposed system

3.5 YOLOv8 models training

Figure 5 depicts a Python code for YOLOv8 models training with 50 epochs and image size is set to 500 for all YOLOv8 variants due to the Graphic Processing Unit (GPU) provided by Google Colab cannot afford the training process for YOLOv8x above 500 image size. This YOLOv8x model training requires the bigger GPU size to run. Therefore, the image size was standardized to 500 to optimize the allocated GPU and 50 epochs to minimize the training time taken for each YOLOv8 model variants.

```
%cd {HOME}
!yolo task=detect mode=train model=yolov8n.pt data={dataset.location}/data.yaml
epochs=50 imgsz=500 plots=True
```

Fig. 5. Code snippet of training phase with 50 epochs and 500 image size

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4. RESULTS AND DISCUSSION

4.1 Training results

The training results for 50 epochs and 500 image size of YOLOv8 models are outlined in Table 2. Examining the training outcomes among YOLOv8 models reveals a consistent increase in the training time across the different variants. YOLOv8m is the benchmark between other YOLOv8 models since it is in the middle. Parameters in this table refers to the number of trainable parameters in the model, measured in millions. These parameters are the weights and biases associated with the neural network's layers. The YOLOv8 architecture consists of layers with numerous parameters that are adjusted during the training phase to optimize the model's performance in object detection. The number of parameters is a crucial factor in understanding the complexity and capacity of a neural network. Larger models with more parameters have a greater capacity to learn intricate patterns but can also require more computational resources and data for training. For example, YOLOv8x model has 68.1 million parameters that indicates that the model has 68.1 million trainable parameters. This parameter gives insights into the model's size and complexity, which can impact aspects like training time and resource requirements. Notably, the more complex models, YOLOv8l and YOLOv8x, demanded extended training durations which are 16.14 minutes and 21.90 minutes respectively, whereas YOLOv8n and YOLOv8s exhibited shorter training times which are 11.22 minutes and 11.76 minutes respectively. While enhance model complexity led to improved object detection precision with prolonged training, it is not the preferred choice for real-world implementations that mandate constraints on time and computational resources. Therefore, YOLOv8l and YOLOv8x is not suitable to be implemented in this cow estrus detection system due to the training time and YOLOv8s and YOLOv8m are among the best option because the balanced of precision and training time compared to YOLOv8n that has the shortest training time.

Table 2: Training results with 50 epochs and 500 image size

Model	Parameters (millions)	Training Time (minutes)	mAP50 (%)	mAP50-95 (%)
YOLOv8n	3.0	11.22	97.9	85.2
YOLOv8s	11.1	11.76	99.1	88.0
YOLOv8m	25.8	15.24	96.6	86.6
YOLOv8l	43.6	16.14	98.7	82.4
YOLOv8x	68.1	21.90	97.5	81.8

Figure 6 depicts a Python code for new YOLOv8 models training with 100 epochs and image size is set to 800 for YOLOv8s and YOLOv8m variants to experiment the relationship between increasing the image size and epochs would affect the accuracy of the models. The training results for these models are outlined in Table 3.

```
%cd {HOME}
!yolo task=detect mode=train model=yolov8s.pt data={dataset.location}/data.yaml
epochs=100 imgsz=800 plots=True
```

Fig. 6. Code snippet of training phase with 100 epochs and 800 image size

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In object detection models, mAP (mean Average Precision) serves as a pivotal metric to assess the precision of object detection. The term mAP50 refers specifically to the mean Average Precision calculated at an IoU threshold of 50%. This metric evaluates the accuracy of object detection by measuring the overlap between predicted bounding boxes and the ground truth bounding boxes. A higher mAP50 signifies improved accuracy when there is at least a 50% overlap. On the other hand, mAP50-95 is a more comprehensive metric that calculates the mean Average Precision across a range of IoU thresholds, specifically from 50% to 95%. This broader evaluation provides insights into the model's accuracy at different levels of bounding box overlap. Both mAP50 and mAP50-95 are valuable tools for understanding and quantifying the effectiveness of object detection models across diverse scenarios and IoU criteria. Observing the training outcomes in Table 3 between YOLOv8s and YOLOv8m models with 100 epochs and 800 for image size to experiment the relationship between increasing the image size and epochs would affect the mAP50 and mAP50-95 value of the models produced a positive result in both values although requires an increment of training time. Both YOLOv8s and YOLOv8m recorded 99.5% of mAP50 value that indicates the overlap precision. However, the mAP50-95 measured about 1.5% difference between these YOLOv8 models. Therefore, YOLOv8s is the best option model for the implementation of cow estrus detection due to its mAP50-95 value and shorter training time that would be the optimum for real-world application.

Table 3: Training results with 100 epochs and 800 image size

Model	**Parameters (millions)**	**Training Time (minutes)**	**mAP50 (%)**	**mAP50-95 (%)**
YOLOv8s	11.1	34.74	99.5	92.3
YOLOv8m	25.8	44.82	99.5	90.8

4.3 Evaluation of optimum model

The optimum model which is YOLOv8s model are tested and evaluated to observe other performance indicator in detecting cow estrus. The confusion matrix in Figure 7 illustrates the evaluation of this model trained to differentiate between *Estrus* and *Normal* classes.

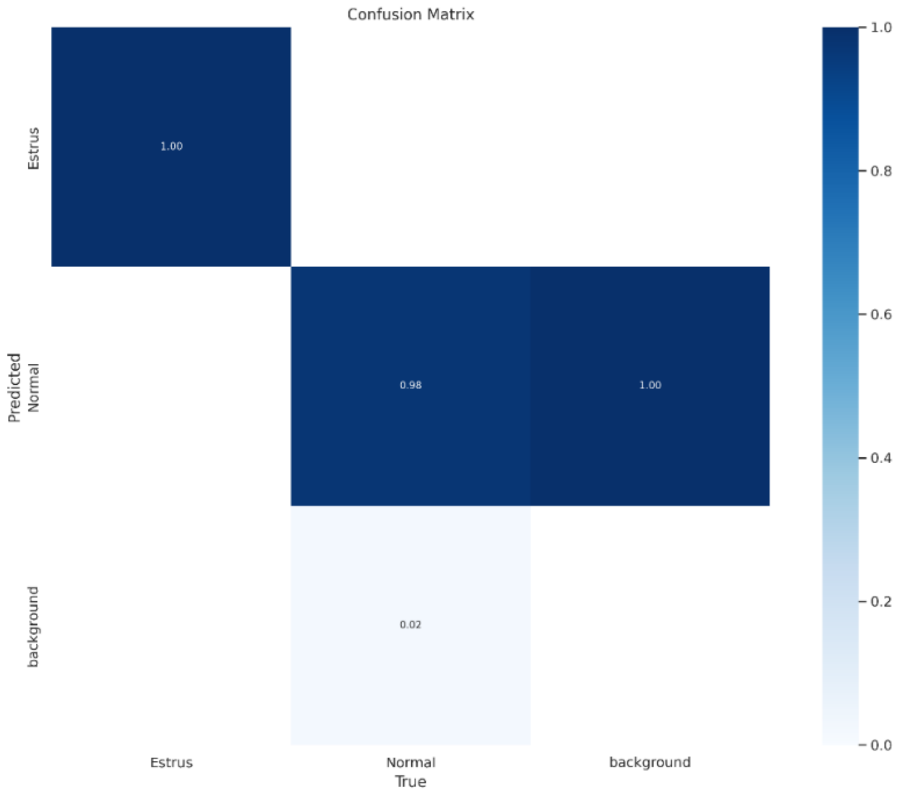

Fig. 7. Normalized confusion matrix for YOLOv8s

The evaluation of the YOLOv8s model, summarized in Table 4, provides valuable insights into its performance. The mAP50 score, which measures the accuracy of the model in detecting objects, is notably high at 99.1%. This indicates that the model demonstrates a strong ability to correctly identify objects in images with an impressive precision of around 99.1%. Moving on to precision, the model achieves a commendable score of 97.8%. This metric signifies that when the model predicts an object belongs to a specific category, it is accurate approximately 97.8% of the time. In simpler terms, the model is reliable and reduce the mistakes in misclassifying objects. The recall score, standing at 98.0%, reflects the model's capability to correctly identify about 98% of actual instances of a class within the dataset. This implies that the model is effective at minimizing false negatives, ensuring the model did not miss many objects present in the images. The fitness score, an amalgamation of precision, recall, and mAP, is calculated at 97.9%. This overall performance metric suggests that the YOLOv8s model maintains a balanced approach, excelling in both precision and recall, making it a robust choice for accurate object detection.

Table 4: Overall performance evaluation of YOLOv8s

Model	**mAP (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
YOLOv8s	99.1	97.8	98.0	97.9

Figure 8 illustrates the comprehensive training graph for YOLOv8s models, showcasing essential metrics and loss values. Within both the training (train) and validation (val) sets, three critical parameters denoted as *box_loss*, *cls_loss*, and *dfl_loss* are highlighted. Specifically,

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box_loss assesses the precision in predicting bounding box coordinates, while *cls_loss* quantifies the accuracy in predicting object classes, ensuring precise object categorization. Additionally, the specialized *dfl_loss* component contributes to enhanced object detection in scenarios involving defocused or blurry images. Moreover, the graph includes *metrics/mAP50(B)* and *metrics/mAP50-95(B)*, offering insights into the mAP with predictions evaluated as an *object detected* at an IoU thresholds. *metrics/precision(B)* evaluates the accuracy in predicting true positives, and *metrics/recall(B)* measures the correct prediction of true positives by the model. This detailed representation provides valuable insights into the YOLOv8s model's training performance.

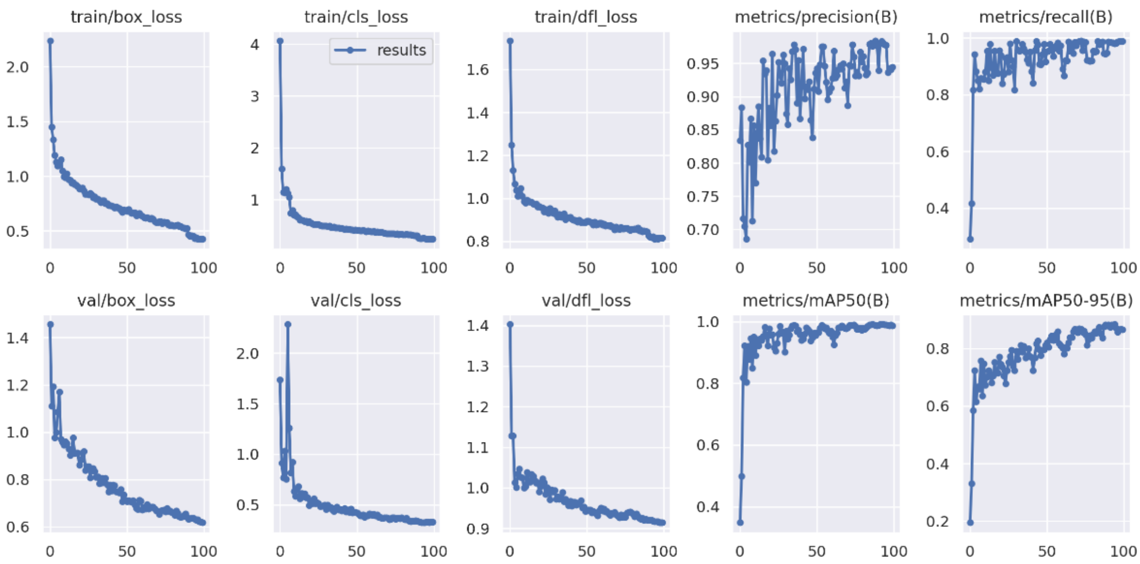

Fig. 8. Training graph for YOLOv8s

Fig. 9. Samples of cow estrus detection using YOLOv8s model

In Figure 9, there are samples of cow estrus detection results using YOLOv8s model that provides a visualization of real-world applications outcome to differentiate the cows either in normal or estrus state.

5. CONCLUSION

In conclusion, the objectives of this project are achieved successfully. This automated cow estrus detection system is equipped with advanced object detection YOLOv8s model algorithm and webcam utilisation managed to detect cow estrus precisely while monitoring the behavioural of cows during estrus and non-estrus periods for the efficiency of reproduction. The YOLOv8s model was recorded 99.1% of mAP value, 97.8% of precision, 98.0% of recall and 97.9% of f1-score that indicates this YOLOv8s model is the best option for real-world cow estrus detection applications. Moreover, this non-invasive cow estrus detection system would provide a comfortable environment for the cows.

6. FUTURE WORKS

This cow estrus detection project has several limitations and could be improved in future works. This cow estrus detection system is equipped with a webcam that struggle to detect the dark colour cows in a low light farm especially in a large farm area. By using a high specification camera that operate efficiently in low light would detect the cows precisely. Other than that, instead of monitoring the cows, this detection system could be improved by allows the camera to capture the cow estrus event in the local library or lock the bounding box of cow that is in estrus for the tracking purposes.

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