DEVELOPMENT OF COW ESTRUS DETECTION USING DEEP LEARNING ALGORITHMS

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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% of mAP, 97.8% of precision, 98.0% of recall and 97.9% of f1-score outperforms the previous works [27] of YOLOv8n by 3.9% of f1-score.

ACKNOWLEDGEMENTS

بسم الله الرحمن الرحيم

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

In the dynamic realm of dairy farming, optimizing breeding practices and ensuring reproductive success are paramount. However, the traditional methods for cow estrus detection, such as visual observation and hormone testing, have limitations and may not always be reliable [1]. Hence, a paradigm shift is imminent, necessitating the development of an automated cow estrus detection system driven by innovative deep learning algorithms and sensor-based monitoring.

Cow estrus detection is a critical task in dairy farming, as it enables farmers to identify the optimal time for breeding cows, thereby maximizing milk production and reproduction rates. Nowadays, lots of advanced technologies used deep learning algorithms due to its accuracy improvement and reduce human errors affected by the traditional methods. These algorithms can analyze large amounts of data collected from sensors on the cow such as accelerometers and temperature sensors, to accurately predict when a cow is in estrus [2]. Compared to traditional methods, the farmers are limited to identify the accurate time for a cow is in estrus due to limited data collected to be analysed. Also, the farmers will need a lot of manpower to detect the behaviour of the cows from time to time. This development of cow estrus detection using deep learning will give a huge help to the farmers to predict the optimal time for breeding cows accurately.

1.2 PROBLEM STATEMENT

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.

1.3 OBJECTIVE

The aim of this research project is to develop an automated system that accurately detects cow estrus based on behavioral and physiological indicators. These are the objectives of this study as summarized below:

i. To detect cow estrus precisely by using advanced object detection algorithm.

ii. To develop a non-invasive and automated cow estrus detector using deep learning algorithms that ensures the comfort of the cows.

1.4 METHODOLOGY

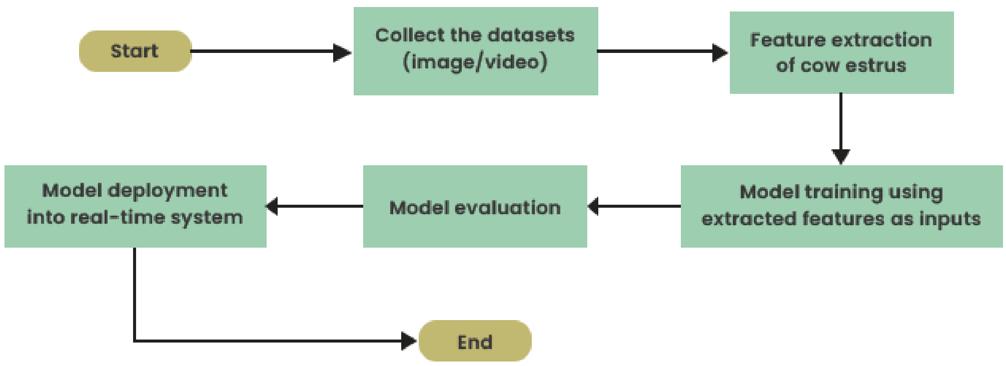

Fig. 1.1. Developing automated cow estrus detection system flowchart

In a way to develop a cow estrus detection system using deep learning algorithms, the most appropriate and suitable algorithms will be selected after reviewing on the previous studies that have been conducted. Next, the process will go through data collection by gathering a dataset of behavioral and physiological data of cows during estrus periods. Then, the pre-processing process will take place to remove any inconsistencies data and standardize the data to produce a uniform and accurate dataset. This data will be used to train the chosen deep learning models and being evaluated in terms of accuracy to determine the model's performance. This developed model will be implemented into a real-time cow estrus detection system to validate its usability in real-world conditions. All of the feedback will be collected to continuously monitor and improve the detection system.

1.5 SCOPE OF THE PROJECT

The scope of this project encompasses the development of a cow estrus detection system using deep learning algorithms. This is because, the aims is to create an automated cow estrus detection that accurately detects the onset of estrus in cows based on behavioral and physiological changes to improve the efficiency of cows' reproduction. The system will involve with several advanced technologies that become important to this world nowadays such as deep learning algorithms that is used to be trained by the dataset to monitor and detect any changes to the cow's behaviour from time to time. This is to improve the efficiency and effectiveness of cow estrus detection to become a reliable tool to the farmers.

1.6 REPORT ORGANIZATION

This study report is organized with the introduction of this research project in Chapter 1. This chapter includes the overall background, problem statement, objectives, methodology and also the scope of the project. Further discussion continues in Chapter 2 that describes the overview of previous research and studies related to cow estrus detection. Also, there are several methods and techniques employed in this study with their limitations are explained in this chapter. Moreover, the methodology of the selected method being covered in Chapter 3. Then, the results of the proposed method are analysed and discussed in Chapter 4. Lastly, the conclusion in Chapter 5 will recap of the project objectives and the summary of the key findings related to this research project with the further improvement in cow estrus detection system.

CHAPTER 2

LITERATURE REVIEW

2.1 OVERVIEW

This chapter highlights an overview of recent studies on the development of cow estrus detection using deep learning algorithms as well as its results, including their performance. All of those elements are incredibly significant as it will be evaluated to determine the technique that will be going to implement for this project. This topic starts with the introduction of cow estrus and the behaviours of the cow during the estrus process. Furthermore, the relationship between cow estrus with the Sustainable Development Goals (SDGs) also being discussed in this subchapter to show how important of cow estrus benefits the world. Then, the next subchapter introduces on cow estrus detector with the working concept to explain on how it is work in performing its responsibility to detect cow estrus and the brief of programming language that may be used in this system development. Other than that, this chapter also exposes the type of sensors that used in recent studies to detect cow estrus by using deep learning algorithms. Next, it proceeds with the representation of cow estrus datasets that have done by other researchers throughout this study to show the process of cow estrus cycle and things related to it. In addition, the deep learning algorithms that have been used also included in this chapter to provide better understanding on how to develop a cow estrus detector. Also, the previous works on this study will be shown in the next subchapter to analyze the current working concept and for the improvement of the detector becomes more efficient and precise. Lastly, a conclusion that covers the method and other details selection will be concluded in the last subchapter to show the best method that will be choose for this development of cow estrus detector using deep learning algorithms.

2.2 COW ESTRUS

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. As shown in **Figure 2.1**, 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 [2].

Fig. 2.1. Cows in estrus [3]

Cow estrus detection is important for maintaining the health and productivity of dairy herds, ensuring efficient use of resources, and promoting animal welfare. In terms of reproduction, detecting cow estrus is critical for successful reproduction and maintaining a healthy herd. Breeding cows at the right time during their estrus cycle can help ensure a higher rate of pregnancy, fewer calving difficulties, and fewer health issues. Then, it also important in milk production. Milk production is linked to the reproductive cycle of cows. If a cow is not bred at the right time, it can result in decreased milk production. In similar, it also vital in financial implications. The economic impact of not detecting estrus can be significant. Unsuccessful breeding attempts can result in the loss of valuable resources such as semen, labor, and time. It can also result in decreased milk production, increased veterinary costs, and longer calving intervals, all of which can have a negative impact on farm profitability. Not to forget is the animal welfare. Cows in estrus may experience discomfort and stress, which can have a negative impact on their overall health and welfare. Detecting estrus and breeding cows at the right time can help reduce the risk of reproductive health issues and promote better overall welfare.

Cow estrus detection can be related to several of the United Nations' Sustainable Development Goals (SDGs). Based on **Figure 2.2**, cow estrus detection related to Goal 2 (Zero Hunger), Goal 3 (Good Health and Well-being), Goal 8 (Decent Work and Economic Growth).

Fig. 2.2. Sustainable Development Goals (SDGs) [4]

Goal 2 which is "Zero Hunger" is the main SDG related to this research because cow estrus detection can help improve breeding programs and increase milk production, which can lead to greater food security and reduce hunger. Accurately detecting cow estrus can help farmers time breeding more effectively, which can result in increased pregnancy rates and ultimately more milk production. This increased milk production can help meet the growing demand for dairy products and contribute to food security by providing a reliable source of nutrition. In addition, cow estrus detection can help farmers optimize the use of their resources, such as feed and water, by reducing the number of non-pregnant cows on the farm. This can lead to more efficient production practices and reduce waste, which can contribute to greater food security by making food production more sustainable.

Next, the relation of cow estrus detection helps in achieving Goal 3 which is "Good Health and Well-being" by accurately detecting cow estrus can lead to better reproductive health for the cows, as well as increased milk production which can contribute to better nutrition and health outcomes for people. Also, by reducing the time and labor required for estrus detection, deep learning algorithms can help to improve the efficiency of dairy farming operations. This can lead to lower costs for farmers, which can help to make dairy products more affordable and accessible to consumers, thus contributing to better nutrition and overall health.

Deep learning algorithms for cow estrus detection can help the dairy farming industry accomplish Goal 8 (Decent Work and Economic Growth) by encouraging efficiency, decent work, and economic growth. First, it can help to increase the efficiency of dairy farming operations by lowering the time and labour necessary for estrus detection. This can result in cheaper expenses for farmers, which can help to boost rural economic growth. Moreover, by minimising the need for manual estrus detection, which may be time-consuming and physically taxing, the adoption of deep learning algorithms for cow estrus detection can assist to improve the working conditions of dairy farmers. This can contribute to the promotion of acceptable work and working conditions for farmers.

2.3 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.

2.3.1 PRIMARY SIGN OF ESTRUS

Among the previous studies, [5] 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. [6] stated that approximately 50% of the cows in several earlier experiments stood to be mounted on the day of estrus. According to [7], the average estrus lasted 7.6 mounts per cow on average, lasting 4 seconds on average, and [8] noted that 8 to 9 hours on average, but it might last as little as 6 hours in some dairy herds [9].

2.3.2 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 [7], 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 [10]. According to a recent study, increasing estrus lasted an average of 12.9 hours [7].

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 [5]. By monitoring cow activity, farmers can identify when cows are in estrus and take appropriate action to breed them. [11] said 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. [5] 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 [5]. Chin-resting and sniffing/licking represented 48.0% and 21.7%, respectively, of all sexual interactions on the day of estrus [11]. 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.

2.4 COW ESTRUS DETECTOR

A cow estrus detector device typically consists of a hardware component and a software component. The hardware component include sensors, such as accelerometers, microphones, or temperature sensors, that measure various physiological or behavioral parameters of the cow [5]. The software component involves a machine learning algorithm, such as a deep learning model, that analyses the data from the sensors and determines whether the cow is in estrus or not. Also, the importance of the camera in a cow estrus detection device that used to capture images or videos of the cow's behavior and activities, especially during the estrus period. These images or videos can then be analysed using computer vision algorithms to detect any changes or patterns that indicate estrus.

2.4.1 SENSOR

There are various sensors can be used in cow estrus detection, depending on the type of data that needs to be collected.

Refer to **Figure 2.3**, an activity sensor is a type of sensor that is used to measure the movement and activity level of an animal. In cow estrus detection, an activity sensor is typically attached to the cow's leg or neck, and it records the cow's movements and activity level over a period of time. These sensors are used to monitor changes in activity level, which can indicate when a cow is in estrus.

When a cow is in estrus, she typically exhibits increased activity levels, such as more walking, running, and jumping [5]. By monitoring changes in activity levels, farmers can detect when a cow is in estrus and can take appropriate action, such as artificial insemination, to increase the chances of successful fertilization.

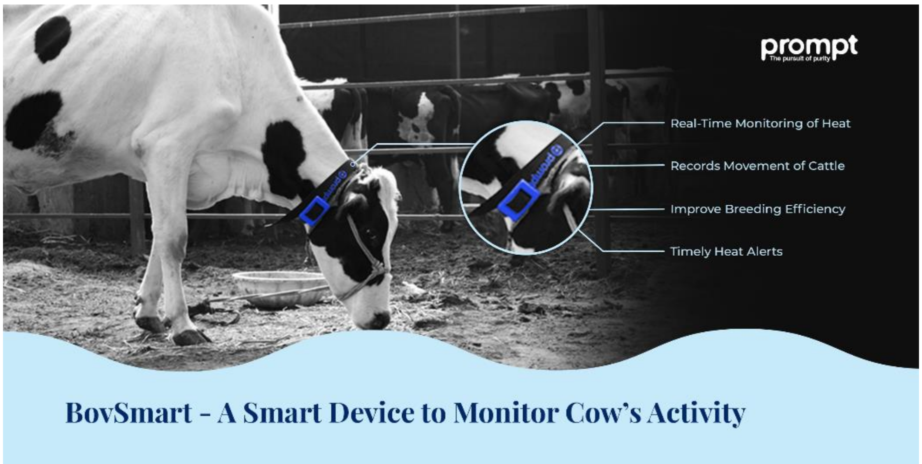

Fig. 2.3. Cow's activity sensor [12]

Next, a temperature sensor used to measure the temperature of the surrounding environment or an object. In cow estrus detection devices, a temperature sensor can be used to measure the body temperature of the cow, which can change during estrus. The sensor can be attached to its skin to measure its temperature [13]. The data collected by the sensor can be used to determine whether the cow is in estrus or not.

Also, sound sensors. Sound sensors can also be used for cow estrus detection. These sensors can detect the sounds produced by cows during estrus, such as mooing or bellowing. Sound sensors can be used as a complementary tool to other sensors, such as activity or temperature sensors, to increase the accuracy of estrus detection. Sound sensors can also be integrated into the cow estrus detection device to provide real-time alerts when a cow is in estrus [14].

Other than that, a pressure sensor can be used in cow estrus detection to measure the pressure distribution on the back of the cow while mounting. This information can be used to identify when a cow is mounted by another cow or bull, which is a primary sign of estrus. The pressure sensor can be incorporated into a cow estrus detection device to collect data on mounting behavior and determine the timing of estrus. The pressure sensor can be designed to be non-invasive and placed on the cow's back to ensure the comfort and safety of the animal.

Moreover, a vaginal mucus sensor is a type of sensor that detects changes in the composition and quantity of vaginal mucus in cows. During estrus, there is a significant increase in the production of mucus in the cow's reproductive tract, which can be detected by a sensor [14]. The sensor can detect the presence of certain proteins or enzymes that are present in the mucus during estrus. By measuring the changes in the composition and quantity of mucus, the sensor can help determine when a cow is in estrus and ready for breeding. This information can be used to optimize breeding efficiency and increase the chances of successful conception.

Lastly, an image sensor also may use in the detector to capture images of a scene or object. For cow estrus detection, image sensors are often used in combination with other sensors to detect changes in behavior and physical characteristics that are associated with the onset of estrus [5]. The images captured by the sensor can be processed using computer vision algorithms to detect these changes and provide an indication of when a cow is in estrus.

2.5 DEEP LEARNING ALGORITHMS

Deep learning algorithms are a type of machine learning algorithm that uses artificial neural networks to learn from data. They are ideal for image and speech recognition, natural language processing, and predictive modelling.

Deep learning algorithms can be trained on massive datasets of cow behaviour, physiological data, or sensor data to identify patterns suggestive of estrus in the context of cow estrus detection. A deep neural network, for example, may be trained on a dataset of cow photos or videos to recognise physical indicators of estrus, such as swelling vulva or increased vaginal discharge. Similarly, a deep neural network might be trained on a dataset of sensor data to recognise estrus-related patterns of activity, body temperature, or feeding behaviour.

Few types of deep learning algorithms that can be used for cow estrus detection, including Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Deep Belief Network (DBN).

Convolutional Neural Network (CNN) is an algorithm for deep learning that is widely used in image and video recognition. It is inspired by the human brain's visual processing capabilities and comprises of many layers of neurons that process input data. In **Figure 2.4**, a convolutional layer is often the first layer in a CNN, and it applies a collection of learnable filters to the input image to extract characteristics such as edges, shapes, and textures. To inject nonlinearity into the model, the output of the convolutional layer is then processed through a nonlinear activation function, such as a Rectified Linear Unit (ReLU) [15]. Subsequent layers in a CNN often include pooling layers, which down sample the input to lower its dimensionality, and additional convolutional and activation layers to extract features. A CNN's final layers are typically fully connected layers that combine the learned features to create a prediction. CNNs have demonstrated outstanding performance in a wide range of image and video recognition tasks, including object detection, facial recognition, and medical image analysis [16]. CNNs have also been used in cow estrus recognition, where it can be trained on photos or videos of cows to recognise primary and secondary indications of estrus automatically.

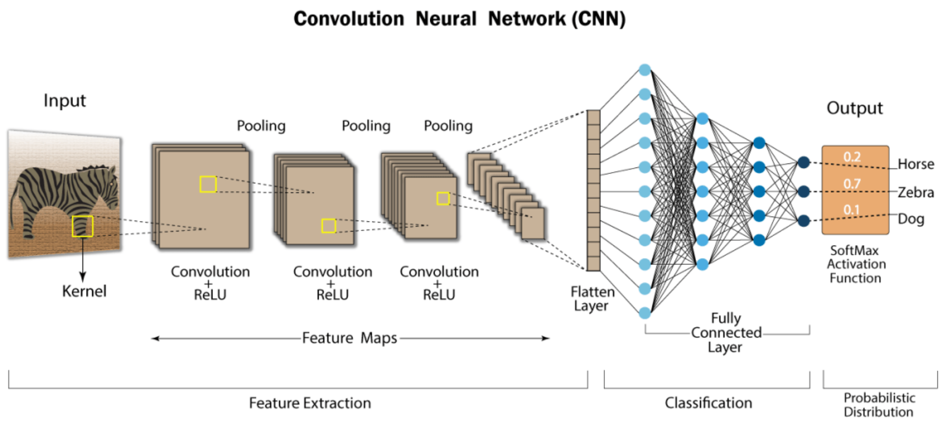

Fig. 2.4. Convolutional Neural Network (CNN) [15]

Next, Recurrent Neural Network (RNN) is a type of neural network that is specifically designed to process sequential data, such as time series data or natural language text. RNNs are capable of processing input sequences of variable length and can remember past inputs in order to inform the processing of future inputs. This is accomplished by introducing a hidden state variable that is updated at each time step based on the current input and the previous hidden state. Referring **Figure 2.5**, the basic structure of an RNN consists of an input layer, a hidden layer, and an output layer. The hidden layer is connected to itself, such that the output of the hidden layer at one time step serves as input to the same hidden layer at the next time step. This recursive connection allows the network to remember information from previous time steps and incorporate it into its processing of current inputs [17]. RNNs have been used for a variety of tasks, including language modeling, speech recognition, and time series prediction. In the context of cow estrus detection, an RNN could be used to process sequential sensor data from an accelerometer or other motion sensor in order to detect patterns indicative of estrus behavior.

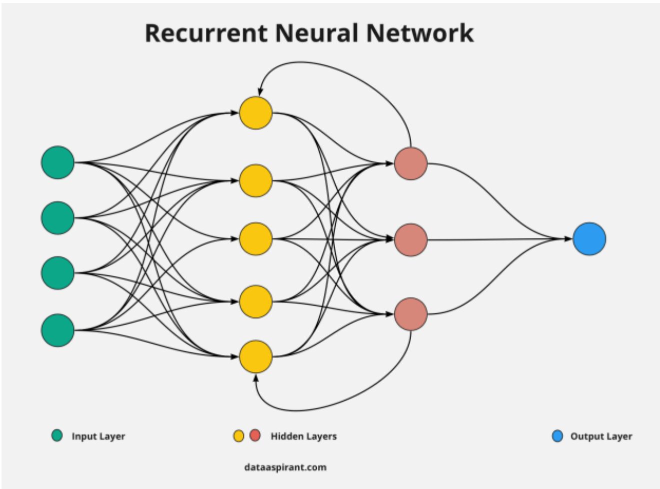

Fig. 2.5. Recurrent Neural Network (RNN) [18]

Deep Belief Network (DBN) is a class of artificial neural networks that are composed of multiple layers of probabilistic hidden units as in **Figure 2.6**. The layers of hidden units are trained in an unsupervised manner using the Restricted Boltzmann Machine (RBM) algorithm [19]. The RBM algorithm allows for the discovery of the underlying structure in the data by learning a set of features that are highly correlated with the input data. Once the features have been learned, the network can be fine-tuned using a supervised learning algorithm to classify the input data. DBNs have been successfully applied in a wide range of applications, including image and speech recognition, natural language processing, and financial modeling. DBN can be used in cow estrus detection by learning the patterns and features of cow behavior that are indicative of estrus. DBNs can process large amounts of data and identify complex patterns, making them well-suited for analysing and classifying cow behavior. For example, a DBN can be trained on data collected from sensors attached to cows, such as accelerometers and temperature sensors, to learn the patterns of activity and temperature changes that are associated with estrus. Once the DBN has learned these patterns, it can be used to classify new data and identify when a cow is in estrus. DBNs can be a powerful tool for automating cow estrus detection and improving reproductive management in dairy farms.

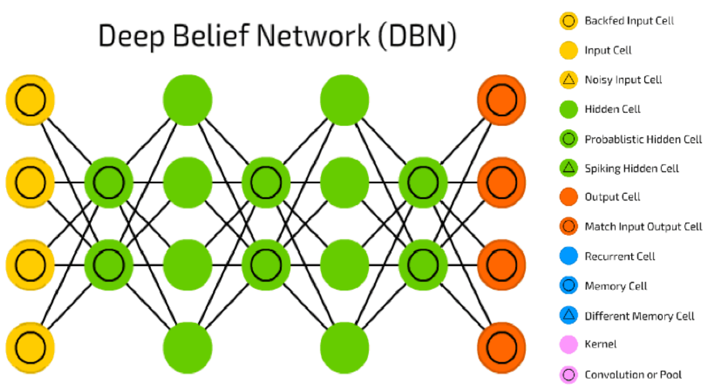

Fig. 2.6. Deep Belief Network (DBN) [20]

2.6 PREVIOUS WORKS

Table 2.1 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 2.1 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 [21]	IP Dome Camera	-	100% (TP) 0.333% (FP)		Only at daytime, Indoor setup
2.	R-CNN Localization, and Tracking [22]	UAV integrated camera	98.13%	-		Only at daytime, Not suitable for marker-less cattle
3.	Motion Detection, Region Segmentation, Foreground Segmentation [23]	Infrared Camera	-	-		Shadow appearances
4.	Motion Analysis [24]	Pedometer and reader	-	91.86%		Indoor setup Lack of cattle identification
5.	BSCTF, SVM, Geometric and Optical Flow Feature extraction [25]	Fixed IP Camera	98.3%	90.9% (TP) 4.2% (FP)		Indoor setup Lack of cattle identification
6.	Faster R-CNN and SSD Localization and Tracking [1]	PTZ Camera	94% (SSD) 50% (FRCNN)	50% (TP) 50% (FP)		Indoor setup, Not suitable for marker-less cattle
7.	YOLOv3 and RetinaNet [26]	Camera	99%	82%		Sensitivity of the new features to body part locations
8.	YOLOv8n [27]	Camera	93.9%	93.50%	93.74%	Missed detection of tiny target

2.7 SUMMARY

From previous studies, it was found that there are various primary and secondary signs that can help in detecting cow estrus. However, the most accurate and reliable way to detect estrus is through the use of advanced technologies such as deep learning algorithms. Based on the literature review, You Only Look Once version 8 (YOLOv8) that falls under CNNs algorithm would be selected for this cow estrus detection due to it is the latest version of YOLO and known for its real-time processing capabilities which make it faster than other deep learning algorithms.

CHAPTER 3

METHODOLOGY

3.1 OVERVIEW

This chapter will discuss the methodology of cow estrus detection using deep learning with the selected method which is YOLOv8 algorithm. This chapter begins with the explanation of the proposed system architecture and its workflow in cow estrus detection process step by step until the targeted result obtained.

3.2 YOLOv8 ALGORITHM ARCHITECTURE

In 2015, researchers Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi introduced the You Only Look Once (YOLO) object-detection algorithm, representing a groundbreaking advancement in real-time object detection [28]. This algorithm, which directly classifies objects in a single pass through a neural network, outperformed its precursor, the Region-based Convolutional Neural Network (R-CNN). YOLO operates as a single-shot algorithm by predicting both bounding boxes and class probabilities using the entire image as input. Over time, the YOLO family of models has continuously evolved, maintaining its prominence in the field.

The architecture comprises a backbone, neck, and head. The backbone, a pre-trained Convolutional Neural Network (CNN), extracts feature maps at different levels from the input image. The neck integrates these feature maps using path aggregation blocks like the Feature Pyramid Network (FPN) and passes them to the head, responsible for classifying objects and predicting bounding boxes. The head can employ either one-stage or dense prediction models, such as YOLO or Single-shot Detector (SSD), or choose two-stage or sparse prediction algorithms, exemplified by the R-CNN series. This adaptable architecture underscores the versatility and enduring significance of YOLO in the continually advancing field of object detection.

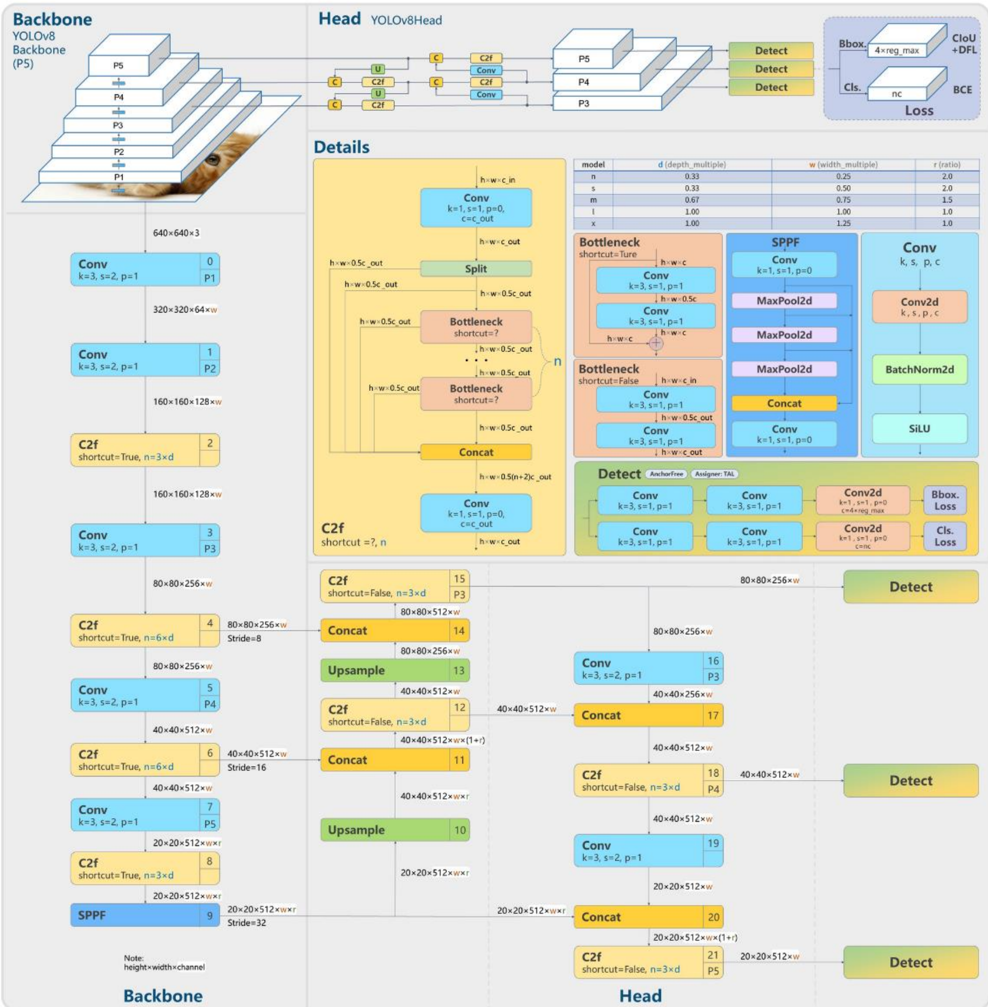

Fig 3.1. YOLOv8 architecture [28]

Released in January 2023, YOLOv8 marks the latest version of the YOLO series, offering five distinct variants denoted as nano (n), small (s), medium (m), large (l), and extra-large (x), each characterized by varying parameter counts.

YOLOv8 introduces several notable features, including mosaic data augmentation to enhance training diversity, anchor-free detection for improved accuracy, a C2f module for efficient contextual information capture, a decoupled head for more effective predictions, and a modified loss function to optimize model training. This version represents a significant step forward in object detection, leveraging innovations to address contemporary challenges in the realm of computer vision applications.

YOLOv8 incorporates mosaic data augmentation, a technique that blends four images to offer the model enhanced contextual information. Noteworthy in the YOLOv8 update is the cessation of augmentation in the final ten training epochs, a strategic move aimed at optimizing performance. Another pivotal shift is the adoption of anchor-free detection, a departure from the anchor-based approach utilized previously. The drawback of predefined anchor boxes, which hinder learning speed for custom datasets, is mitigated through anchor-free detection. Here, the model directly predicts an object's mid-point, thereby reducing the number of bounding box predictions and expediting the Non-max Suppression (NMS) pre-processing step that filters out inaccurate predictions. YOLOv8's revamped backbone now integrates a C2f module in lieu of a C3 module. This change involves concatenating the output of all bottleneck modules, which are comprised of bottleneck residual blocks that economize computational costs in deep learning networks, resulting in accelerated training and improved gradient flow. **Figure 3.1** illustrates a distinct approach where the head no longer concurrently handles classification and regression tasks. The decoupled head performs these tasks separately, potentially causing misalignment. To address this, a task alignment score is introduced based on positive and negative samples. This score, derived from the Intersection over Union (IoU) and classification scores, informs the model's selection of top-k positive samples, guiding the computation of classification and regression losses using Binary Cross-Entropy (BCE), Complete IoU (CIoU), and Distributional Focal Loss (DFL). The BCE loss gauges label prediction disparities, while CIoU considers the relative positioning of predicted and ground truth bounding boxes. Meanwhile, DFL optimizes the distribution of bounding box boundaries, prioritizing samples misclassified as false negatives.

3.3 SYSTEM PROTOTYPE

The prototype of the proposed cow estrus detection system is shown in **Figure 3.2**. 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.

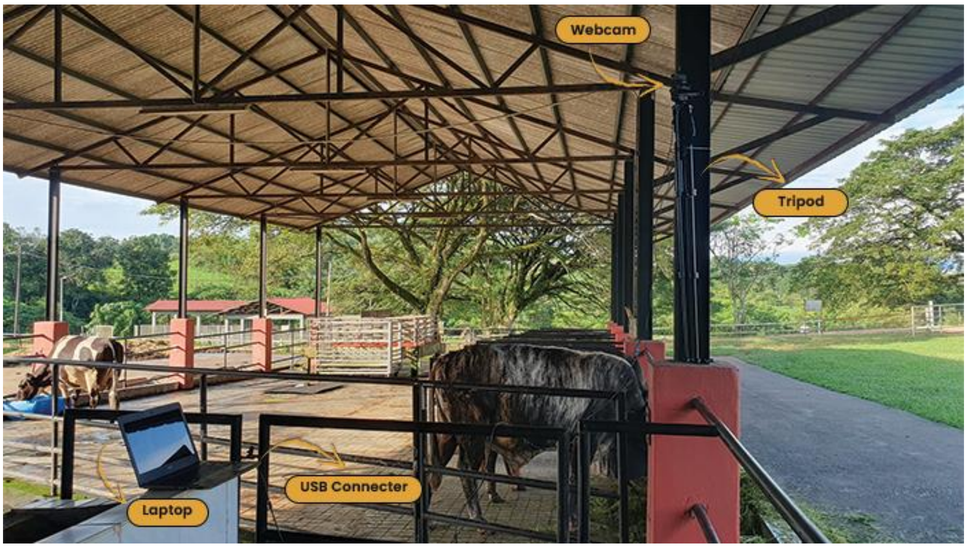

Fig. 3.2. Prototype of proposed cow estrus detection system

3.4 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 3.3**. 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. 3.3. Labelling cow images into two classes

3.5 SYSTEM ARCHITECTURE

Referring **Figure 3.4**, 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.

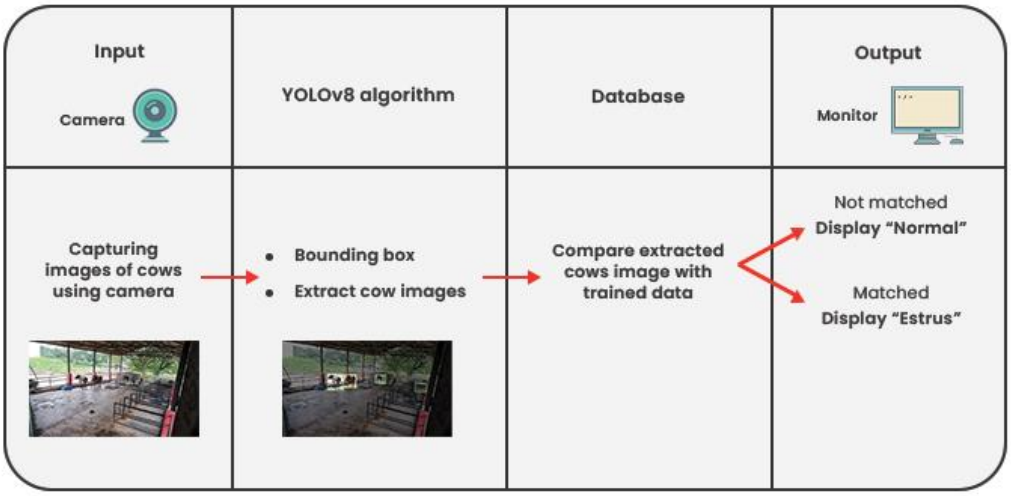

Fig. 3.4. Cow estrus detection system flowchart

3.6 WORKFLOW OF THE PROPOSED COW ESTRUS DETECTION

Figure 3.5 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. After *Estrus* has been displayed, the farmers separated the cow is in estrus into another section for the mating process.

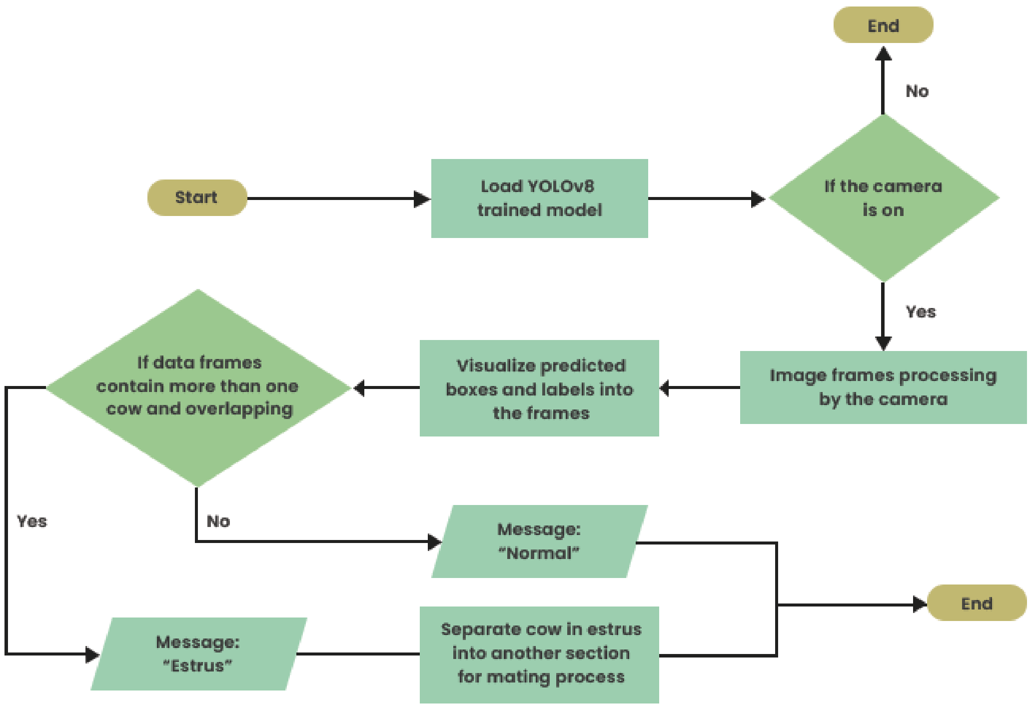

Fig. 3.5. Flowchart of the proposed system

3.7 YOLOv8 MODELS TRAINING

Figure 3.6 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. 3.6. Code snippet of training phase with 50 epochs and 500 image size

3.8 SUMMARY

In conclusion, the methodology of the cow estrus detection using YOLOv8 algorithm and its process flow have been explained in this chapter including the discussion of the proposed system prototype.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 OVERVIEW

In this section, we delve into the process of preparing the dataset, examine the training results using different YOLOv8 models, and assess the effectiveness of the cow estrus detection system by analysing the performance of the best-performing model.

4.2 TRAINING RESULTS

The training results for 50 epochs and 500 image size of YOLOv8 models are outlined in **Table 4.1**. 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 4.1. 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

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 4.2** 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 4.2. 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 4.1** illustrates the evaluation of this model trained to differentiate between *Estrus* and *Normal* classes.

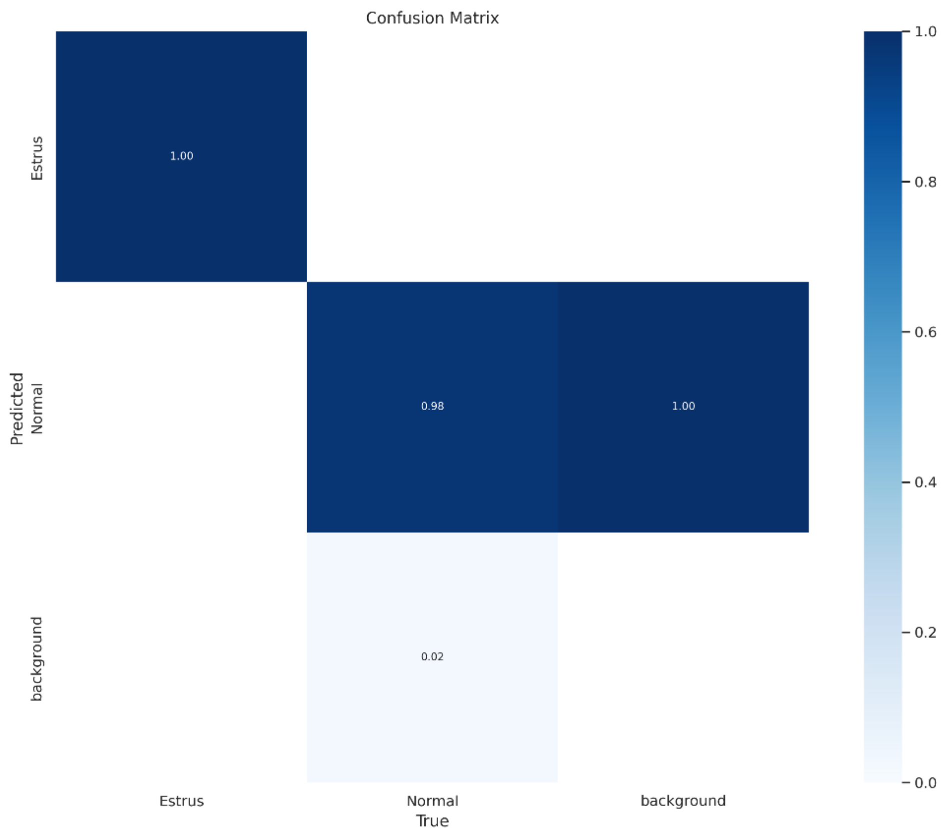

Fig. 4.1. Normalized confusion matrix for YOLOv8s

The evaluation of the YOLOv8s model, summarized in **Table 4.3**, 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 4.3. Overall performance evaluation of YOLOv8s

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

Figure 4.2 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, *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.

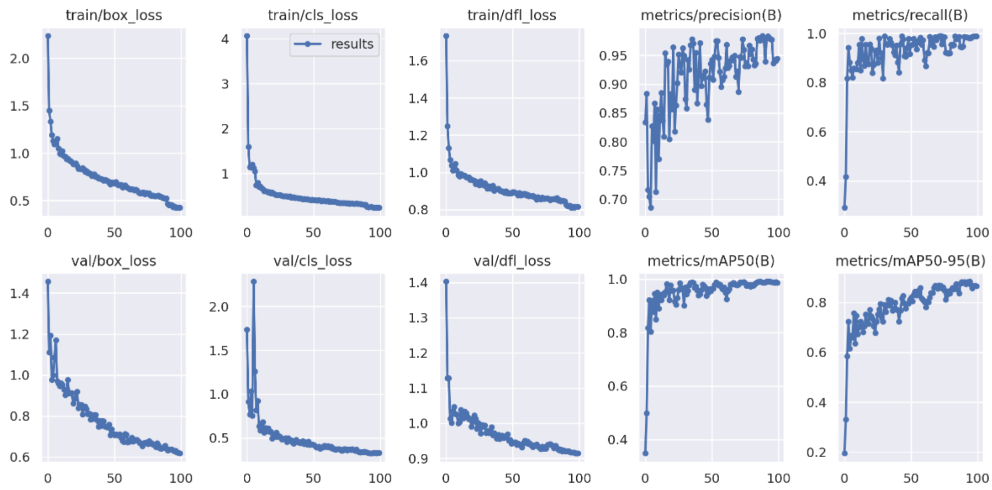

Fig. 4.2. Training graph for YOLOv8s

In **Figure 4.3**, 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.

Fig. 4.3. Samples of cow estrus detection using YOLOv8s model

4.4 SUMMARY

As a conclusion, the YOLOv8s model's performance is marked by a prominent level of accuracy and precision in object detection tasks. Its versatility in handling challenging scenarios and robust performance across various evaluation metrics make it a reliable choice for real-world applications that demand accurate and efficient object detection capabilities. Notably, this YOLOv8s model outperforms previous work [27] that used YOLOv8n by 3.9% in F1-score.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 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 performance of this proposed method was evaluated under a series of tests. 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.

5.2 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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