

# BEHAVIOR RECOGNITION FOR ESTRUS MONITORING IN CATTLE COWS



# INTRODUCTION

- Estrus detection is essential for cattle breeding efficiency and farm productivity.
- Traditional observation is manual, time-consuming and inaccurate.
- Computer vision and deep learning can automate monitoring using video data.



# PROJECT OBJECTIVE



## OBJECTIVES

- Develop a model to classify cow behaviors (standing, lying, grazing & mounting) using video.
- Support estrus detection through automated behavior recognition,



# PROJECT SCOPE



## SCOPE

- Hardware: CCTV Camera, WiFi Access point (For now open-source dataset)
- Software: YOLO models, image processing & machine learning
- Output: Behavior recognition & visualization annotated data

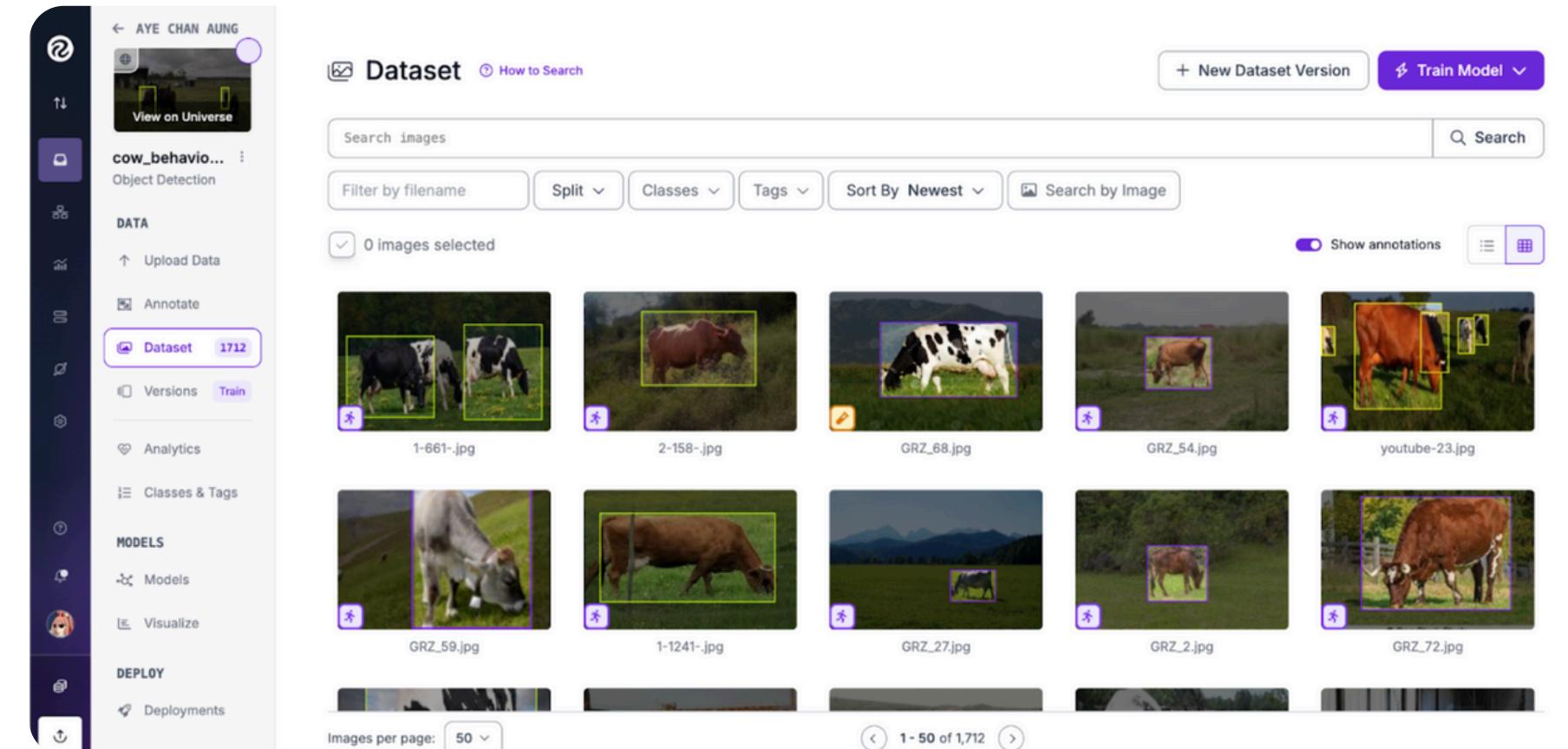
## METHODOLOGY

This project focuses on building a cow posture object detection baseline.

The system takes images or video frames as input and outputs bounding boxes with one of four posture labels: grazing, lying, mounting, standing.

The workflow consists of five main stages:

1. Data collection from public sources
2. Annotation and dataset construction in Roboflow
3. Image preprocessing and augmentation
4. Model training with YOLOv8 and YOLOv11
5. Quantitative evaluation on a held-out test set
6. Qualitative testing on real farm CCTV footage

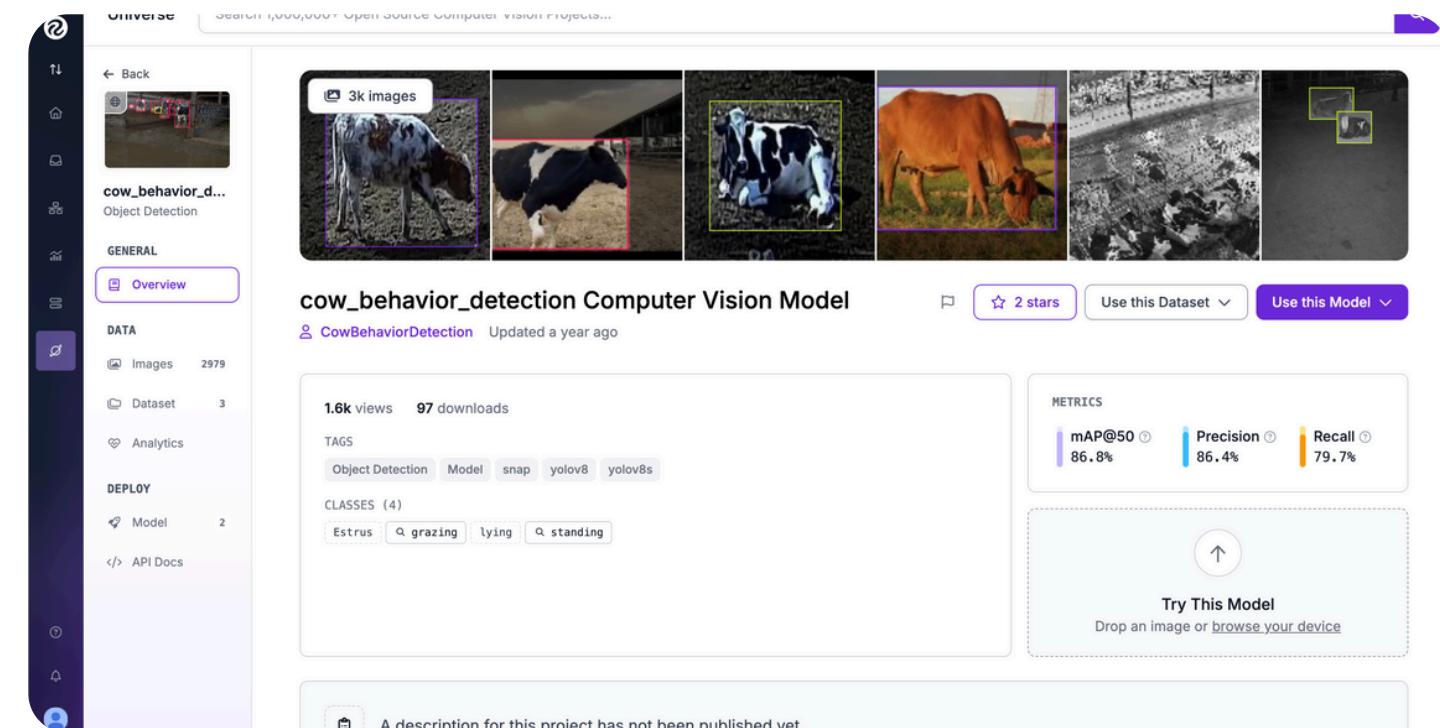


## DATA COLLECTION

Images were obtained from two public sources:

- Roboflow Universe project – “Cow\_Behavior\_Detection”
- Web-scraped images using keywords such as “cow”, “cattle”, “cow farm”, “grazing cattle”, “lying cow”, and “mounting cow”

Only images where cows were clearly visible and posture was recognizable were kept. Duplicates, very low-resolution, heavily blurred, or extremely dark images were discarded. All selected images were uploaded into a single Roboflow project.



```
 1 google_images_download import google_images_download
 2 response = google_images_download.googleimagesdownload()
 3
 4 word = "cow_mounting"
 5
 6 # Set the number of images you want to download
 7 it = 50
 8
 9
10 # Arguments
11 arguments = {
12     "keywords": keyword,
13     "limit": limit,
14     "print_urls": True, # Display the URLs being downloaded
15     "output_directory": "downloaded_images", # Name of the main folder
16     "image_directory": keyword # Name of the sub-folder inside the main folder
17 }
18
19 # Start the download
20 print(f"Starting download of {limit} images for keyword: '{keyword}'...")
21
22 try:
23     paths = response.download(arguments)
24     print("\n--- Download Complete ---")
25     print(f"Images saved to the folder: {arguments['output_directory']}/{keyword}")
26     # print(paths) # Uncomment to see the full path dictionary
27 except Exception as e:
28     print(f"An error occurred during download. This is often due to changes in the search engine's website structure.")
29     print(f"Error details: {e}")
30
31 print(f"\nDownload of {it} images for keyword: '{word}'...")
```

## ANNOTATION AND DATASET CONSTRUCTION

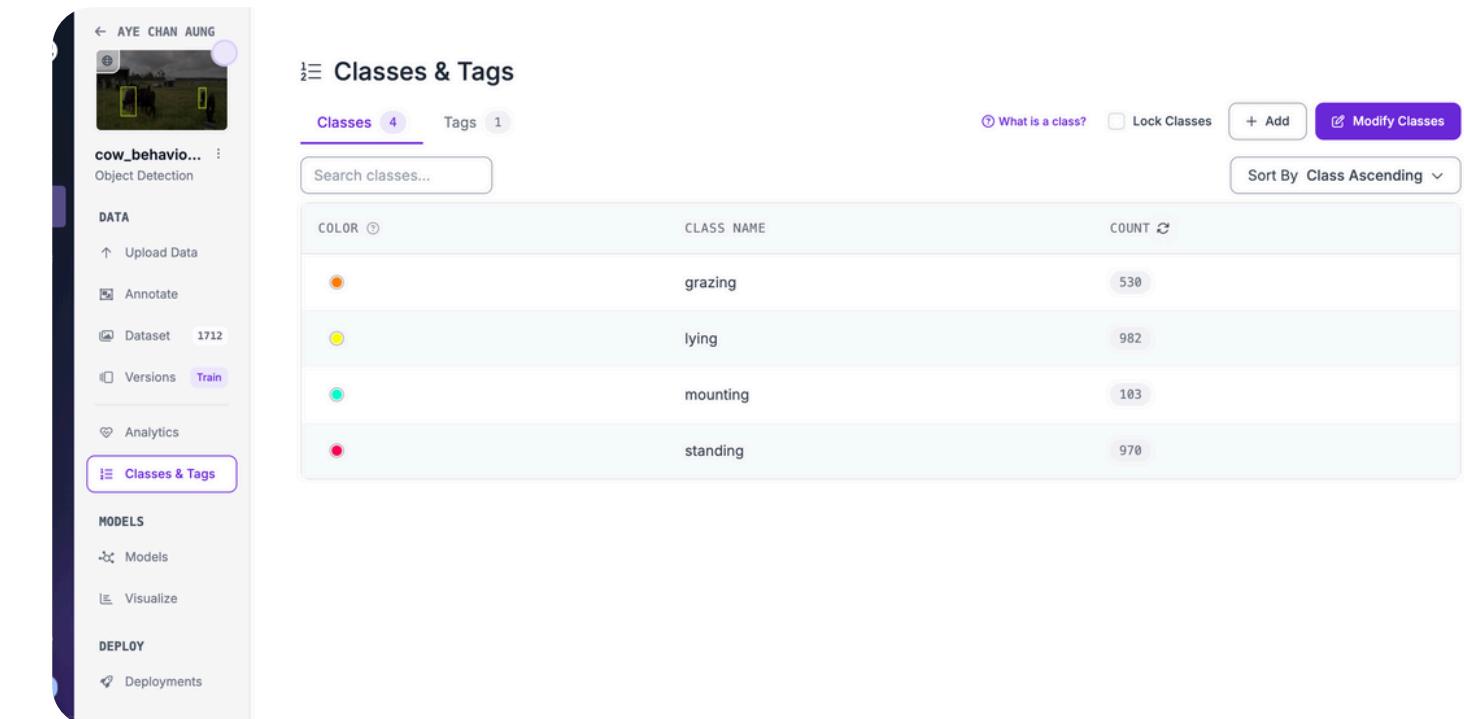
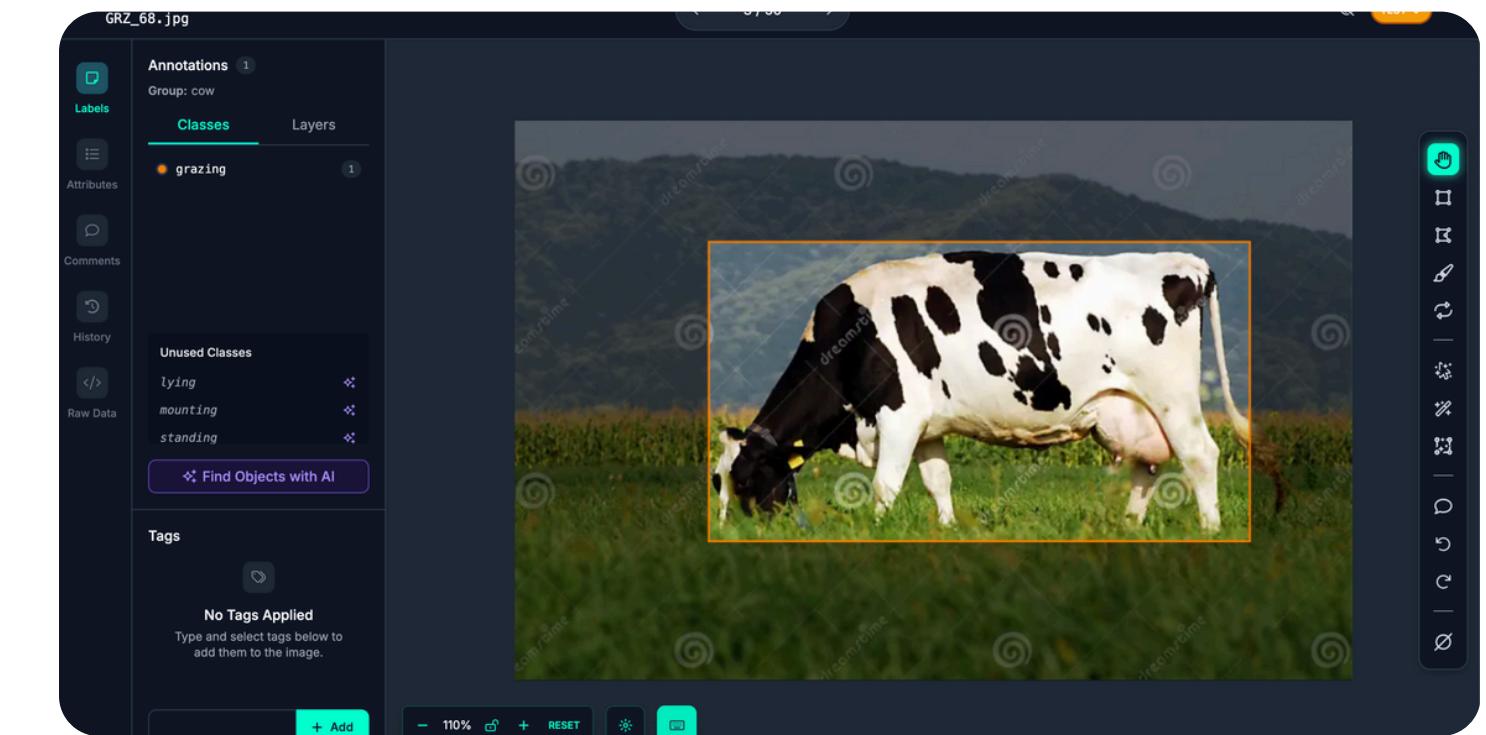
Annotation was done in Roboflow using bounding boxes. Four posture classes were defined:

- grazing
- lying
- mounting
- standing

Every visible cow was annotated with one of these classes. The final dataset contains 1712 images with 530 grazing, 982 lying, 103 mounting, and 970 standing instances, revealing a strong class imbalance for mounting.

Roboflow exported the dataset in YOLO format (TXT labels + images). The data were randomly split into:

- 70% training set
- 15% validation set
- 15% test set



## IMAGE PREPROCESSING AND AUGMENTATION

Before training, YOLO's built-in preprocessing pipeline is applied:

- Images are resized and letterboxed to  $640 \times 640$  pixels (`imgsz = 640`).
- Pixel values are normalized to the range  $[0, 1]$  and arranged in 3-channel RGB.

During training we use extensive data augmentation to increase robustness and help control overfitting.

The main augmentation parameters are:

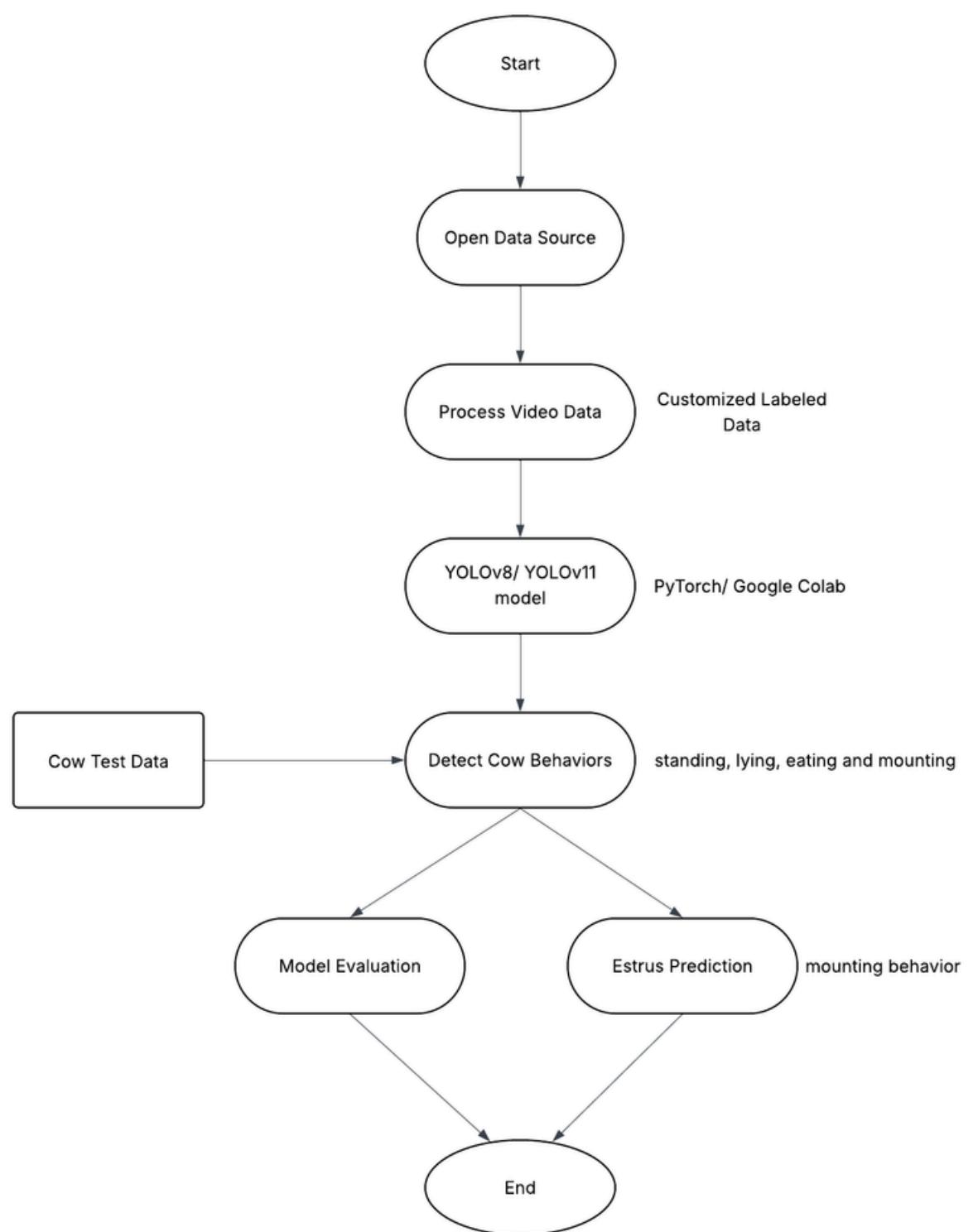
- Color jitter (HSV space):
  - `hsv_h = 0.015, hsv_s = 0.7, hsv_v = 0.4`
- Geometric transforms:
  - `translate = 0.1` ( $\pm 10\%$  translation)
  - `scale = 0.6` (scaling factor range)
  - `degrees = 0.0, shear = 0.0, perspective = 0.0` (no rotation/shear in this setup)
- Flips:
  - vertical flip disabled: `flipud = 0.0`
  - horizontal flip enabled: `fliplr = 0.5`
- Advanced augmentations:
  - `mosaic = 1.0`
  - `mixup = 0.1`
  - `copy_paste = 0.0`

## OVERALL RESULTS OF OBJECT DETECTION MODELS (TEST SET)

| Model    | Params (M) | Inference (ms/img) | ~FPS         | Training time (h) |
|----------|------------|--------------------|--------------|-------------------|
| YOLOv8s  | 11.1       | 4.4                | 227.3        | 0.359             |
| YOLOv8n  | 3          | <b>2.1</b>         | <b>476.2</b> | 0.332             |
| YOLOv11n | 2.6        | 3.2                | 312.5        | 0.347             |
| YOLOv8m  | 25.8       | 10.3               | 97.1         | 0.64              |
| YOLOv11s | 9.4        | 4.8                | 208.3        | 0.384             |
| YOLOv8l  | 43.6       | 15.4               | 64.9         | 1.043             |
| YOLOv11m | 20         | 10.5               | 95.2         | 0.639             |
| YOLOv11l | 25.3       | 13.5               | 74.1         | 1.019             |
| RTDETR-M | 32         | 16.3               | 61.3         | 2.079             |

Key point: YOLOv8s gives best accuracy, YOLOv8n is slightly less accurate but faster → both good candidates for real-time use.

# SYSTEM FLOW (DIAGRAM)



System workflow from data collection to estrus prediction

# TECHNOLOGY USED



## Technologies

- YOLOv8/ YOLOv11 model - behavior detection
- Google Colab
- OpenCV + Pytorch - video processing & prediction

# MODELS AND TRAINING

## MODELS: YOLOV8 & YOLOV11

- YOLOv8 and YOLOv11 → modern single-stage detectors with Ultralytics API. Cow Posture Detection in Cattle...
- Model scales: n, s, m, l
- n = nano (fastest, smallest)
- s = small (good balance)
- m, l = medium & large (higher capacity)
- YOLOv11 adds:
- Improved C3k2 blocks, attention mechanisms
- Refined SPPF-like module for better accuracy–efficiency

## TRAINING ENVIRONMENT & INTEGRATION

- Initial training on Google Colab with NVIDIA Tesla T4 GPU.
- Later training & testing on local machine + VS Code, using Ultralytics YOLO API. Cow Posture Detection in Cattle...
- Best-performing models saved as .pt:
- Easy to deploy later on web service / edge device.
- Current prototype:
- Offline Python script: read images/videos → output bounding boxes + posture labels.

## TRAINING HYPERPARAMETERS

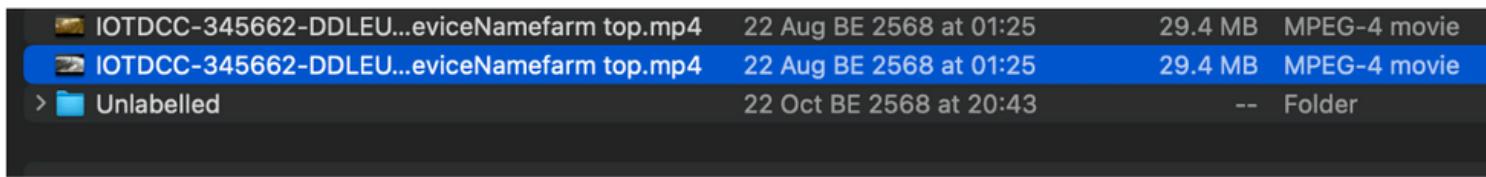
- Common settings for all YOLOv8/YOLOv11 variants (fair comparison): Cow Posture Detection in Cattle...
- Epochs: 50
- Batch size: 16, imgsz: 640
- Optimizer: SGD-like defaults
- lr0 = 0.001, lrf = 0.01
- Momentum = 0.937, Weight decay = 0.0005
- Warmup: 3 epochs, warmup momentum 0.8
- Early stopping with patience = 20 to reduce overfitting.

## DATA AUGMENTATION

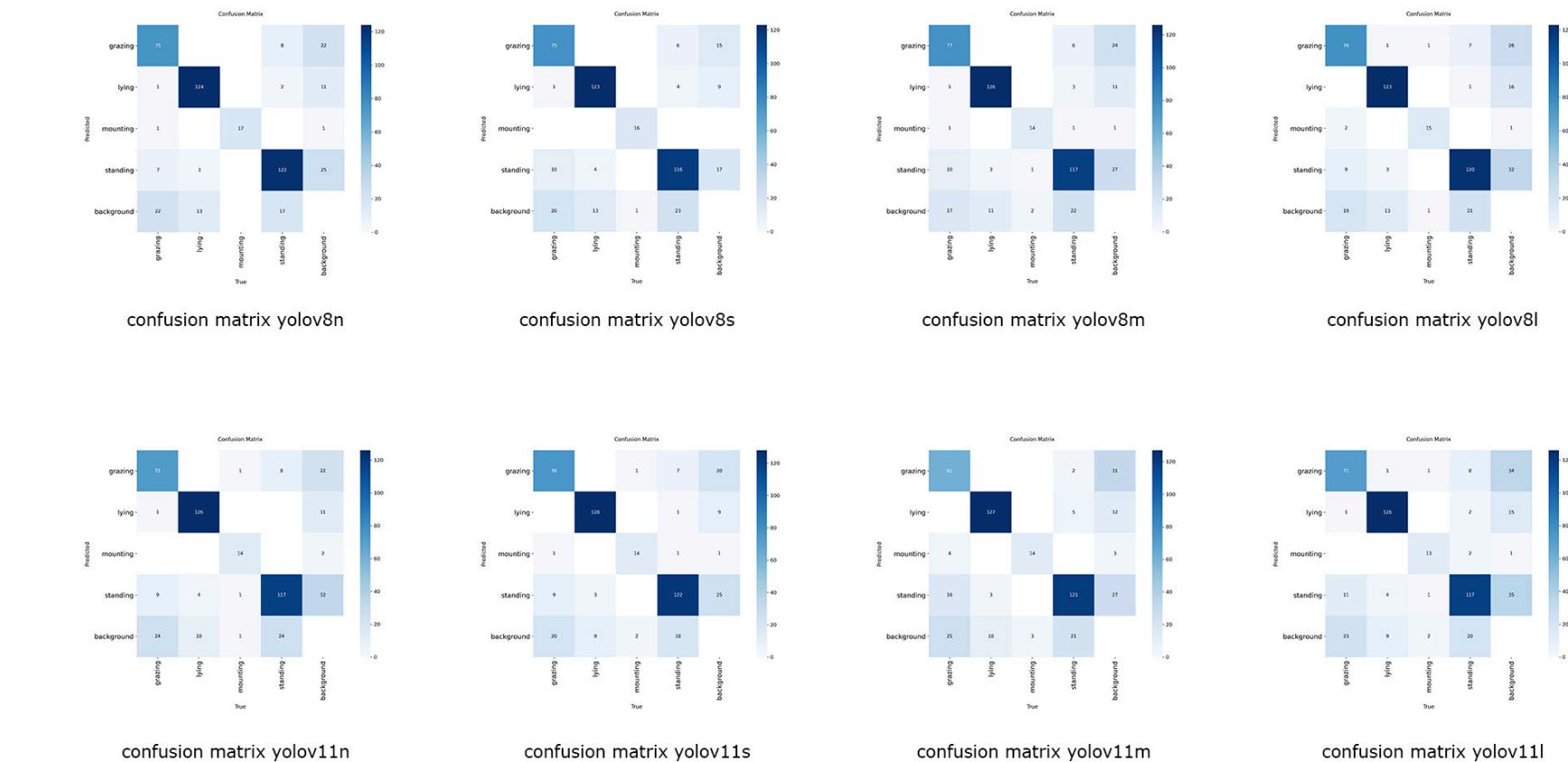
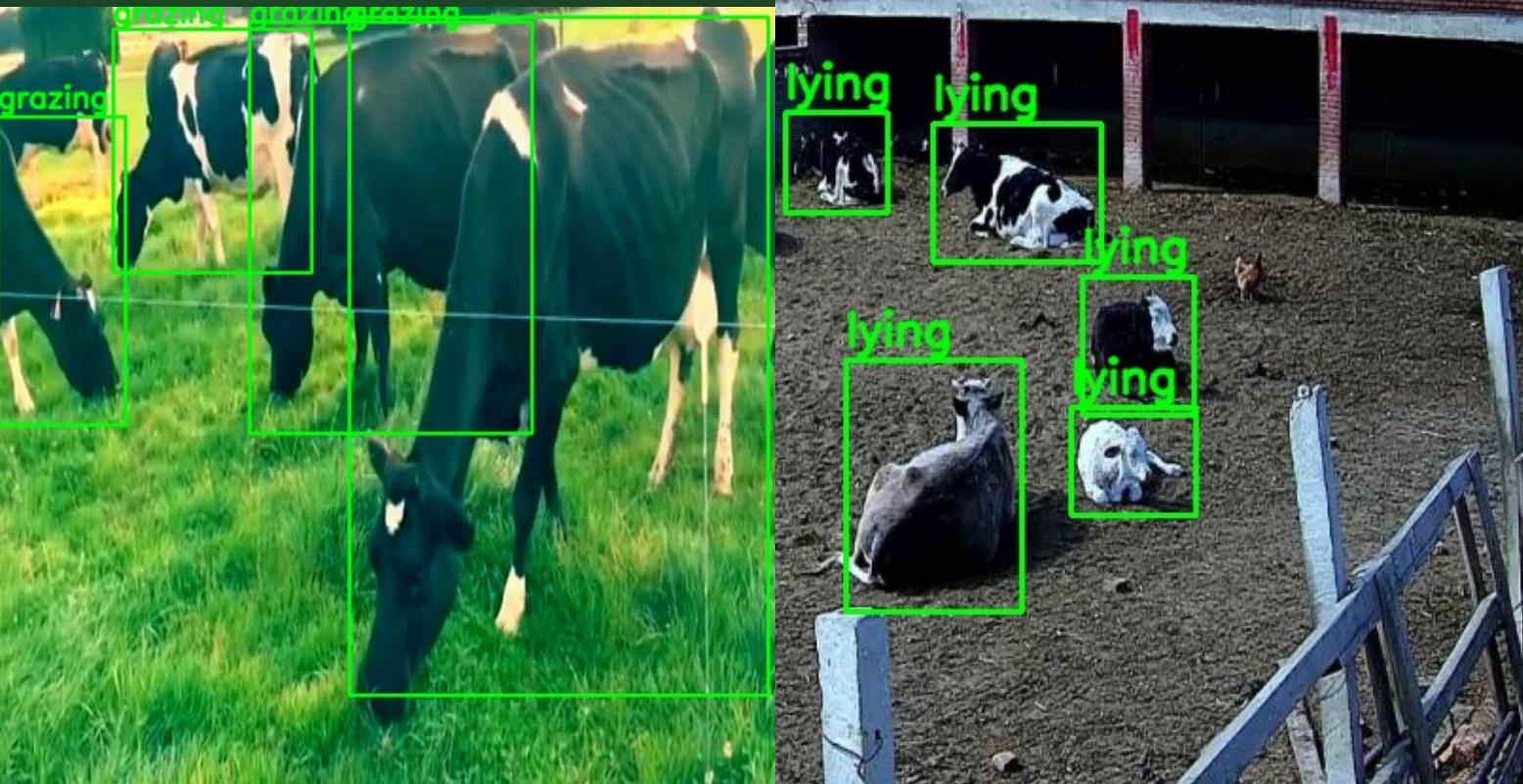
- Applied inside Ultralytics training pipeline: Cow Posture Detection in Cattle...
- HSV: h = 0.015, s = 0.7, v = 0.4
- Transform: translate = 0.1, scale = 0.6
- Flips: horizontal = 0.5
- Mosaic = 1.0, MixUp = 0.1
- Purpose:
- Increase robustness to lighting, background clutter, camera distance/orientation
- Reduce overfitting on relatively small dataset.

# EXPERIMENT SETUP

Example test using actual farm CCTV  
footage and YOLO detection model



- Strong diagonal for standing & lying → consistently correct.
- Grazing sometimes misclassified as background under tall grass.
- Mounting occasionally confused with standing/grazing under occlusion.



# CONFUSION MATRIX & SAMPLE OUTPUTS

# PER-CLASS PERFORMANCE – TOP 3 MODELS

**YOLOv8s (best overall mAP)**

| Class          | Precision | Recall       | AP@50        | AP@50–95     |
|----------------|-----------|--------------|--------------|--------------|
| <b>Overall</b> | 0.877     | 0.834        | 0.888        | 0.675        |
| grazing        | 0.801     | 0.698        | 0.792        | 0.491        |
| lying          | 0.909     | 0.886        | 0.922        | 0.761        |
| mounting       | <b>1</b>  | <b>0.985</b> | <b>0.995</b> | <b>0.808</b> |
| standing       | 0.797     | 0.766        | 0.845        | 0.641        |

**YOLOv8n (fastest, strong standing/mounting)**

| Class          | Precision | Recall       | AP@50 | AP@50–95    |
|----------------|-----------|--------------|-------|-------------|
| <b>Overall</b> | 0.873     | 0.824        | 0.866 | 0.667       |
| grazing        | 0.809     | 0.689        | 0.755 | 0.479       |
| lying          | 0.925     | 0.876        | 0.925 | 0.729       |
| mounting       | 0.903     | <b>0.941</b> | 0.931 | 0.802       |
| standing       | 0.855     | 0.792        | 0.851 | <b>0.66</b> |

**YOLOv11s (best for grazing & lying)**

| Class          | Precision    | Recall       | AP@50        | AP@50–95     |
|----------------|--------------|--------------|--------------|--------------|
| <b>Overall</b> | 0.835        | 0.802        | 0.849        | 0.65         |
| grazing        | <b>0.801</b> | 0.685        | 0.777        | <b>0.503</b> |
| lying          | <b>0.948</b> | <b>0.913</b> | <b>0.946</b> | <b>0.772</b> |
| mounting       | 0.792        | 0.824        | 0.818        | 0.668        |
| standing       | 0.799        | 0.785        | 0.856        | 0.658        |

# CHALLENGES: OVERFITTING & UNDERFITTING

## ISSUES FOUND WHEN TESTING ON REAL FARM CCTV:

- Differences from open-source images:
  - Lighting changes, occlusions, motion blur, varying camera angles
- Overfitting:
  - Good performance on training data, degraded on real farm videos
- Underfitting:
  - Model fails to learn some behaviors robustly

## MITIGATION STRATEGIES

- Collect more real farm data in Northern Thailand
- Stronger augmentation (brightness, blur, rotation, scaling)
- Early stopping, regularization (L2, dropout)
- Adjust model size, learning rate, and epochs
- Integrate pose-based learning (DeepLabCut, etc.)



# CONCLUSION

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- Built a reproducible posture detection baseline using YOLOv8 & YOLOv11. Cow Posture Detection in Cattle...
- Achieved strong performance:
- mAP@50 up to 0.888 (YOLOv8s)
- ≈ 93% foreground micro accuracy
- Demonstrated that compact YOLO models can be used as:
- First step toward camera-only estrus monitoring
- Foundation for future behavior analytics and health anomaly detection.



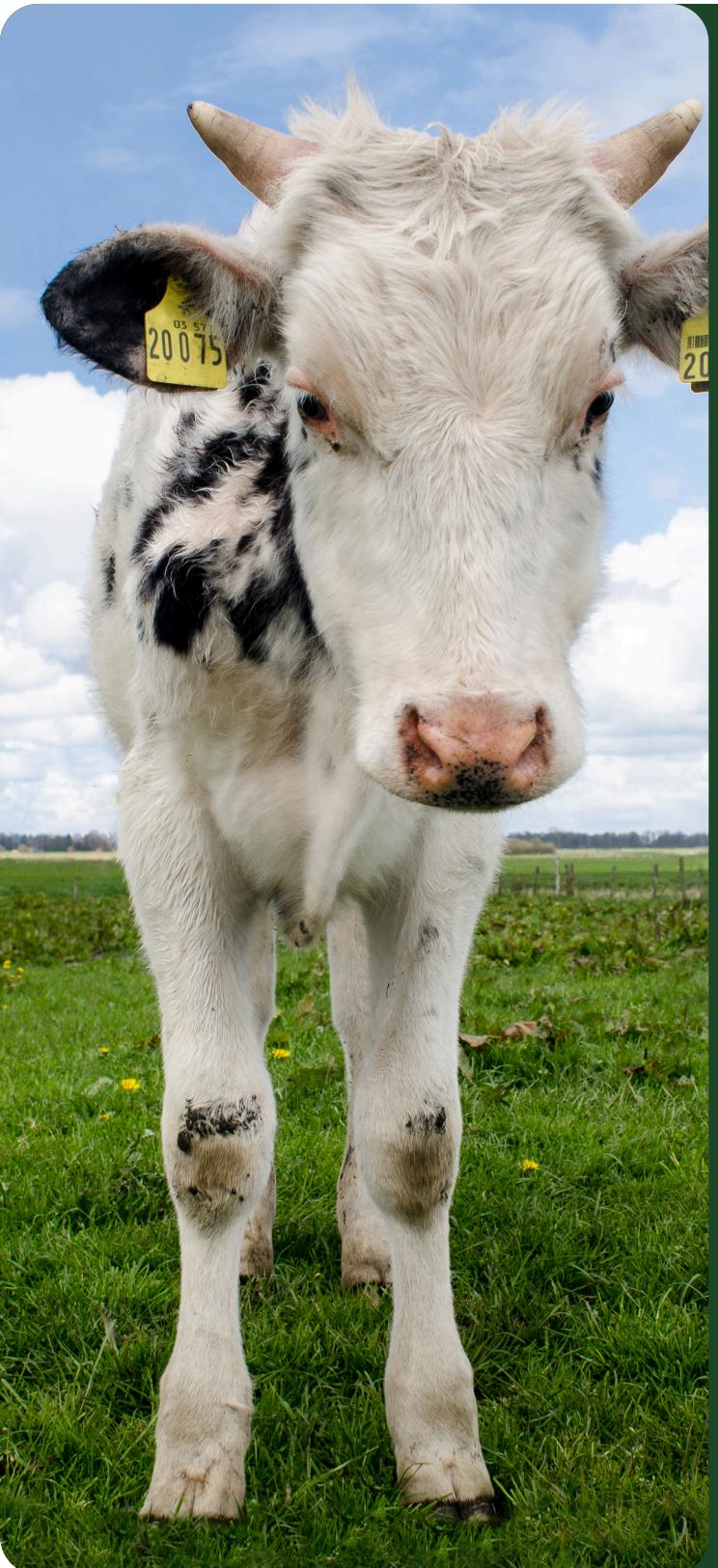


# FUTURE WORK

- Collect & label day/night CCTV data from multiple Thai farms. Cow Posture Detection in Cattle...
- Use DeepLabCut / Roboflow pose / SLEAP to get keypoints (head, back, legs, tail) for fine-grained posture.
- Add temporal models (temporal CNN, RNN, transformer) to:
- Detect mounting bursts
- Track long-term lying/grazing changes
- Integrate into a real-time pipeline with dashboard + alerts for estrus and health events.



# THANK YOU



Thank you for supporting our project. We are very grateful for your advice and support.