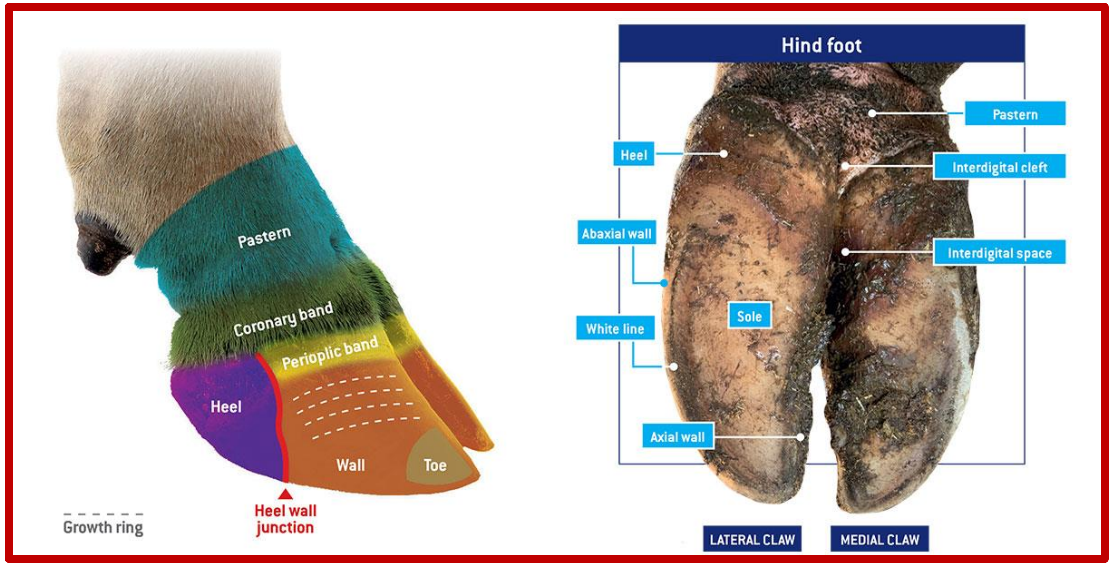
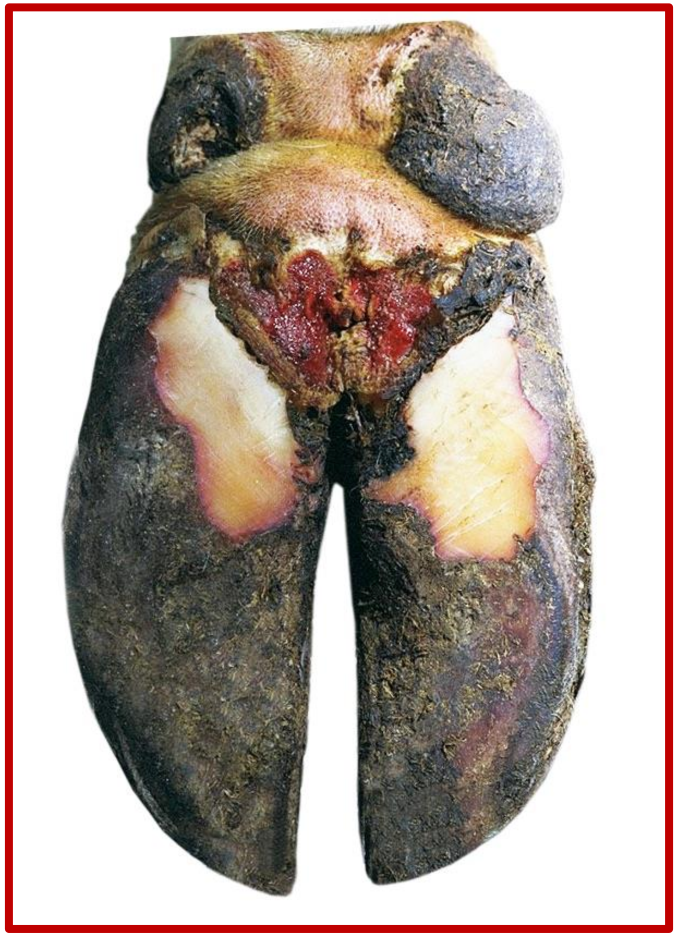
Early Detection of Digital Dermatitis in Dairy and Beef Cattle using Artificial Intelligence

Srikanth Aravamuthan
Dr. Dörte Döpfer Laboratory
Department of Medical Sciences, School of Veterinary Medicine, University of Wisconsin, Madison 53706
aravamuthan@wisc.edu

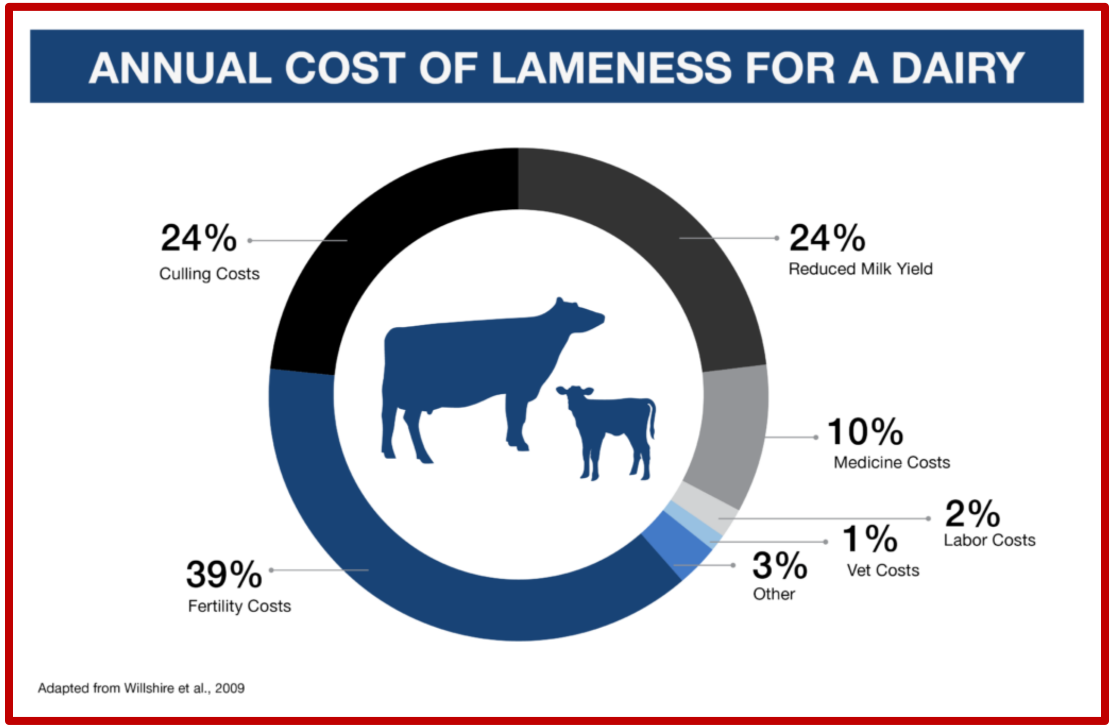
Digital Dermatitis





M-Stage Classification System

Lameness



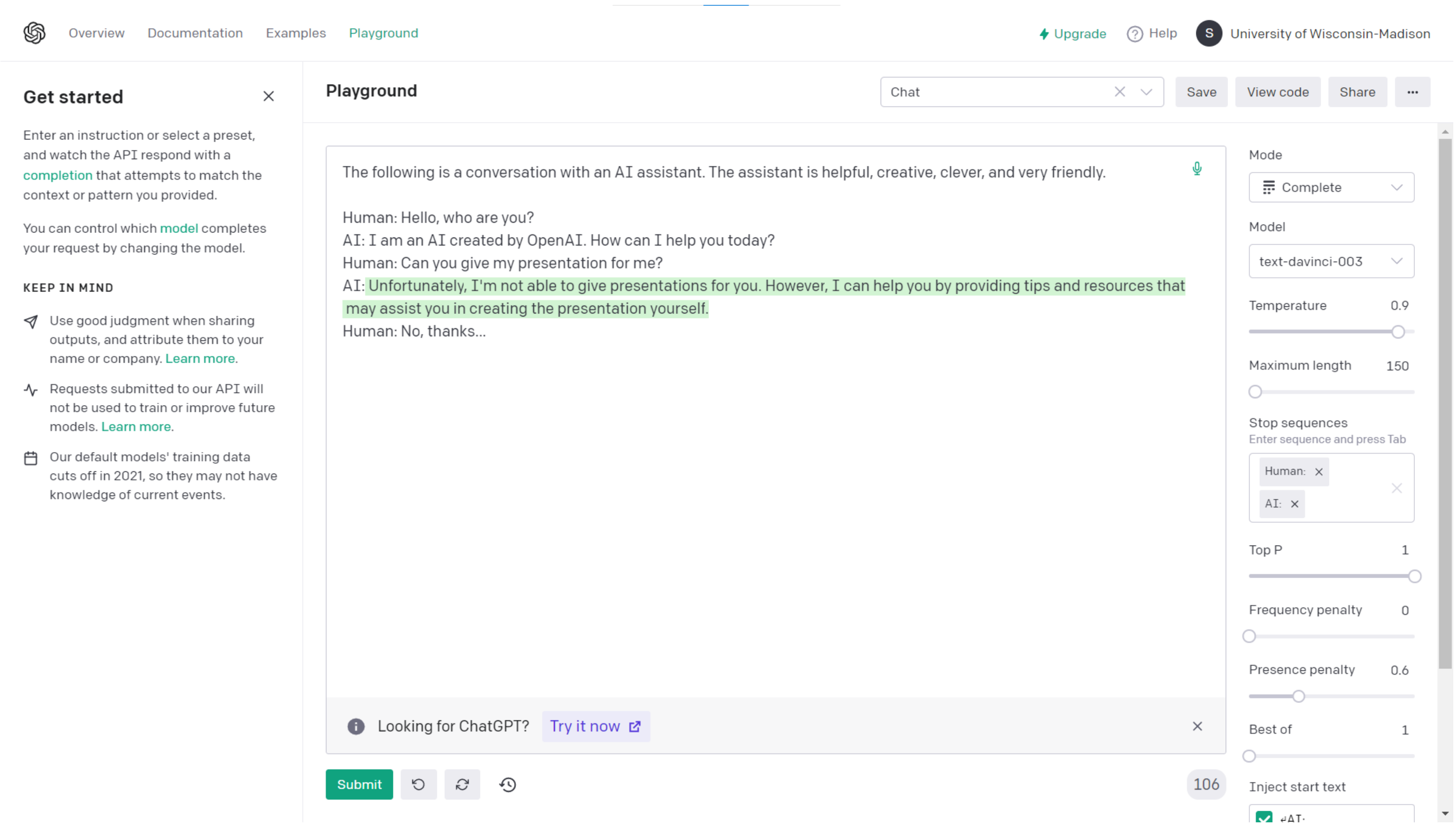
ANNUAL COST OF LAMENESS FOR A DAIRY
24%
Culling Costs
24%
Reduced Milk Yield
10%
Medicine Costs
2%
Labor Costs
1%
Vet Costs
3%
Other
39%
Fertility Costs
Adapted from Willshire et al., 2009

Artificial Intelligence

- Artificial intelligence (AI) is used to perform a variety of advanced functions
  - Ability to see
  - Understand and translate spoken and written language
  - Analyze data
  - Make recommendations

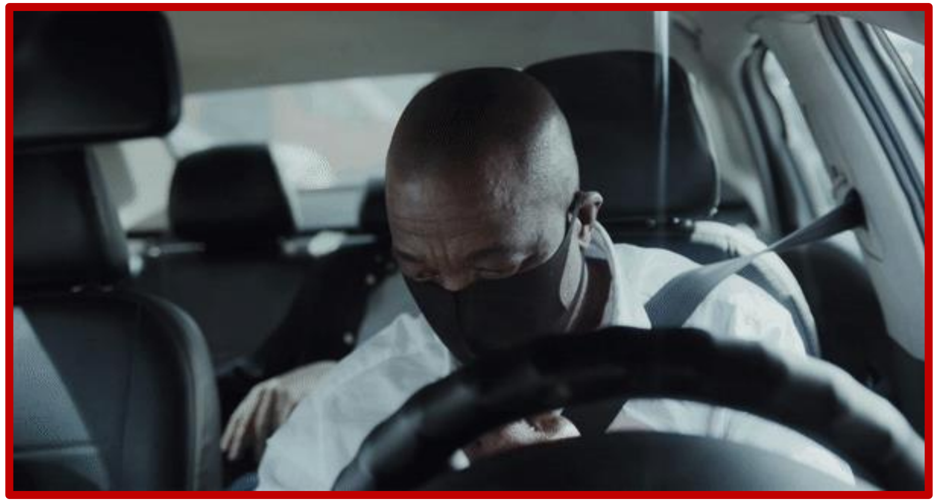
OpenAI | Microsoft

Artificial Intelligence



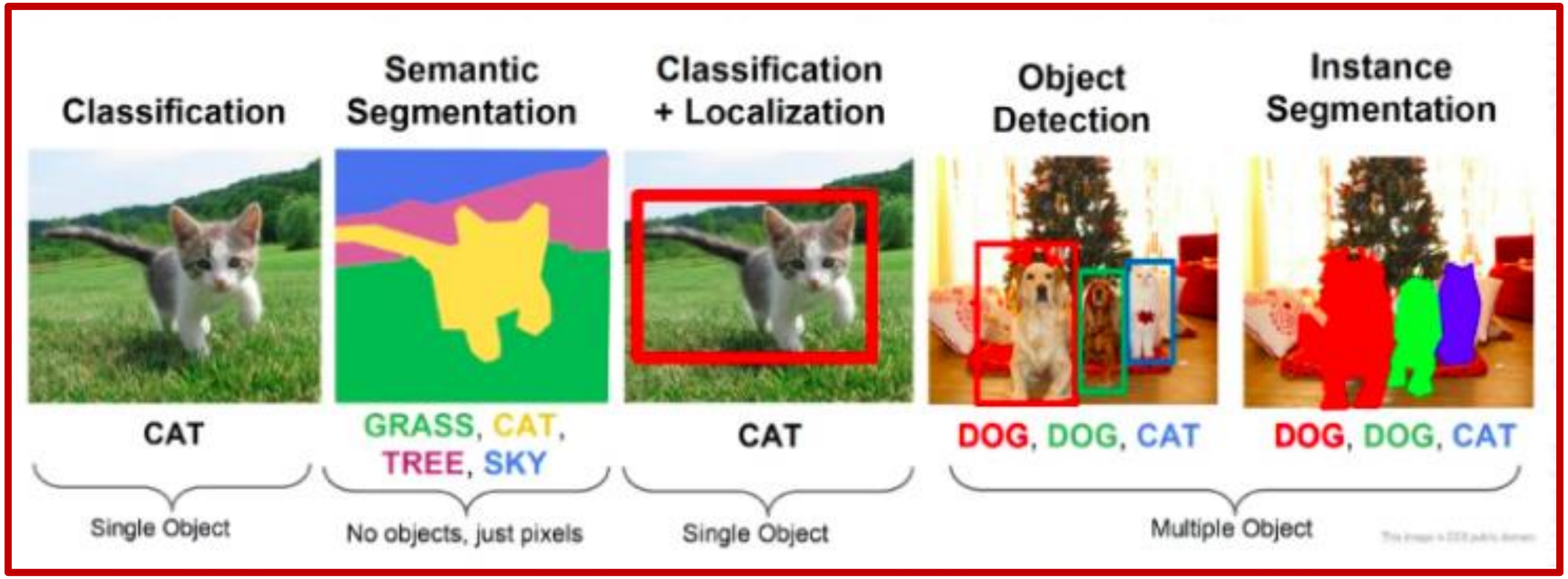
Computer Vision

- Computer vision (CV) is used to acquire, process, analyze, and interpret images and videos.
  - Helps systems see and identify objects



Computer Vision

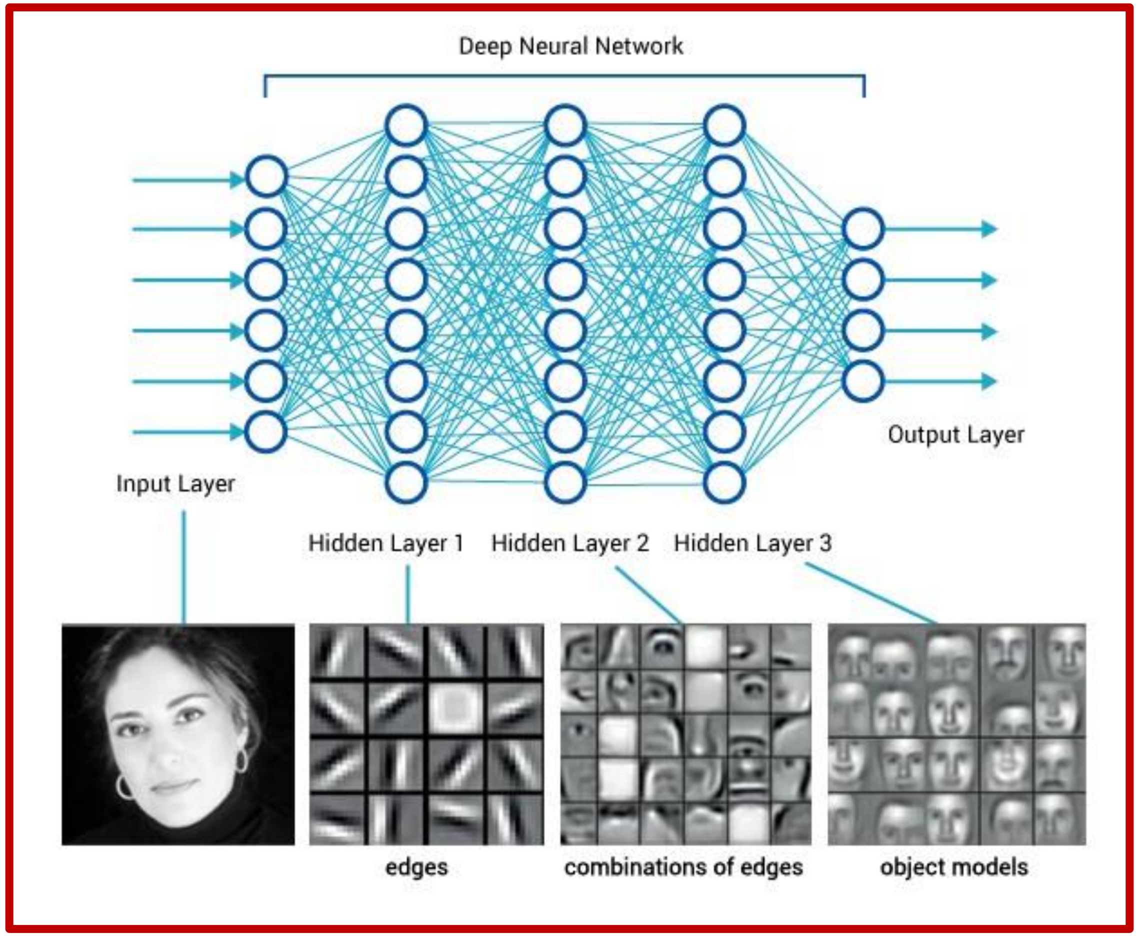
Computer Vision



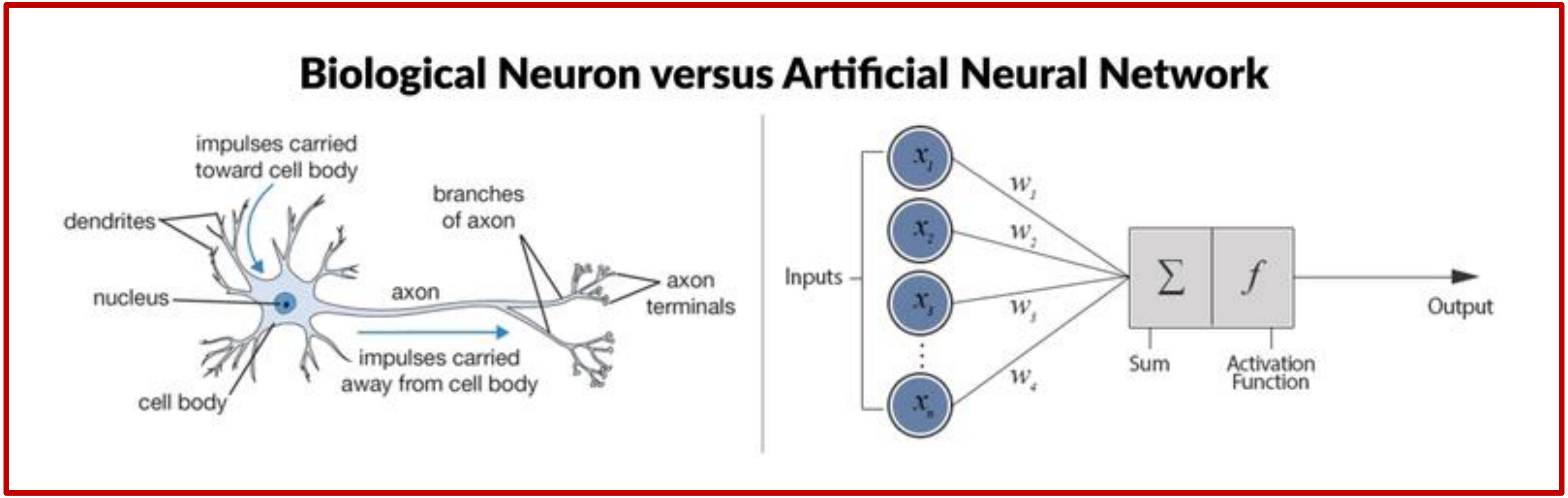
Object Detection

- Object detection locates the presence of objects with a **bounding box** and **class labels** of the located objects in an image.
  - Two-stage object detectors
    - Region-Based Convolutional Neural Networks (R-CNNs)
  - One-stage object detectors
    - Single-Shot Detectors (SSD)
    - You Only Look Once (YOLO)

Neural Network (NN)



Neural Network (NN)

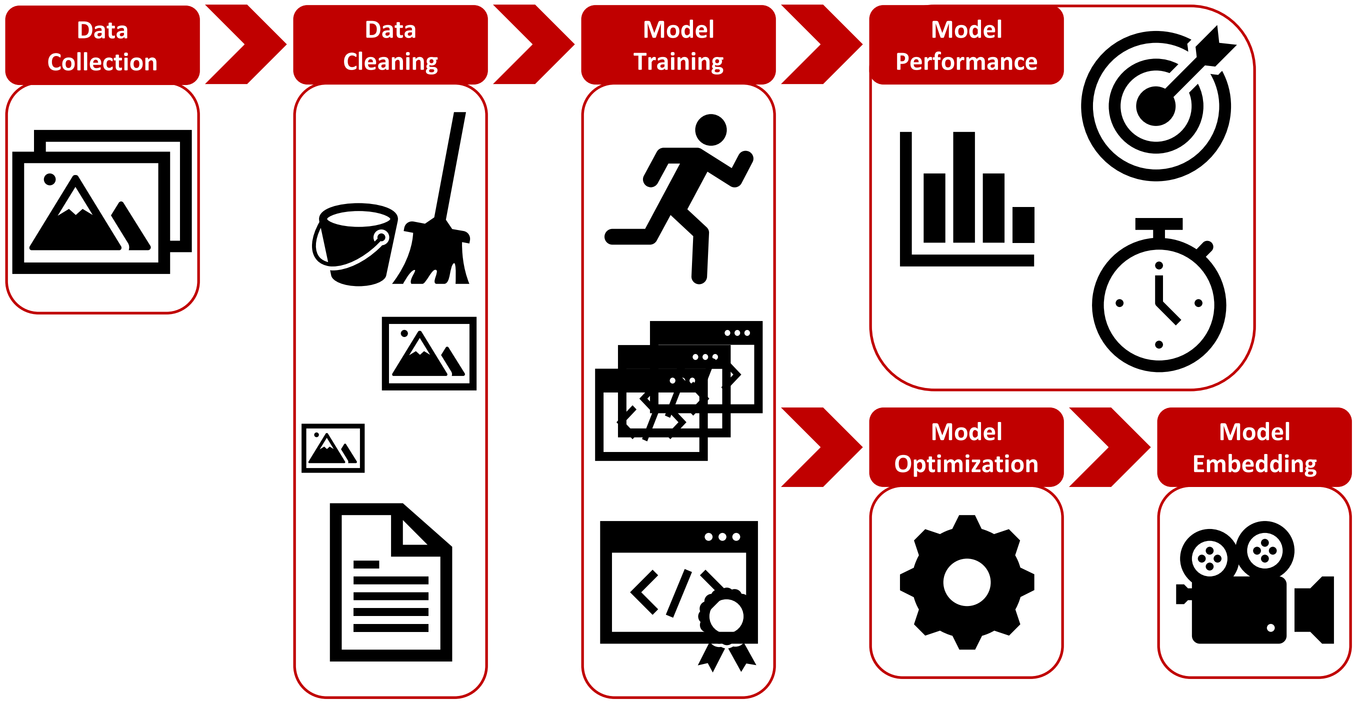


Motivation

- The purpose of this project is to implement a CV model for the **real-time detection of DD** in dairy and beef cattle.
- The motivation is to **minimize the effects of DD-associated lameness** in all cattle by means of early detection, prevention, and prompt treatments.

Approach

1. Data Collection
2. Data Cleaning
3. Model Training
4. Model Performance
5. Model Optimization
6. Model Embedding



Workflow

Data Collection

- Camera facing the backside of the hind foot with a clear view of the interdigital space of the hoof
- Two sets of images
  - 2,227 JPEG images of **single lesion** for Dataset 1
  - 409 JPEG images of **multiple lesions** for Dataset 2
- Scored for M-stages of DD by a trained investigator
  - **M0/M4 and M2** for Dataset 1
  - **M0, M2, M2P, M4H, and M4P** for Dataset 2

Workflow

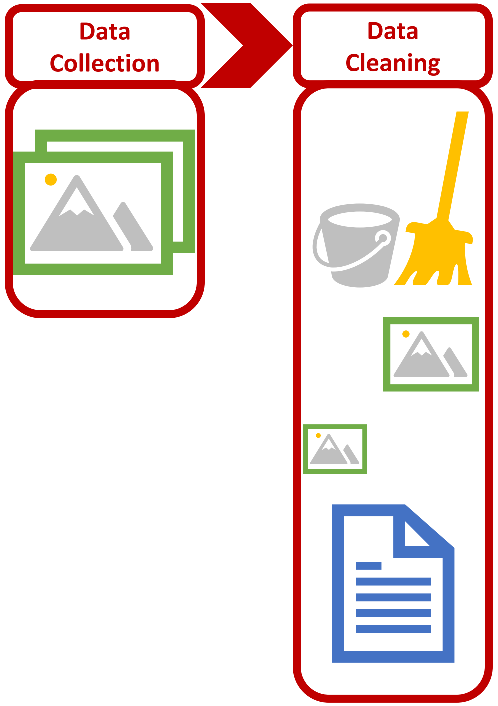
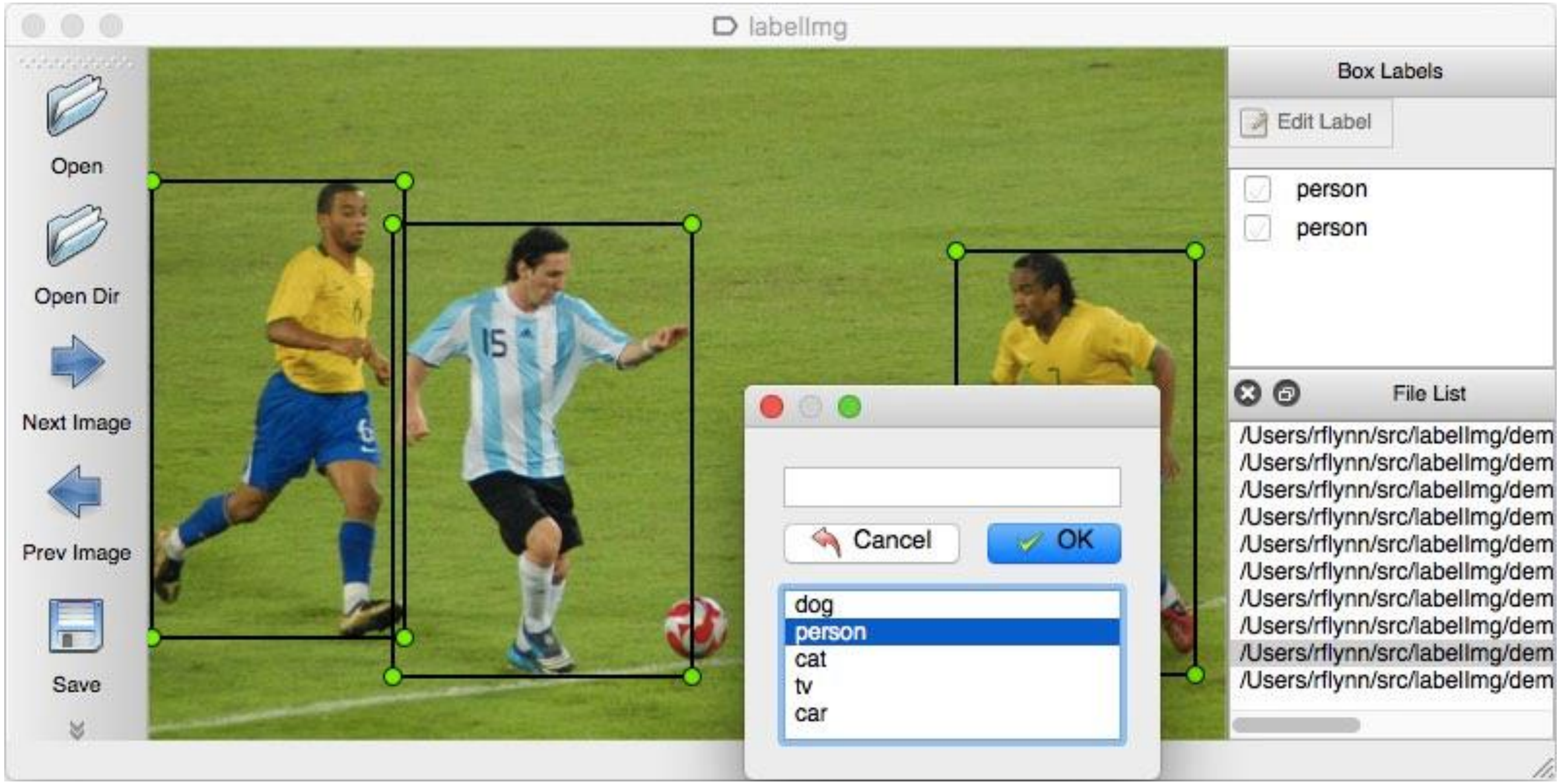
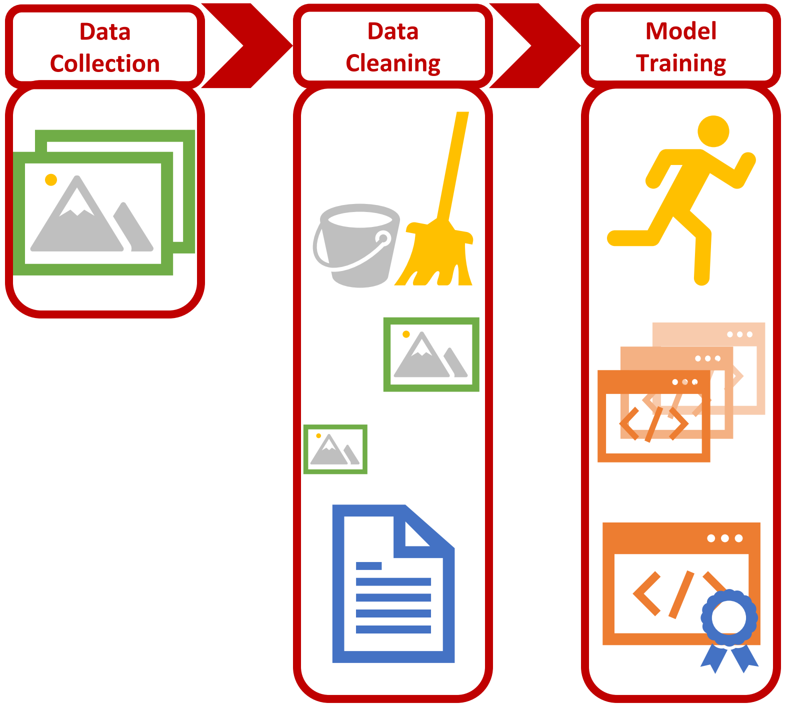


Image Labeling and Data Processing



Workflow

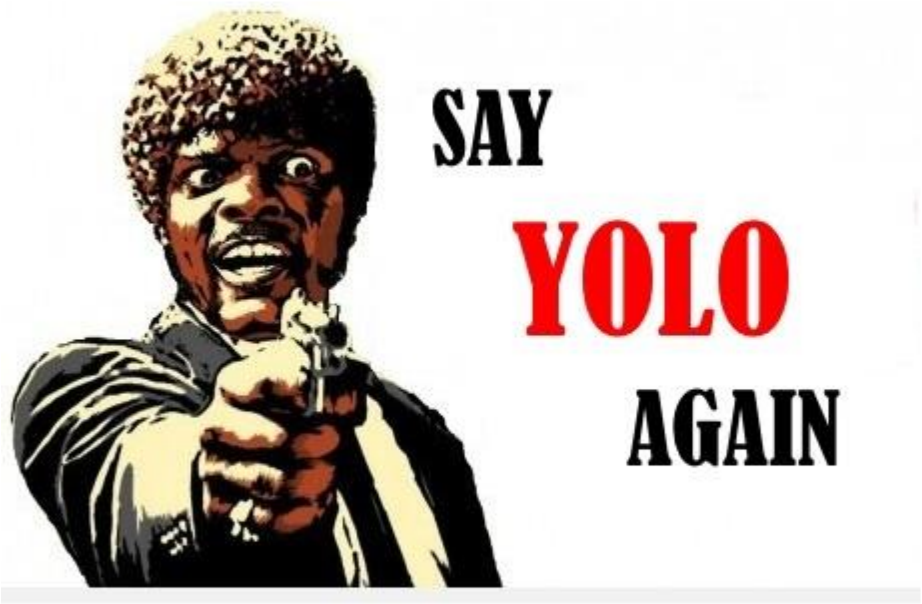


Model Training

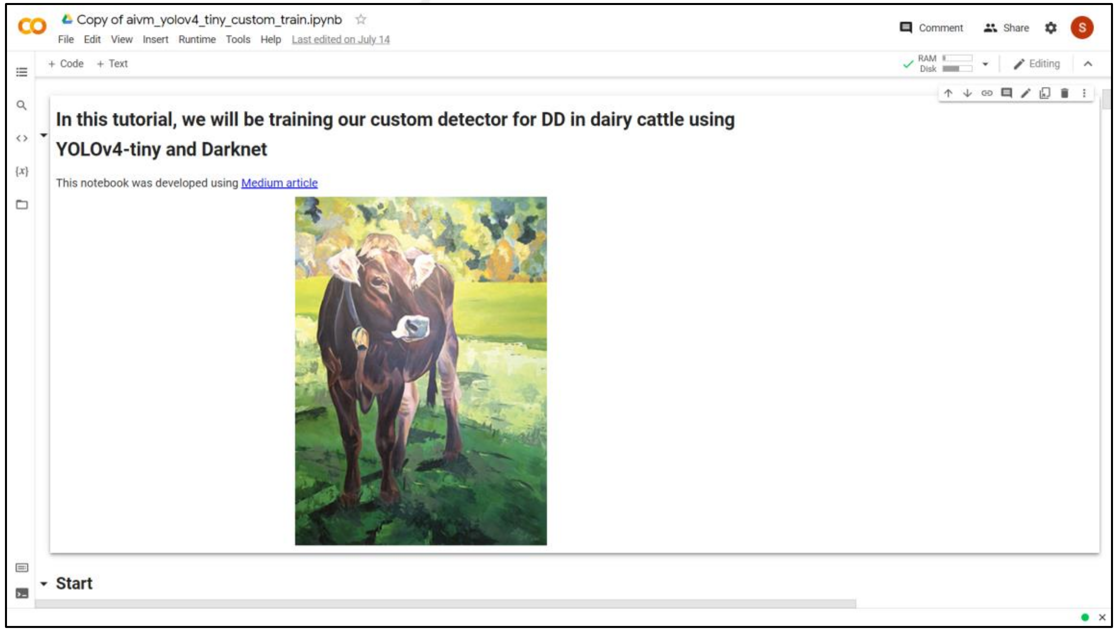
- 90% images for training and 10% images for testing
- 8 object detection models
  - Faster R-CNN & Cascade R-CNN
  - SSD & SSD Lite
  - YOLOv3 & Tiny YOLOv3
  - YOLOv4 & Tiny YOLOv4

Model Training

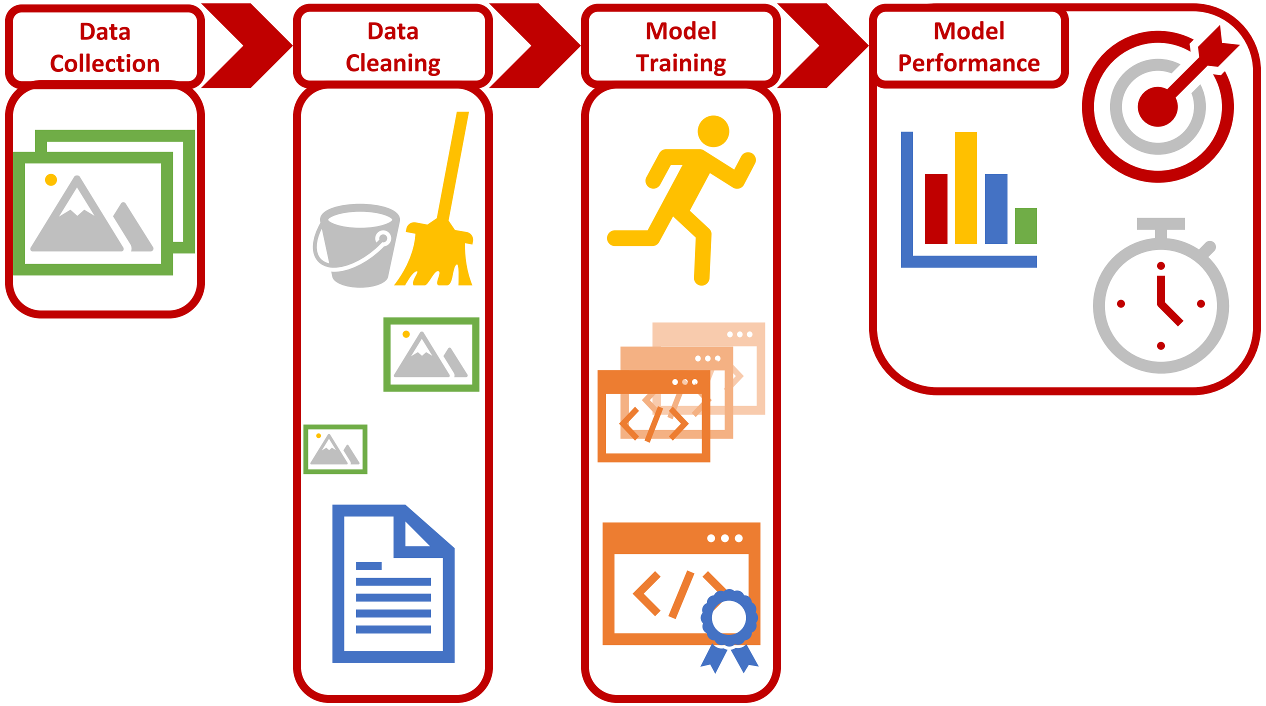
- 90% images for training and 10% images for testing
- 8 object detection models
  - Faster R-CNN & Cascade R-CNN
  - SSD & SSD Lite
  - YOLOv3 & Tiny YOLOv3
  - YOLOv4 & Tiny YOLOv4



Model Training

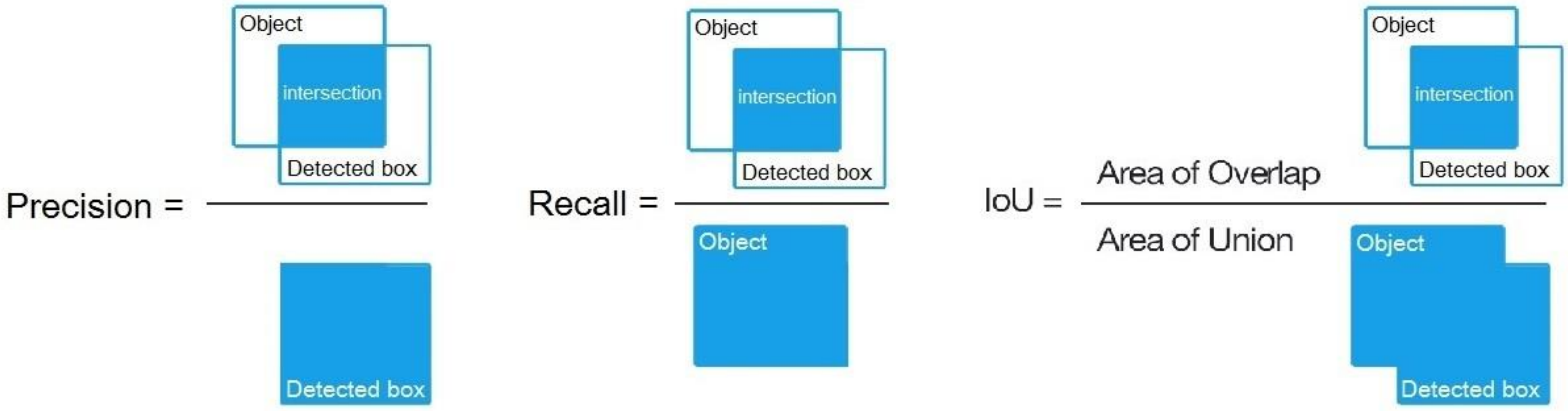


Workflow

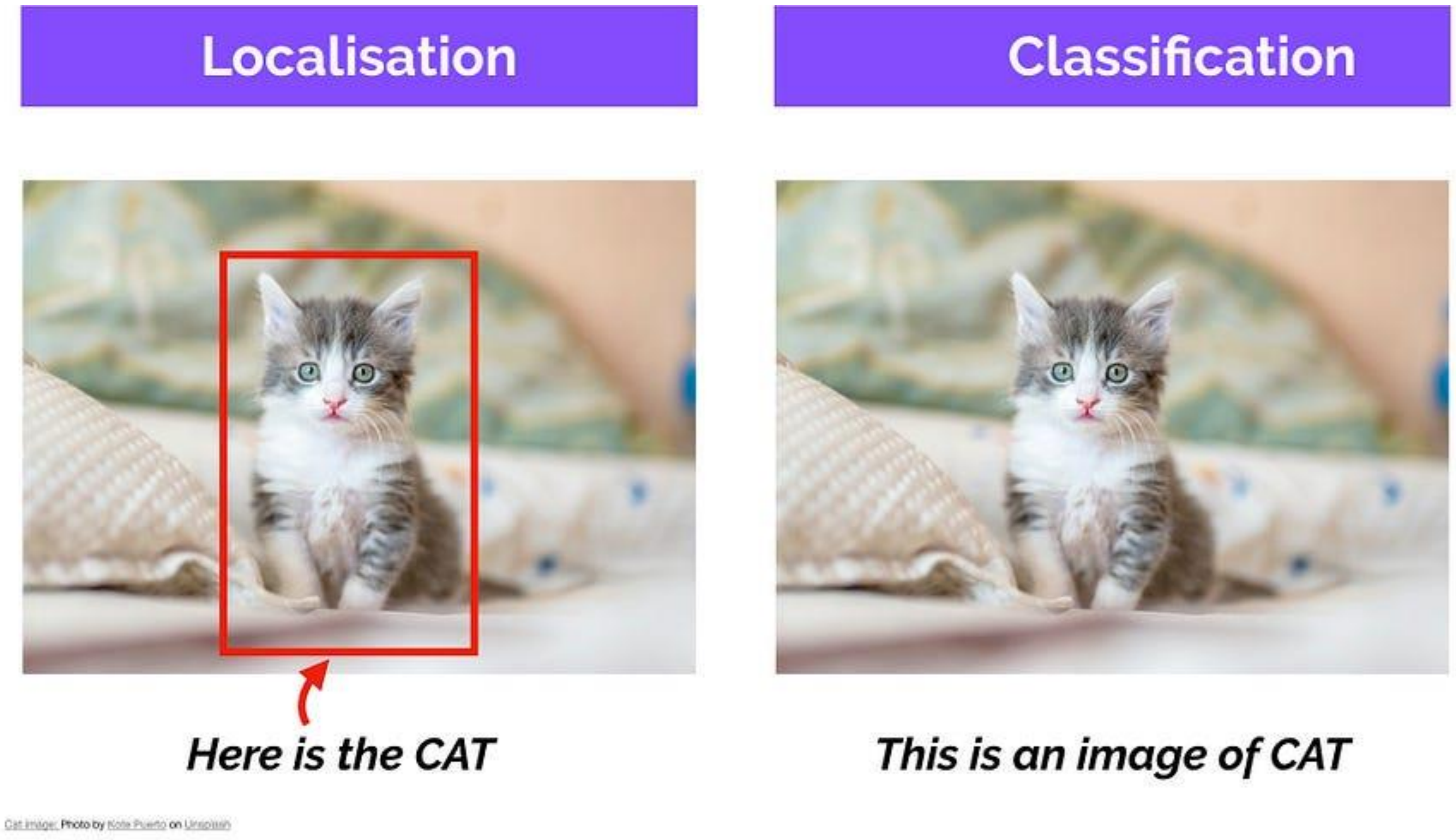


Data Collection
Data Cleaning
Model Training
Model Performance

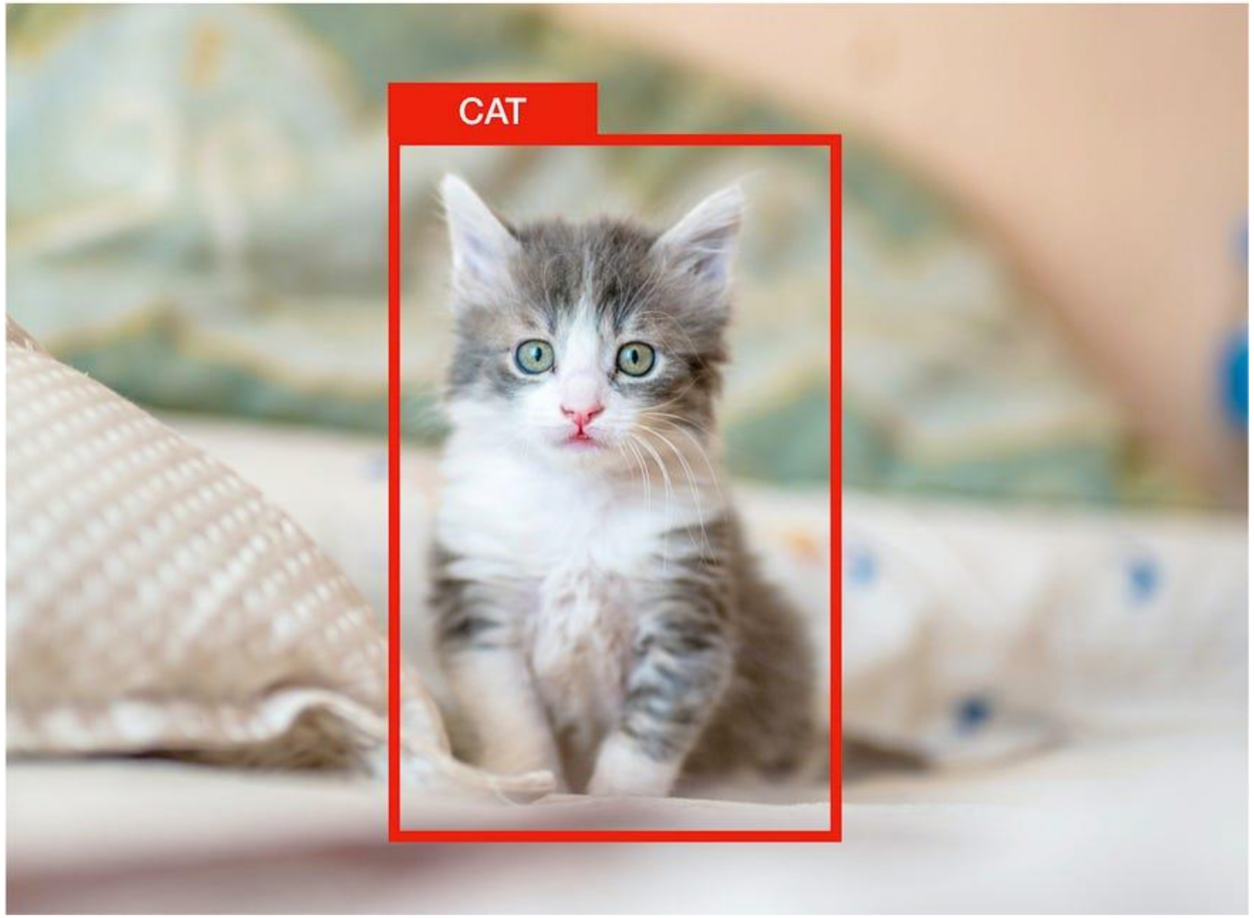
Model Evaluation



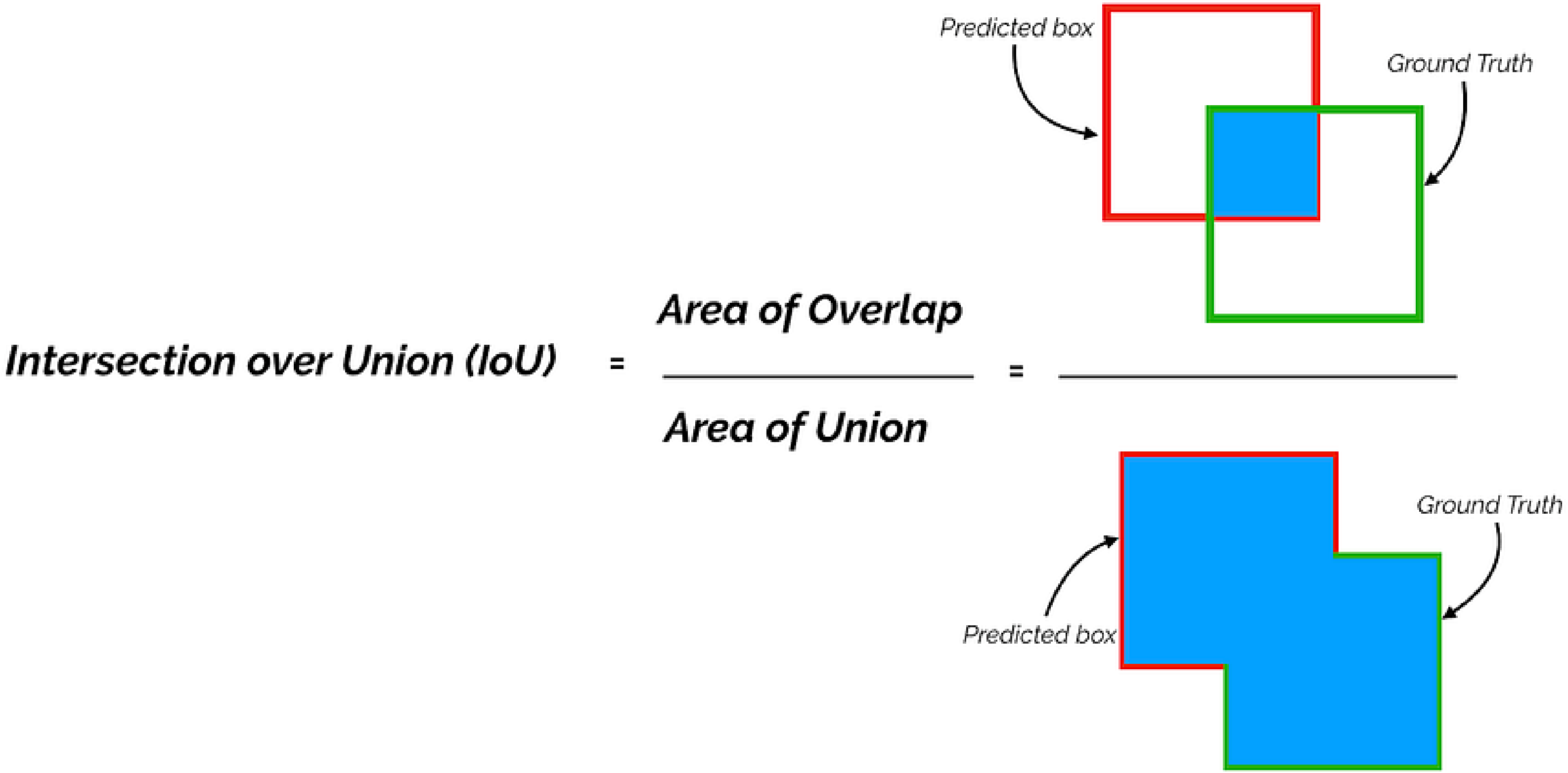
Model Evaluation



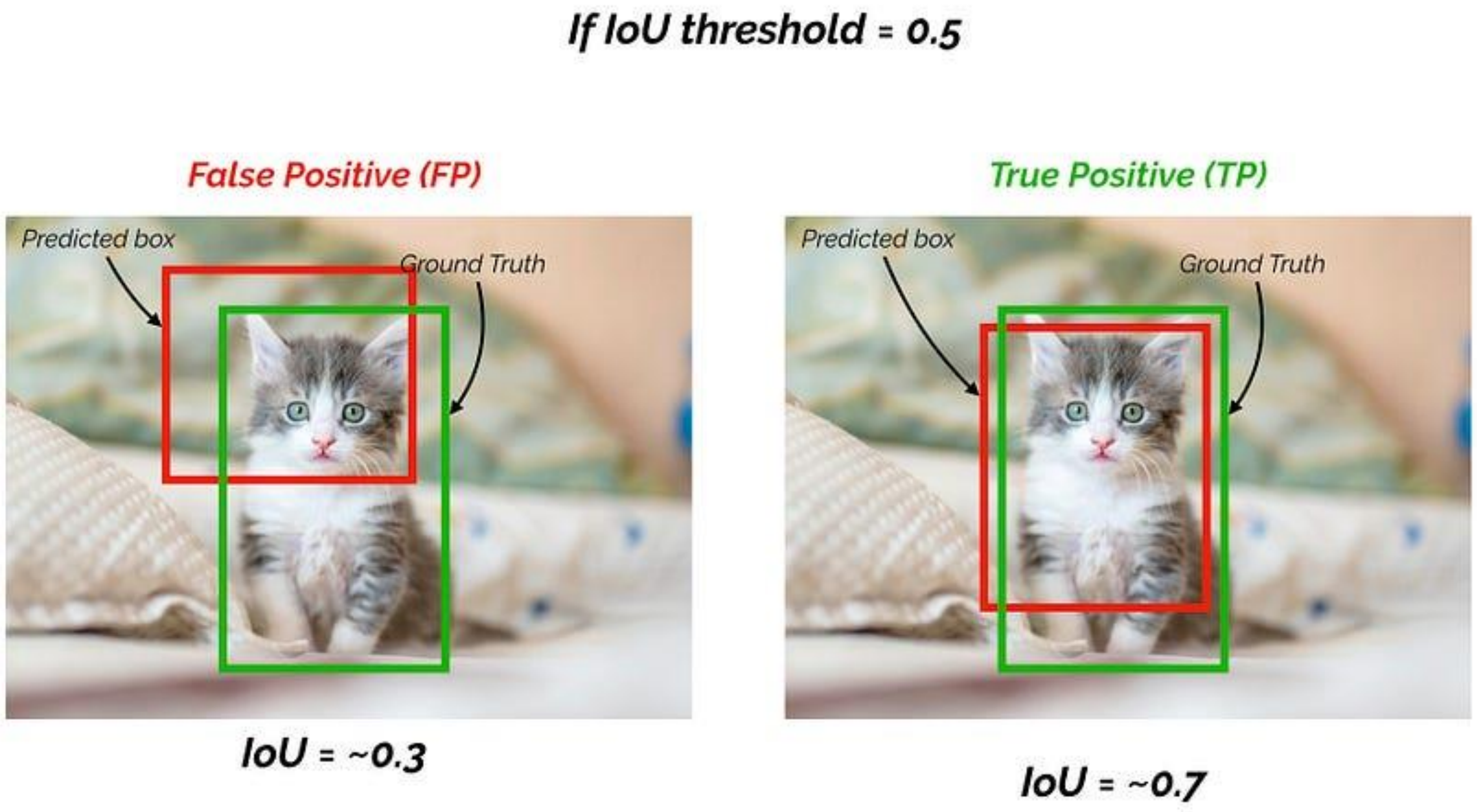
Model Evaluation



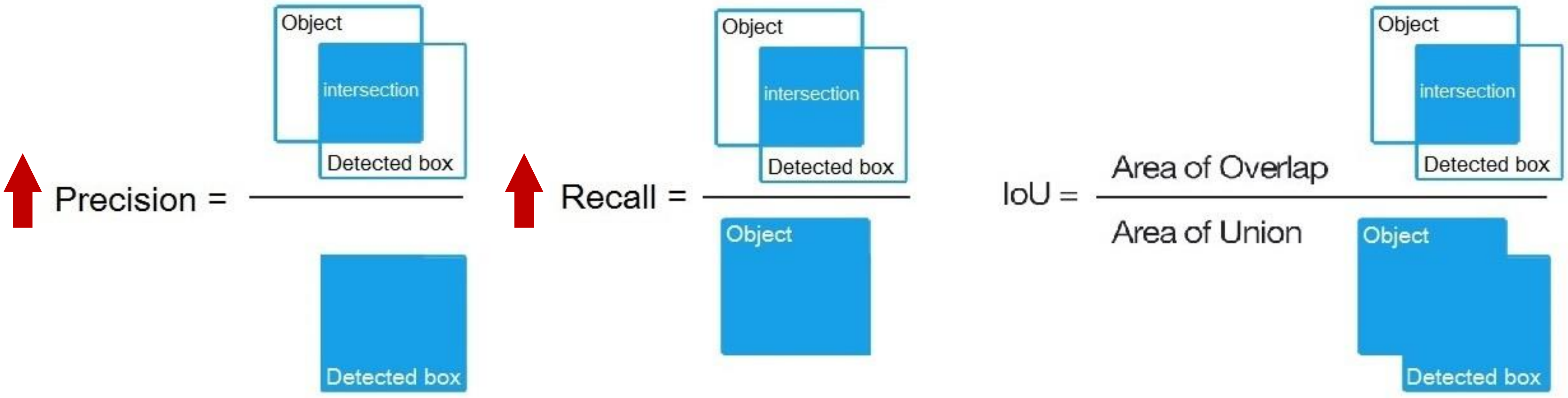
Model Evaluation



Model Evaluation



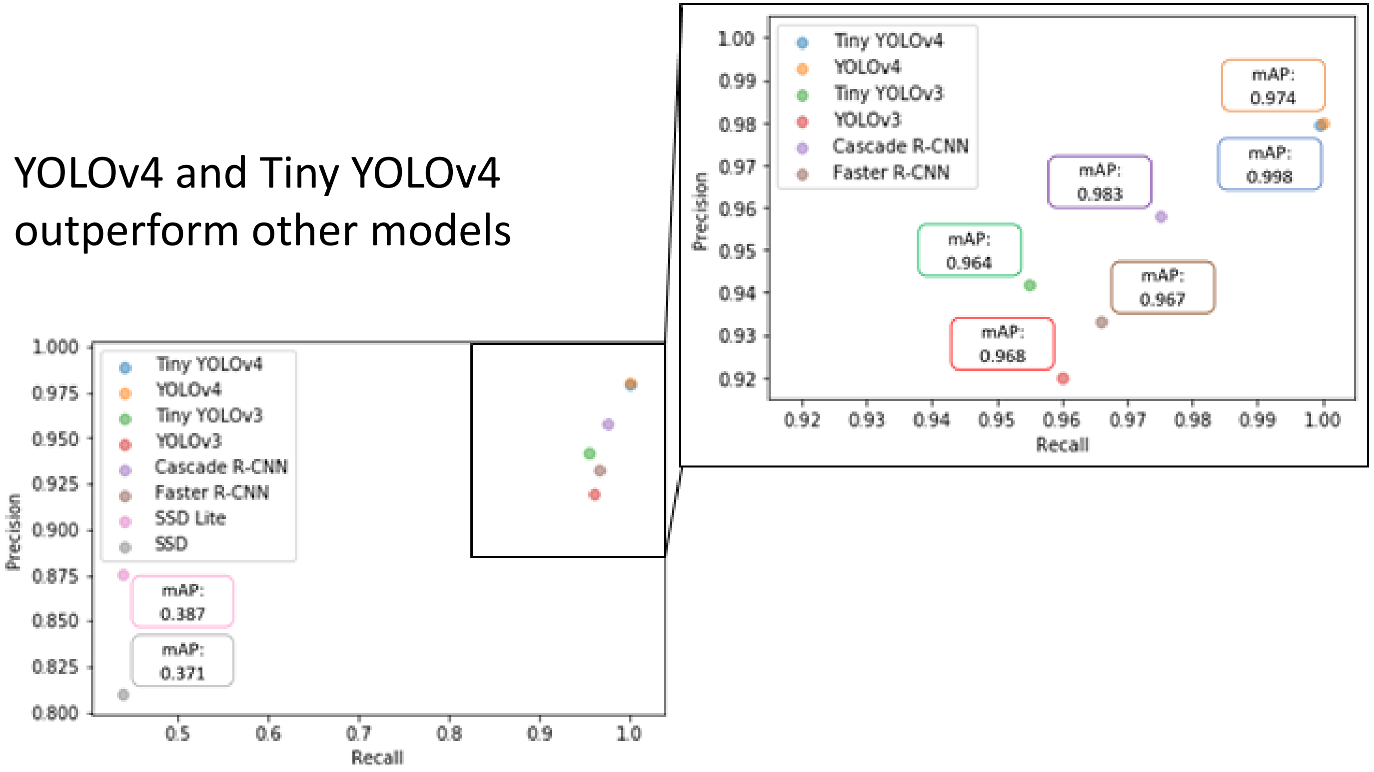
Model Evaluation



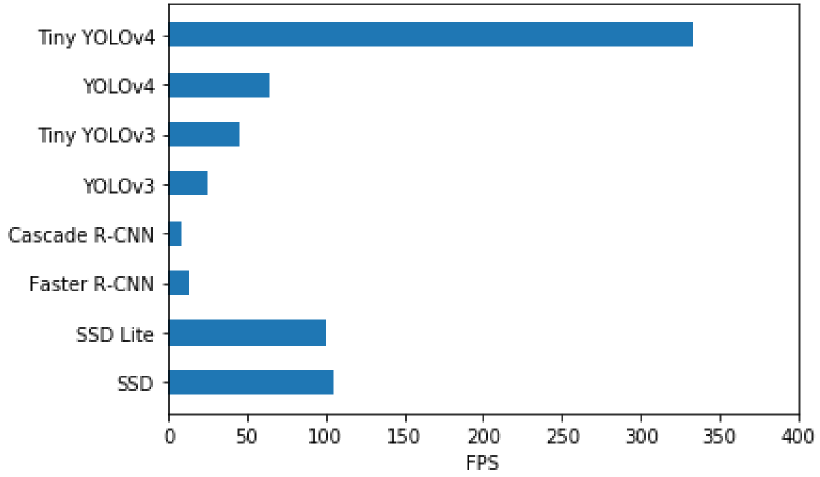
Model Performance

Real-world dataset containing single object per image and two class labels for object detection (Dataset 1)

YOLOv4 and Tiny YOLOv4 outperform other models

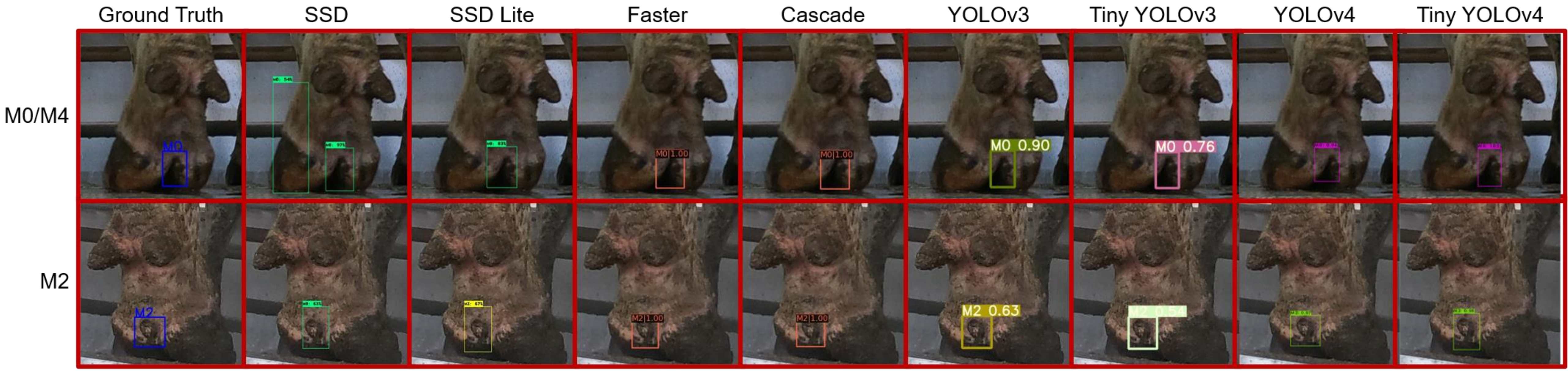


Tiny YOLOv4 is the best model for our use case

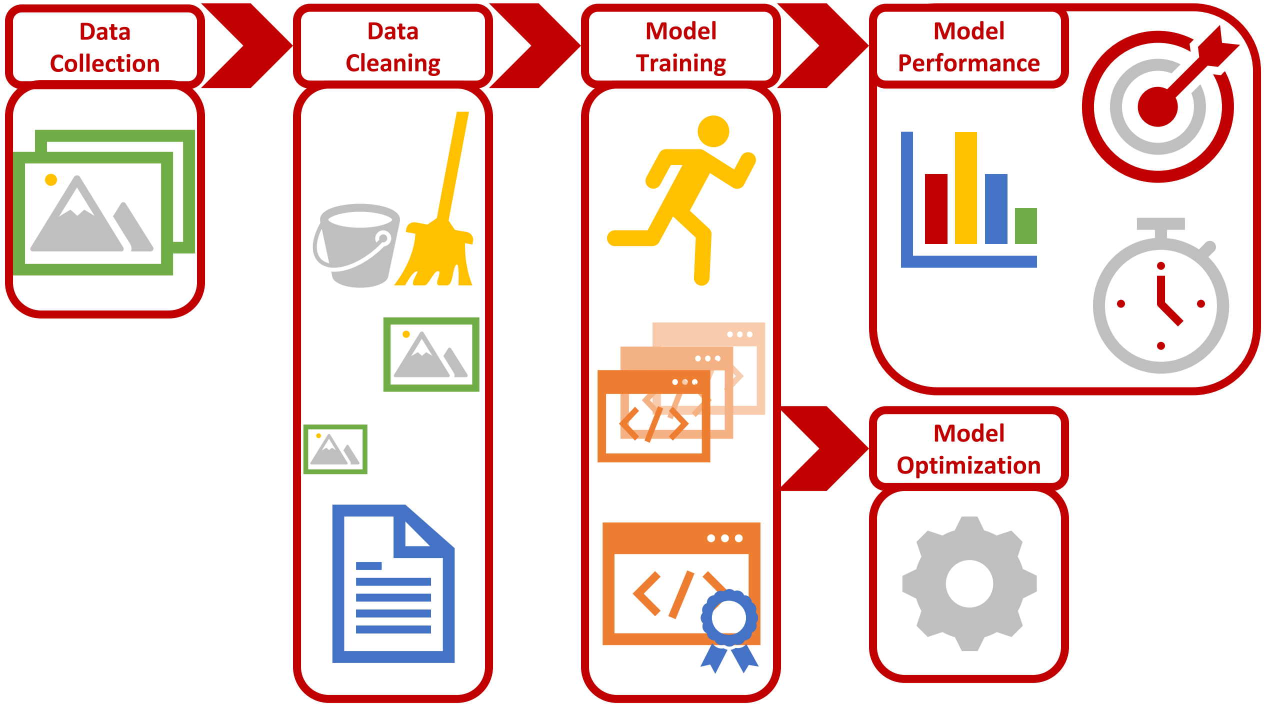


Model Performance

Real-world dataset containing single object per image and two class labels for object detection (Dataset 1)



Workflow

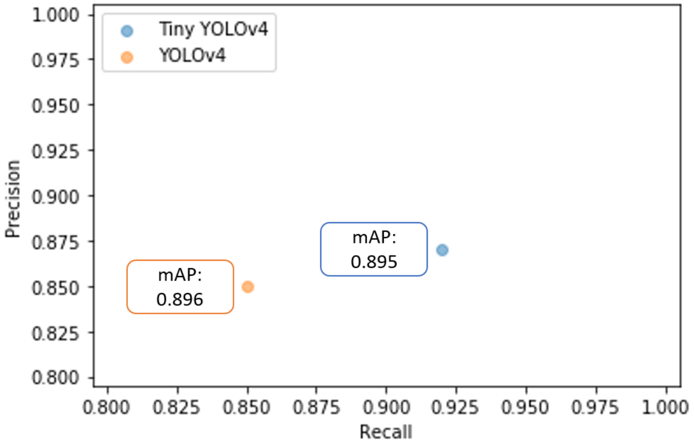


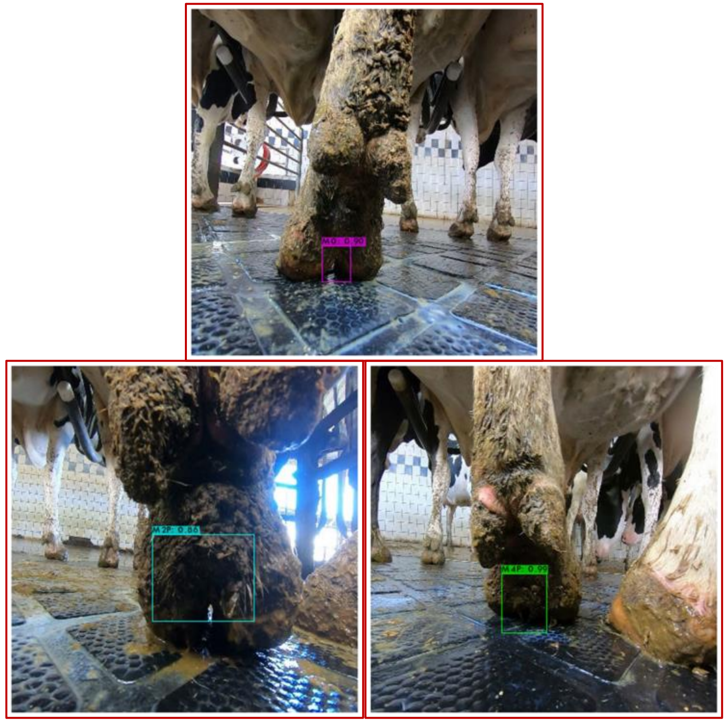
Data Collection
Data Cleaning
Model Training
Model Performance
Model Optimization

Model Optimization

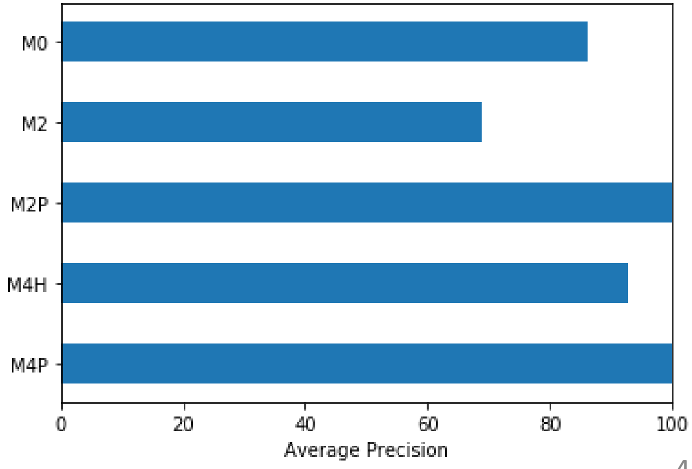
Real-world dataset containing multiple objects per image and more class labels for object detection (Dataset 2)

Similar performance for
Tiny YOLOv4 and YOLOv4



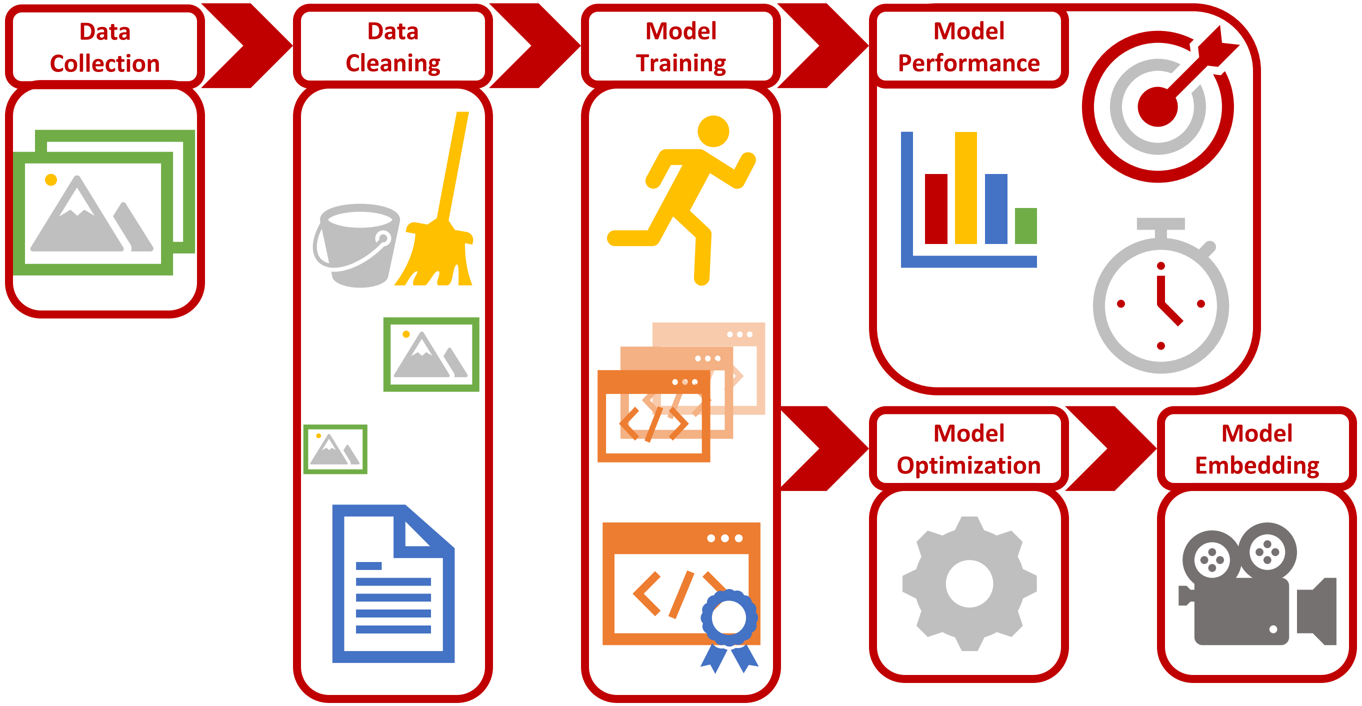


Difference in performance between
classes for Tiny YOLOv4



Best Model

Workflow



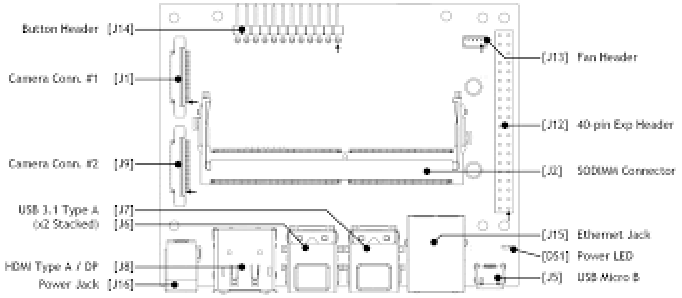
Data Collection
Data Cleaning
Model Training
Model Performance
Model Optimization
Model Embedding

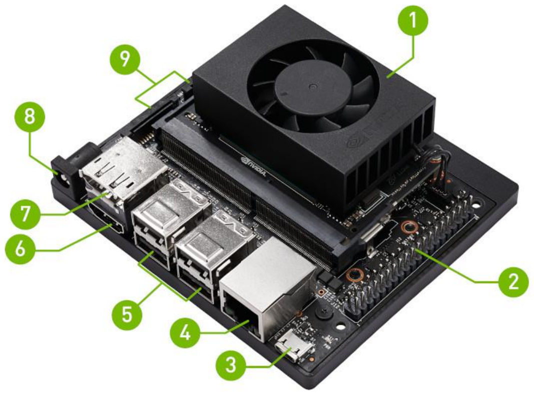
Device-Based Implementation

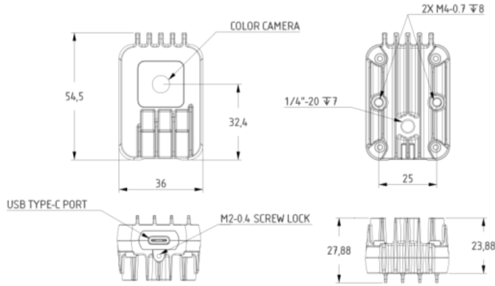
- Raspberry Pi
- Jetson Nano and Xavier
- OAK-1 and OAK-D Lite

Model Embedding

- NVIDIA Jetson Xavier NX
  - Single-board computer (SBC)
  - Small, lightweight, and energy efficient
- OAK-1 camera
  - Edge accelerator
  - Intel Neural Compute Stick2
  - USB3 Type-C device power and connectivity
- LCD screen
- Power source

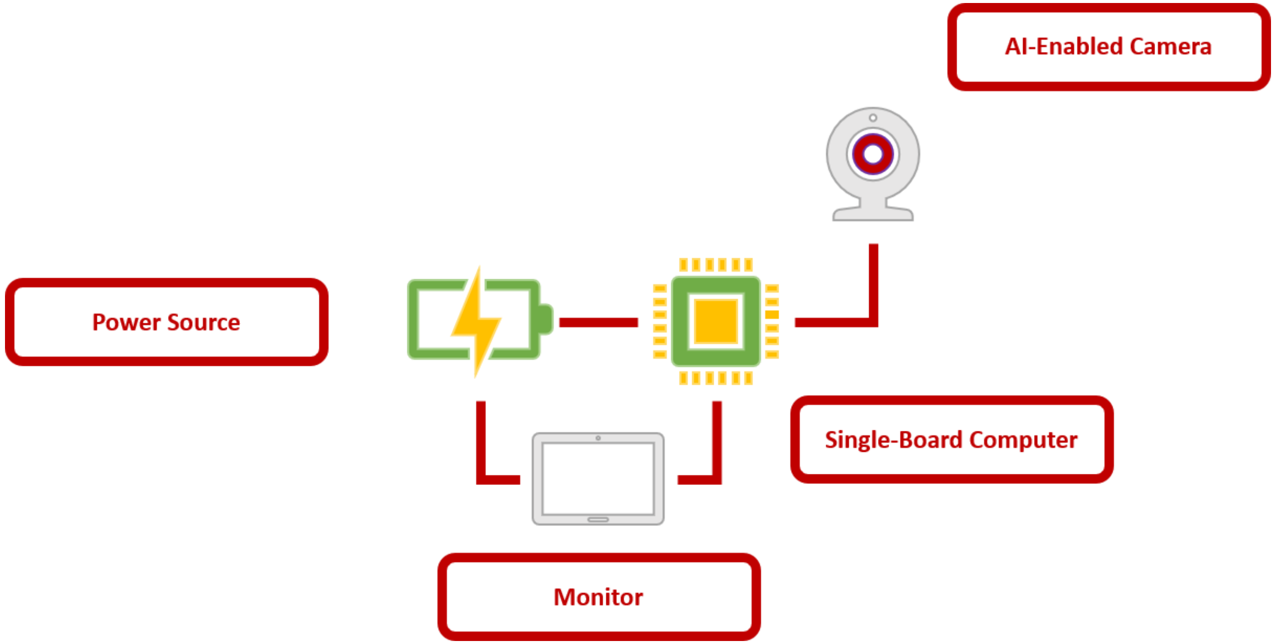






Model Embedding

- NVIDIA Jetson Xavier NX
  - Single-board computer (SBC)
  - Small, lightweight, and energy efficient
- OAK-1 camera
  - Edge accelerator
  - Intel Neural Compute Stick2
  - USB3 Type-C device power and connectivity
- LCD screen
- Power source

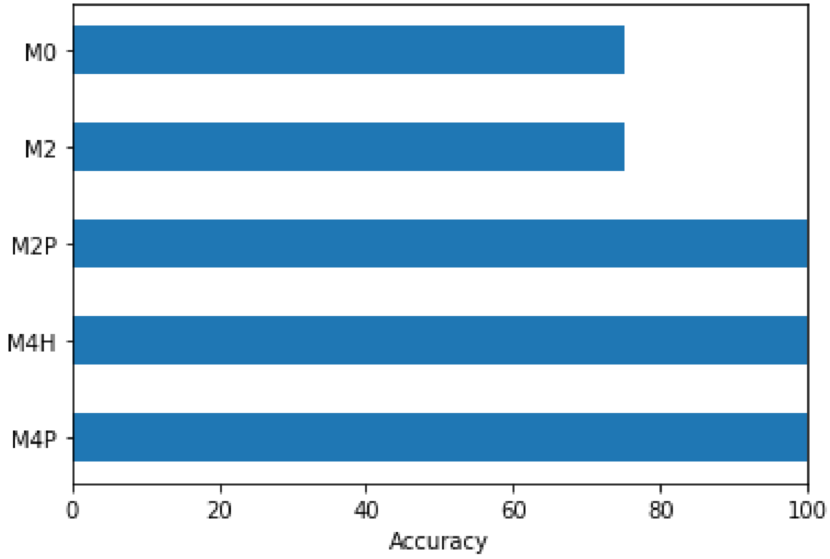


Model Embedding

Implementation processed images at 40 FPS

Excellent agreement with Cohen’s kappa of 0.83

Detect all five class labels on video and webcam



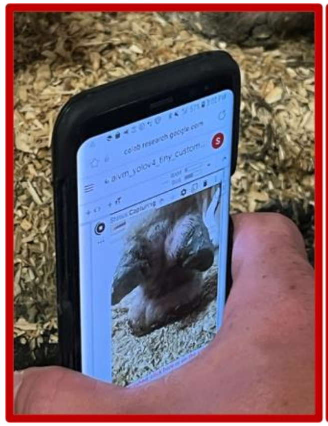
Summary

SCAN ME

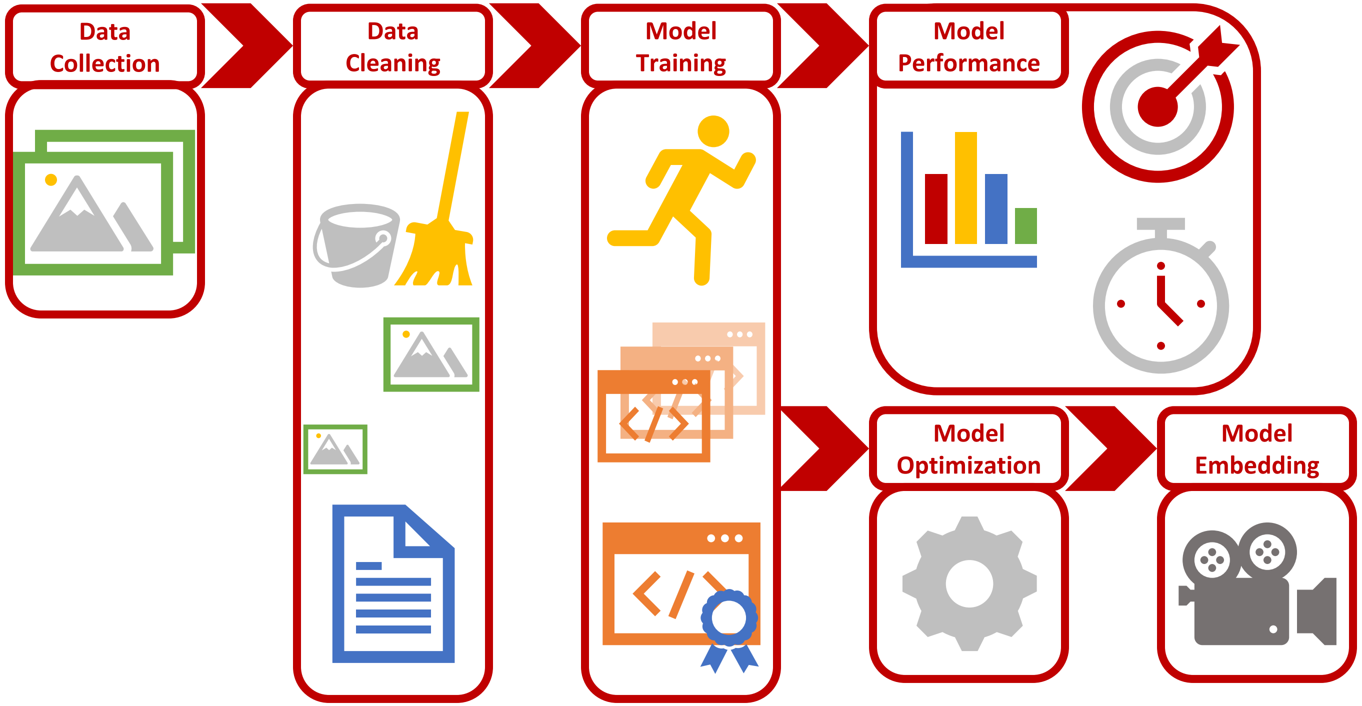
- The workflow was able to accurately and speedily detect DD on edge devices.
- YOLOv4 and Tiny YOLOv4 outperformed all other models
- Tiny YOLOv4 was the best model for our use case
- Tiny YOLOv4 on OAK-1 x NVIDIA Jetson Xavier NX edge device was fast and accurate
- Computer vision for veterinary medicine

Cloud-Based Implementation

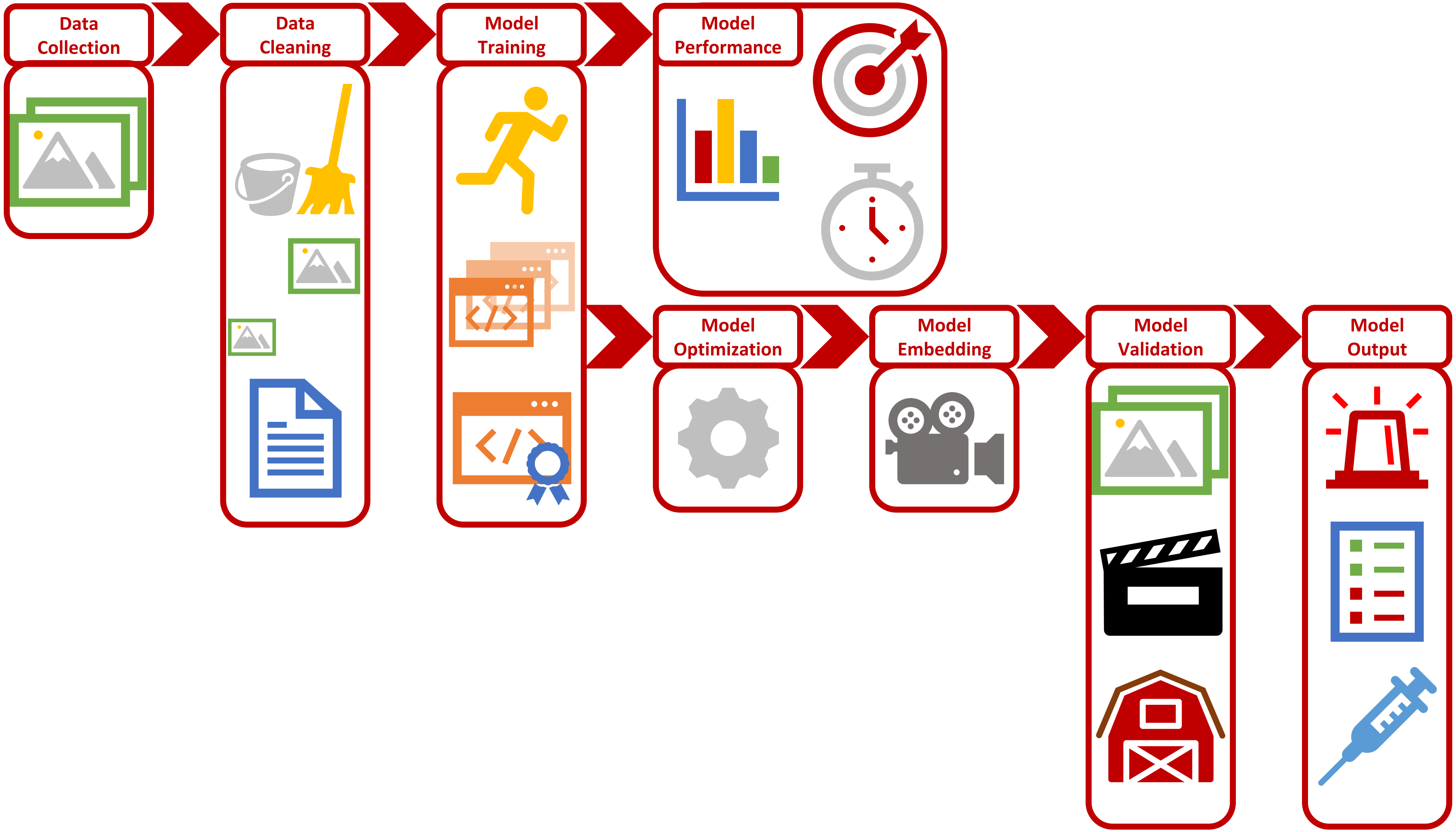
- AWS Website
- Docker Environment
- Android Application



Workflow


Data
Collection
Data
Cleaning
Model
Training
Model
Performance
Model
Optimization
Model
Embedding

Summary and Future Directions



On-Going Projects

- Application using video and real-time detection
  - Device-Based Implementation
  - Cloud-Based Implementation
- Model optimization
- Model validation
- Expand to beef cattle
- Extend to other model organisms
- Other object detection algorithms
- Other programming frameworks

Acknowledgements

- Döpfer Lab (former and current)
  - Allie Hoerth
  - Juan Francisco Mandujano Reyes
  - Nathan Bollig
  - Emil Walleser
- Dr. Neoklis Apostolopoulos
- Thesis Committee
  - Prof. Guilherme Rosa
  - Prof. João Dórea
  - Prof. Paul Merkatoris
  - Prof. Brian Yandell
- US Department of Agriculture
- National Institute for Food and Agriculture - Animal Health Grant (WIS03082)

WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

USDA NIFA
United States Department of Agriculture
National Institute of Food and Agriculture

References

[1] R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Region-based convolutional networks for accurate object detection and segmentation,” *IEEE transactions on pattern analysis and machine intelligence,* vol. 38, no. 1, pp. 142-158, 2015.
[2] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” in *Proceedings of the IEEE conference on computer vision and pattern recognition,* pp. 779-788, 2016.
[3] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, “Ssd: Single shot multibox detector,” in *European conference on computer vision,* pp. 21-37, Springer, 2016.
[4] S. Ren, K. He, R. B. Girshick, and J. Sun, “Faster R-CNN: towards real-time object detection with region proposal networks,” *IEEE Trans. Pattern Anal. Mach. Intell.,* vol. 39, no. 6, pp. 1137–1149, 2017.
[5] Z. Cai and N. Vasconcelos, “Cascade r-cnn: Delving into high quality object detection,” in *Proceedings of the IEEE conference on computer vision and pattern recognition,* pp. 6154–6162, 2018.
[6] J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” *arXiv preprint arXiv:1804.02767*, 2018.
[7] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “Yolov4: Optimal speed and accuracy of object detection,” *arXiv preprint arXiv:2004.10934,* 2020.
[8] G. Jocher, “ultralytics/yolov5: v3.1 – bug, fixes and performance improvements.” https://github.com/ultralytics/yolov5, 2020.
[9] P. Adarsh, P. Rathi, and M. Kumar, “Yolo v3-tiny: Object detection and recognition using one stage improved model,” in *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS),* pp. 687-694, 2020.
[10] P. Cernek, N. Bollig, K. Anklam, and D. Döpfer, “Hot topic: Detecting digital dermatitis with computer vision,” *Journal of Dairy Science,* vol. 103, no. 10, pp. 9110-9115, 2020.
[11] “Custom training — DepthAI documentation | Luxonis,” Luxonis. https://docs.luxonis.com/en/latest/pages/training/.
[12] “The World’s Smallest AI Supercomputer,” NVIDIA. https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-xavier-nx/.
[13] “OAK-1 — DepthAI Hardware Documentation 1.0.0 documentation,” Luxonis. https://docs.luxonis.com/projects/hardware/en/latest/pages/BW1093.html.

Thank you!