Performance Evaluation for the Real-Time Detection of Digital Dermatitis in Dairy Cattle on Edge Devices

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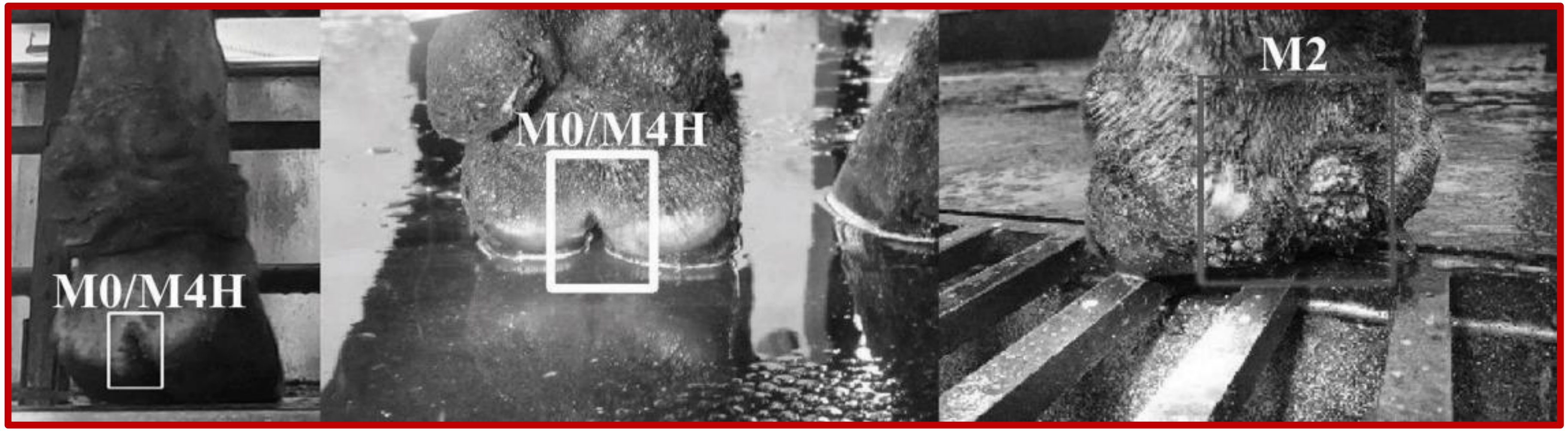
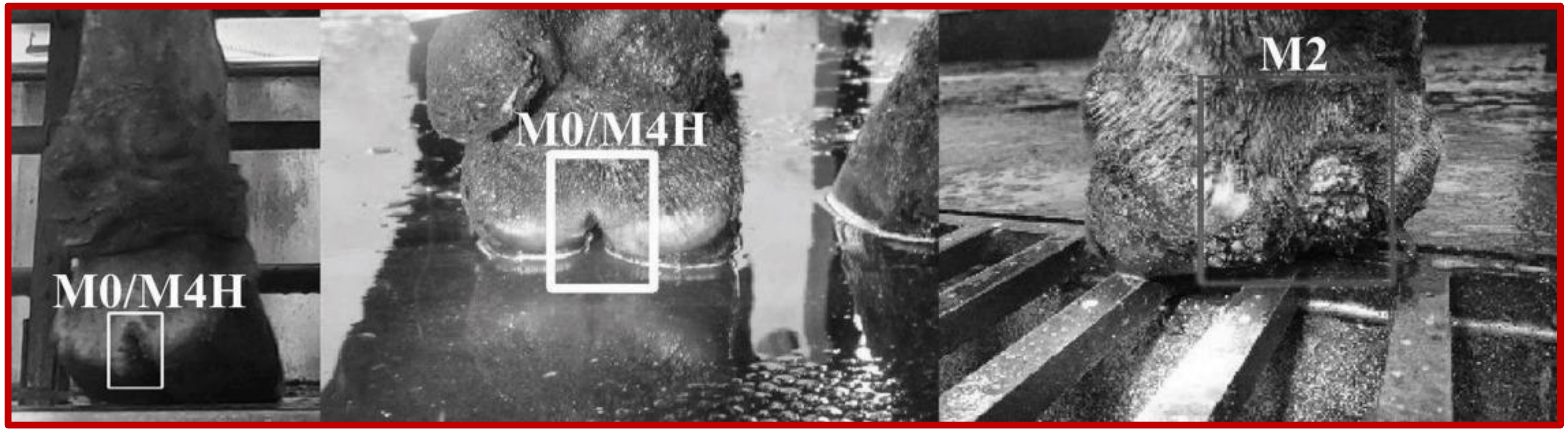
Digital dermatitis

- **Digital dermatitis** (**DD**) is the most prevalent bovine infectious claw disease in North American and global cattle industries.
  - **Painful lesions** on the skin-horn border of the hoof
  - **Severe lameness**, decreased milk production, increased infertility rate
- Visual inspection is traditionally used to detect DD.
  - Requiring extensive training, time, and labor



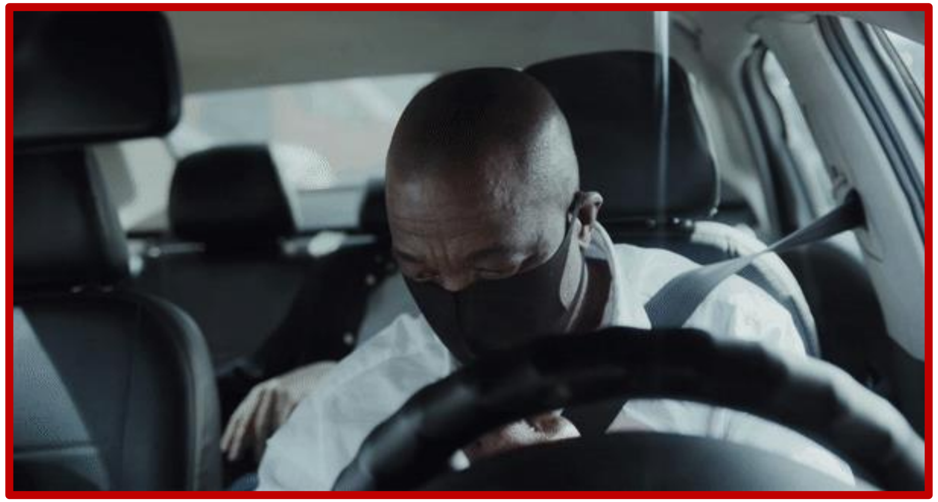
M-Stage Classification System

- The M-stage classification system represents **different stages during the course of DD** based on color, size, and texture of the lesion.
- This system has been used for clinical trials, **herd monitoring**, and for models of transmission of DD.



Computer Vision

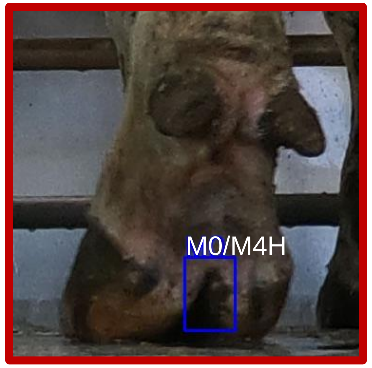
- Computer vision (CV) can be used to perform **object detection** and calculate the associated **class probabilities**.
  - Unique opportunity to improve early detection, prevention, and optimized treatment plans
  - Detection and classification of health events are still rare in veterinary medicine

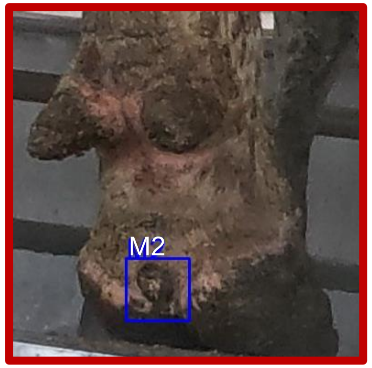


Computer Vision

Object Detection

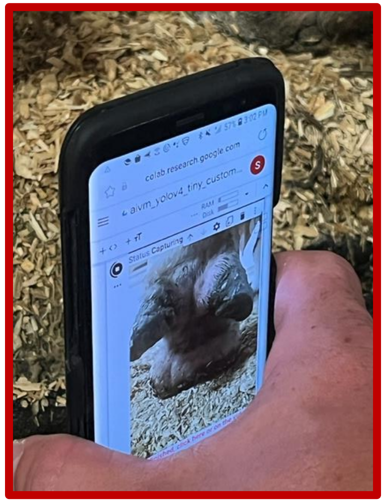
- Object detection locates the presence of objects with a **bounding box** and **class labels** of the located objects in an image.
  - Two-stage object detectors
    - Region-Based Convolutional Neural Networks (R-CNNs)
  - One-stage object detectors
    - Single-Shot Detectors (SSD)
    - You Only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





Edge Devices

- Edge devices can accommodate advanced capabilities with **built-in processors** and **onboard computations**.
  - Smart devices improves processes, automates tasks, and creates better user experiences.
  - By adding cameras and CV capabilities to edge devices, systems can “see” and identify objects.

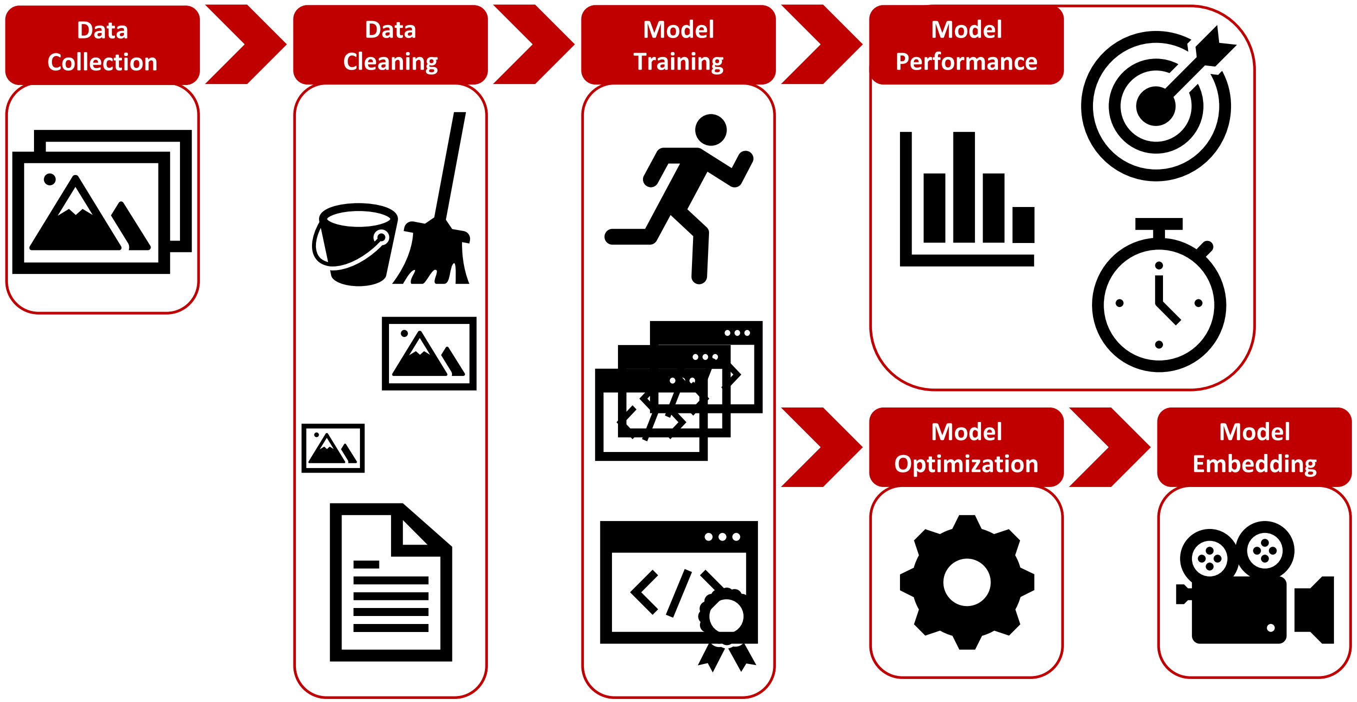



Motivation

- The purpose of this project is to implement a lightweight CV model for constrained environments on edge devices 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



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

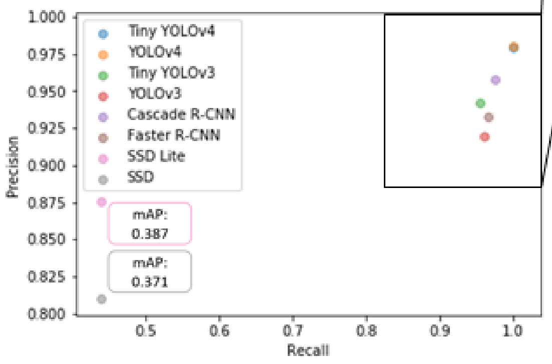
Model Training

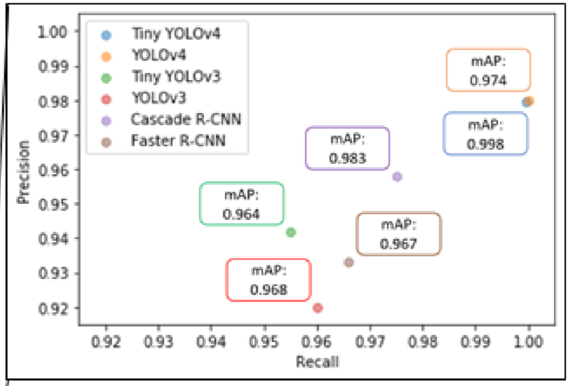
- 90% images for training and 10% images for testing
- 8 object detection models (TensorFlow 1.X)
  - Faster R-CNN & Cascade R-CNN
  - SSD & SSD Lite
  - YOLOv3 & Tiny YOLOv3
  - YOLOv4 & Tiny YOLOv4

Model Performance

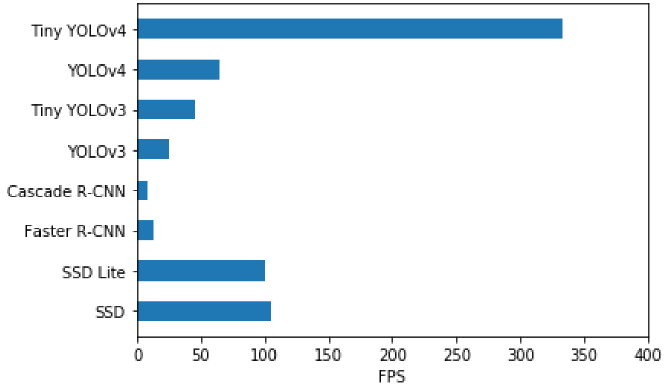
- Real-world dataset containing single object per image and two class labels for object detection (Dataset 1)

YOLOv4 and Tiny YOLOv4 outperform other models





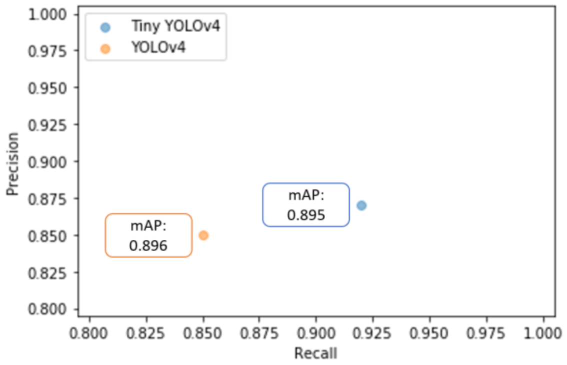
Tiny YOLOv4 is the best model for our use case

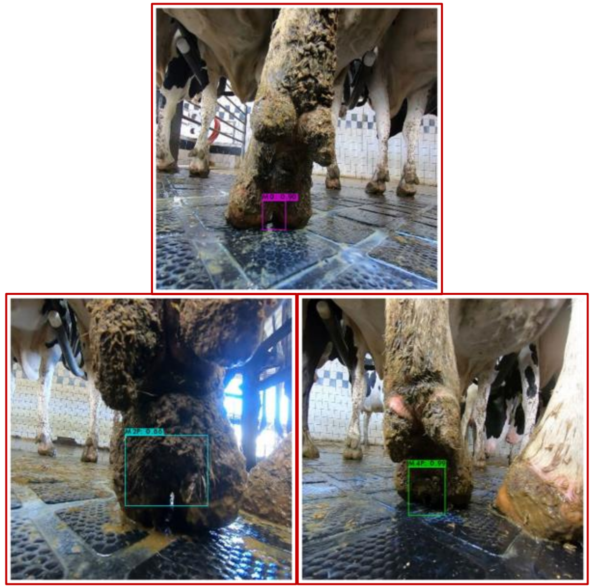


Model Performance

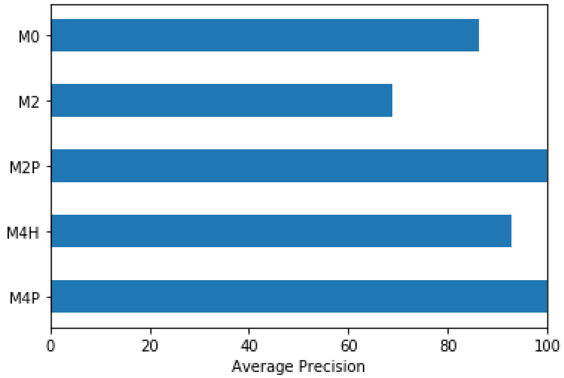
Real-world dataset containing multiple objects per image and more class labels for object detection (Dataset 2)

Similar performance for
Tiny YOLOv4 and YOLOv4





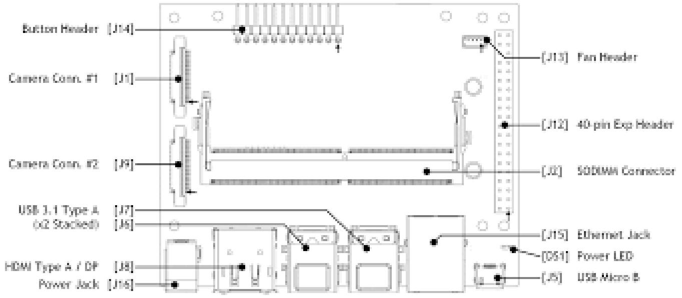
Difference in performance
between classes for Tiny
YOLOv4

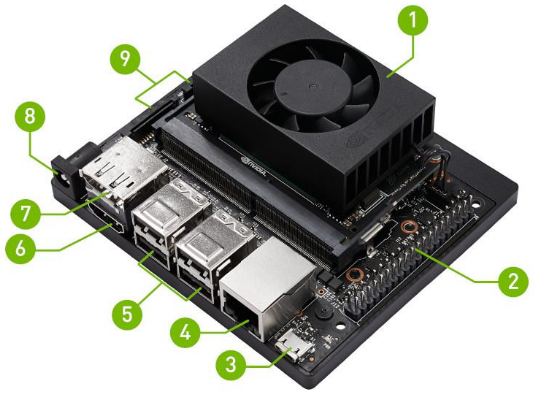


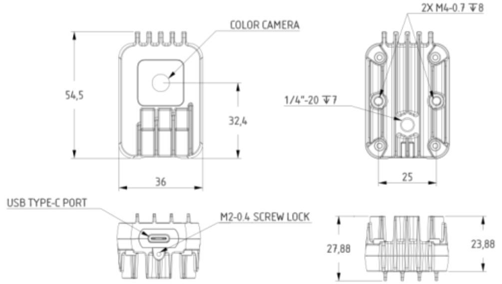
Model Performance

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





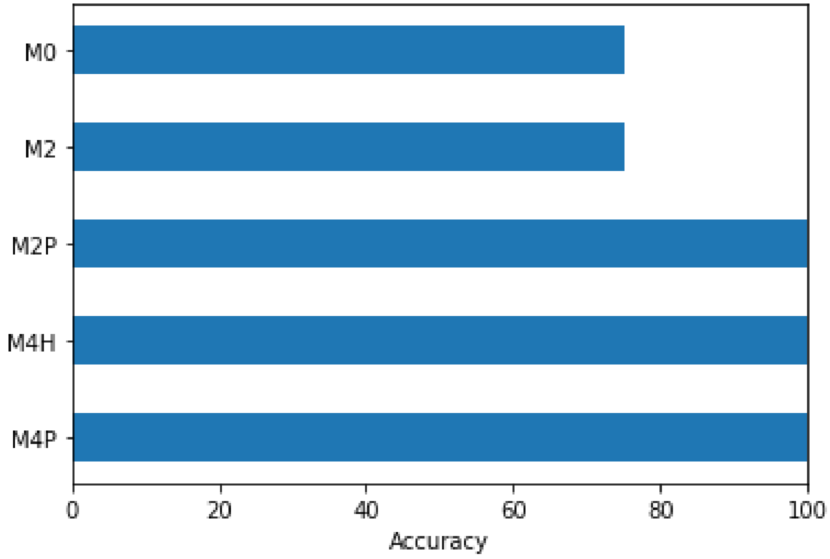


Model Embedding

Implementation processed images at 40 FPS

Excellent agreement with Cohen’s kappa of 0.83

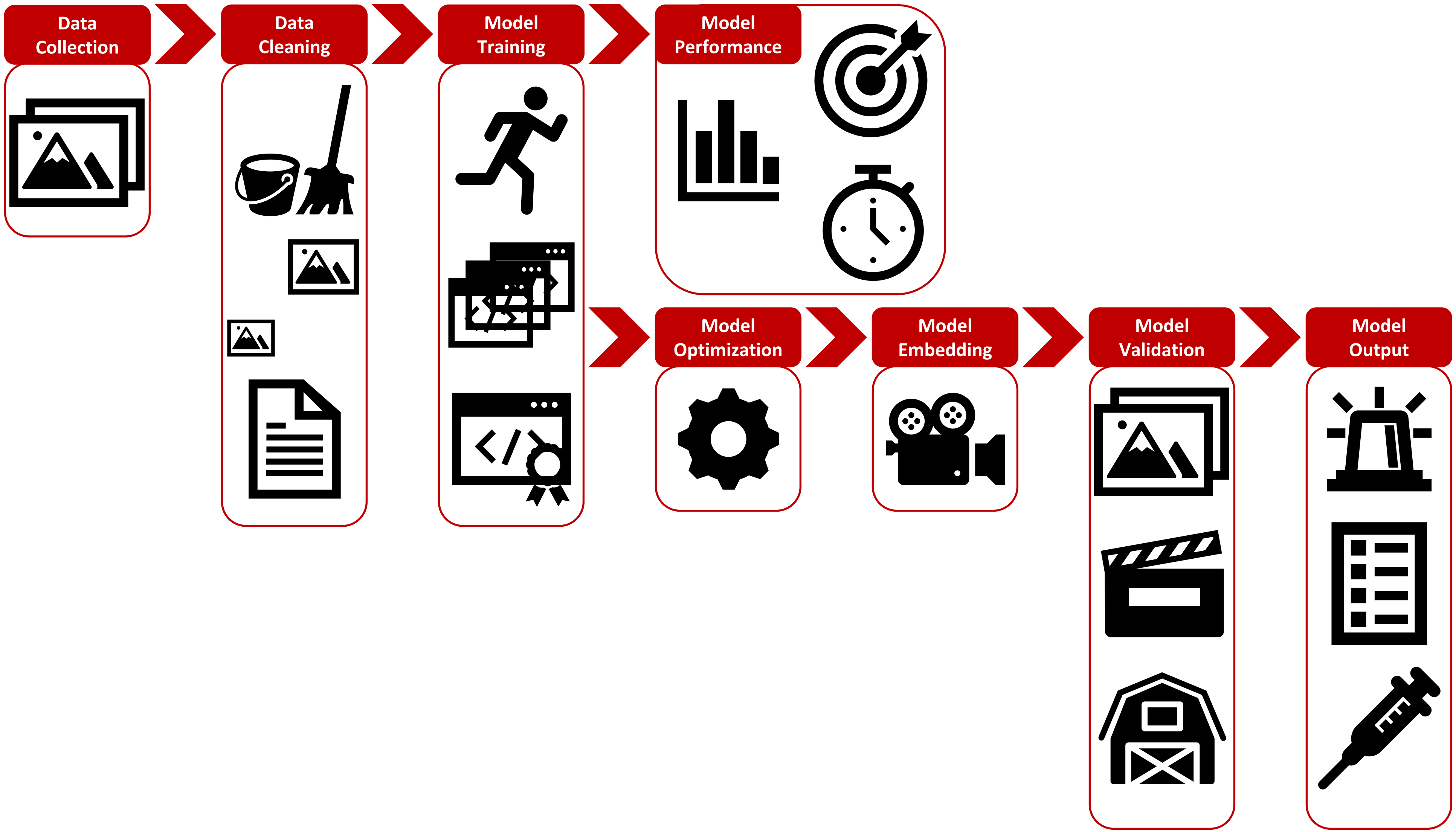
Detect all five class labels on video and webcam



Summary and Future Directions

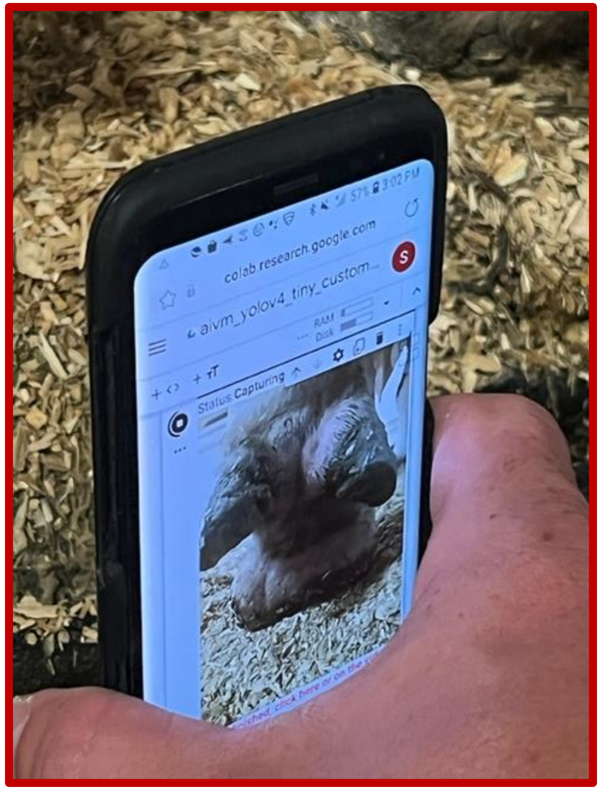
- The workflow was able to accurately and speedily detect DD on edge devices.
- YOLOv4 and Tiny YOLOv4 outperformed all other models
- Tiny YOLOv4 was the best model for our use case
- Tiny YOLOv4 on OAK-1 x NVIDIA Jetson Xavier NX edge device was fast and accurate
- Computer vision for veterinary medicine

Summary and Future Directions



Summary and Future Directions

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



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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.

SCAN ME

Thank you!