Portable Solutions for Custom Tasks using Computer Vision Models on Edge Devices: A Case Study on Real-Time Detection of Digital Dermatitis in Dairy Cattle

S. Aravamuthan and D. Döpfer

Department of Medical Science, School Of Veterinary Medicine, University of Wisconsin, Madison, WI, 53706

WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

Objective

Digital dermatitis (DD)

- DD is a bovine claw disease responsible for ulcerative lesions on the coronary band of the foot. DD is associated with massive herd outbreaks of lameness and influences cattle welfare and production.
- Early detection of DD can lead to prompt treatment and decrease lameness.

Computer vision (CV)

- CV can be used to perform object detection and calculate the associated class probabilities from a series of images or videos.
- CV provides a unique opportunity to improve early detection.

Edge devices

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

The study aims to train lightweight CV models for constrained environments and compare edge devices for the real-time detection of DD in dairy cows.

Figure 1. Bounding box predictions of M-stages by YOLOv2: M0/M4H (healthy claw/chronically affected claw) and M2 (active ulcerative lesions) (Cernek et al., 2020).

Approach

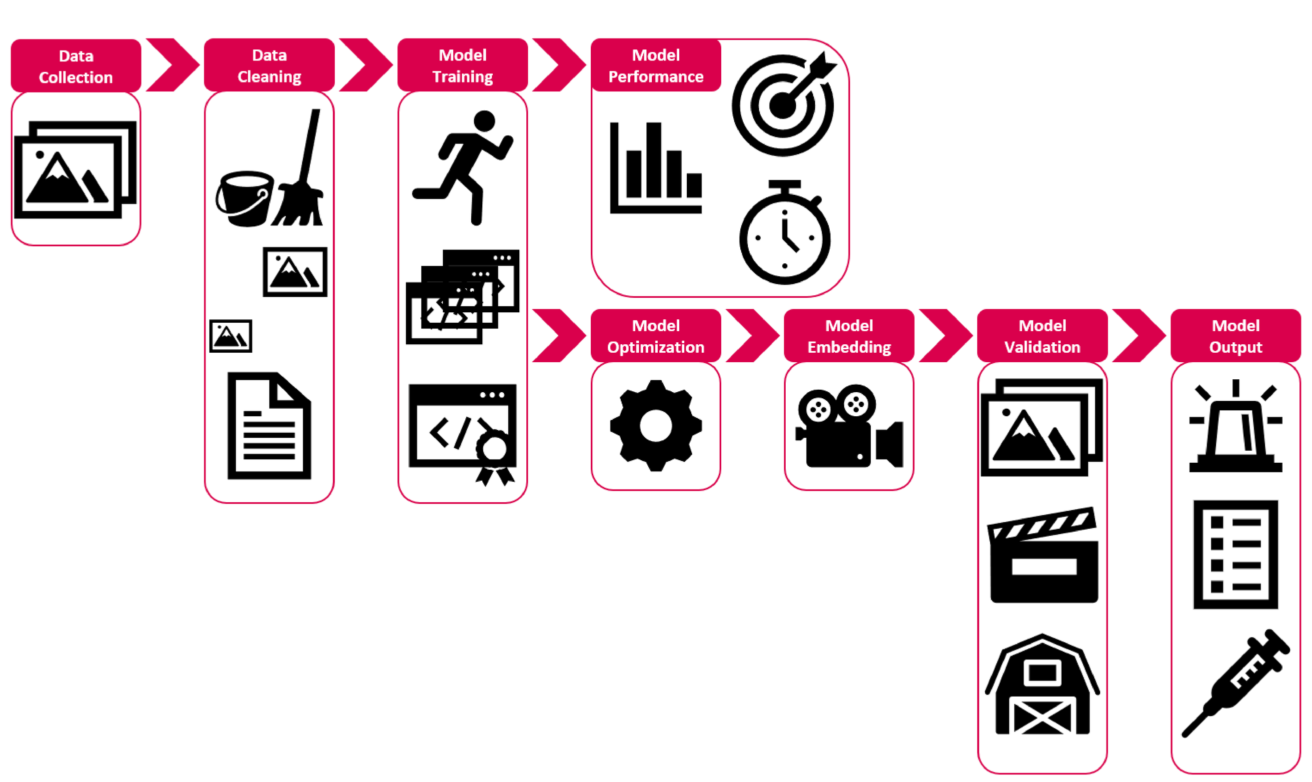


Figure 2. Workflow for implementing an object detection model with custom data.

Data Collection

Dataset 1

- 2,227 JPG images
- 1,177 M0/M4H and 1,050 M2 class labels
- Single foot per image

Dataset 2

- 409 JPG images
- 240 M0, 17 M2, 51 M2P, 114 M4H, and 108 M4P class labels
- Multiple feet per image

Dataset 3

- 1,059 JPG images
- 257 M0, 61 M2, 354 M2P, 213 M4H, and 303 M4P class labels
- Multiple feet per image

Model Performance

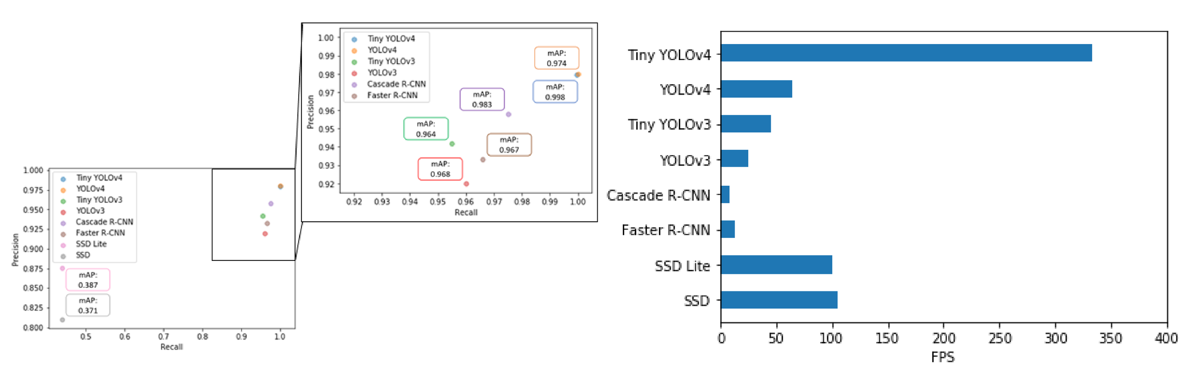


Figure 3. Performance of the eight CV algorithms (bottom-left) with inset of the top six CV model (top-right) for Dataset 1 (left panel).
Six of the eight CV models achieved an mAP between 0.964 to 0.998. Tiny YOLOv4 achieved the highest mAP of 0.998, whereas SSD and SSD Lite achieved the lowest mAP of 0.371 and 0.387 respectively.

Figure 4. Inference time of the eight CV algorithms for Dataset 1 (right panel).
Tiny YOLOv4 outperformed all other models with a speed of 333 FPS. The next closest models were SSD and SSD Lite at 100 FPS.

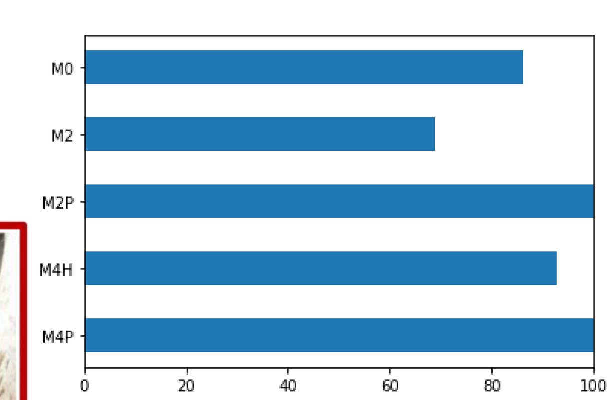


Figure 5. Bounding box predictions of M-stages by Tiny YOLOv4 for Dataset 2 (left panel).
Tiny YOLOv4 was able to detect all five class labels on images.

Figure 6. Average precision of the five M-stages by Tiny YOLOv4 for Dataset 2 (right panel).
Tiny YOLOv4 was able to detect M2P, M4H, and M4P lesions with a higher average precision compared to M2 lesions.

Model Training

Object detection models (TensorFlow 1.X)

- Faster R-CNN & Cascade R-CNN
- SSD & SSD Lite
- YOLOv3 & Tiny YOLOv3
- YOLOv4 & Tiny YOLOv4

- All models were trained and tested using Google Colab on a 12GB NVIDIA Tesla K80 GPU.
- Frames per second (FPS) were used to evaluate the inference time. Precision, recall, and mean average precision (mAP) at intersection over union (IOU) of 0.5 were used to evaluate performance.

Model Embedding

Figure 7. Implementation of Tiny YOLOv4 using DepthAI on OAK-1 connected to Jetson Xavier NX.
Implementation processed images at 40 FPS.

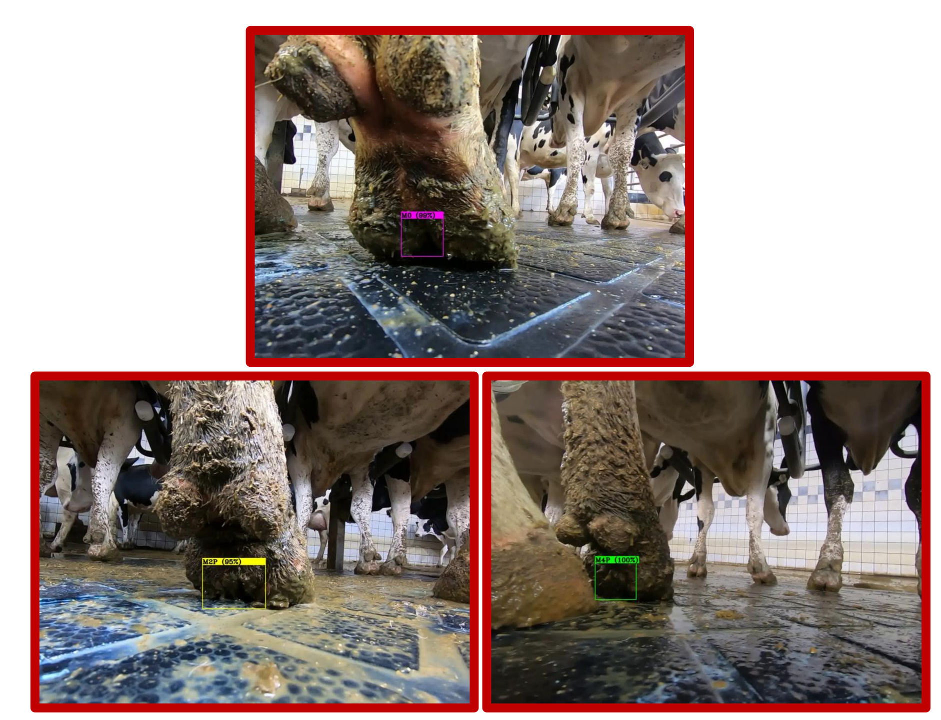
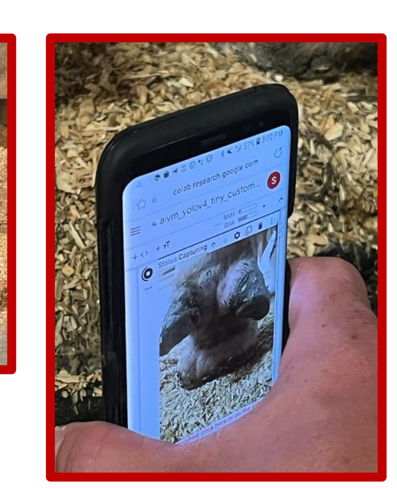


Figure 8. Bounding box predictions of M-stages by Tiny YOLOv4 using Google Colab on laptop or smartphone.
Tiny YOLOv4 was able to detect all five class labels on video and webcam.

SCAN ME



Scan the QR Code to preview the Tiny YOLOv4 in action on the OAK-1 or on the laptop or smartphone.

Conclusions

- The workflow was able to accurately and speedily detect DD on edge devices.
- YOLOv4 and Tiny YOLOv4 outperformed all other models with near perfect precision, perfect recall, and a higher mAP.
- Tiny YOLOv4 outperformed all other models with respect to inference time. SSD and SSD Lite were the next closest model.
- Tiny YOLOv4 was able to detect all five M-stages of DD on images and video files.
- Tiny YOLOv4 and SSD Lite processed images at 40 FPS on an OAK-1 or OAK-D-Lite connected to a Raspberry Pi or Jetson Xavier NX.
- The study is a step towards applying CV algorithms to veterinary medicine and implementing real-time DD detection on dairy farms.

Acknowledgements

Funding support for the research was provided by the US Department of Agriculture through the National Institute for Food and Agriculture - Animal Health Grant (WIS03082).

USDA National Institute of Food and Agriculture
U.S. DEPARTMENT OF AGRICULTURE

References

[1] P. Cernek, N. Bollig, K. Anklam, and D. Döpfer, "Hot topic: Detecting digital dermatitis with computer vision," J. Dairy Sci., vol. 103, no. 10, pp. 9110–9115, Oct. 2020, doi: 10.3168/jds.2019-17478.

[2] R. Girshick, "Fast R-CNN," 2015, pp. 1440–1448. Accessed: Jul. 30, 2022. [Online]. Available: https://openaccess.thecvf.com/content_iccv_2015/html/Girshick_Fast_R-CNN_ICCV_2015_paper.html

[3] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in Advances in Neural Information Processing Systems, 2015, vol. 28. Accessed: Jul. 30, 2022. [Online]. Available: https://proceedings.neurips.cc/paper/2015/hash/14bfa6bb14875e45bba028a21ed38046-Abstract.html

[4] Z. Cai and N. Vasconcelos, "Cascade R-CNN: Delving Into High Quality Object Detection," 2018, pp. 6154–6162. Accessed: Jul. 30, 2022. [Online]. Available: https://openaccess.thecvf.com/content_cvpr_2018/html/Cai_Cascade_R-CNN_Delving_CVPR_2018_paper.html

[5] Z. Cai and N. Vasconcelos, "Cascade R-CNN: High Quality Object Detection and Instance Segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 43, no. 5, pp. 1483–1498, May 2021, doi: 10.1109/TPAMI.2019.2956516.

[6] J. Redmon, "YOLO: Real-Time Object Detection," 2018. https://pjreddie.com/darknet/yolo/ (accessed Feb. 24, 2022).

[7] J. Redmon and A. Farhadi, "YOLO9000: Better, Faster, Stronger," 2017, pp. 7263–7271. Accessed: Jul. 30, 2022. [Online]. Available: https://openaccess.thecvf.com/content_cvpr_2017/html/Redmon_YOLO9000_Better_Faster_CVPR_2017_paper.html

[8] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," ArXiv180402767 Cs, Apr. 2018, Accessed: Feb. 24, 2022. [Online]. Available: http://arxiv.org/abs/1804.02767

[9] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," ArXiv200410934 Cs Eess, Apr. 2020, Accessed: Feb. 24, 2022. [Online]. Available: http://arxiv.org/abs/2004.10934

[10] W. Liu et al., "SSD: Single Shot MultiBox Detector," in Computer Vision – ECCV 2016, Cham, 2016, pp. 21–37. doi: 10.1007/978-3-319-46448-0_2.