Early Detection of Digital Dermatitis in Dairy Cattle using Computer Vision: Portable Solutions for Custom Tasks in Veterinary Medicine

Srikanth Aravamuthan and Dörte Döpfer

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

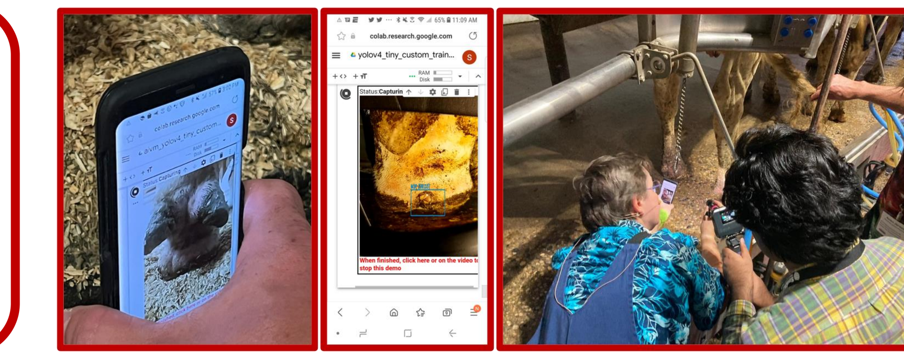
WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

SCAN ME

Train multiple CV models for DD detection and M-stage scoring and compare for speed and accuracy.

Embed the best CV model on portable, stand-alone edge devices and implement for real-time DD detection.

Deploy the best tool for use in remote, rural locations and automate for DD detection.



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 outbreaks of lameness and reduces economic wellbeing and animal welfare.
- The M-stage scoring system is a highly effective way to classify and monitor DD lesions and signs of chronicity.
- Early detection of DD can lead to prompt treatment and preventive strategies.

Computer vision (CV)

- CV can be used to identify objects and calculate the associated class probabilities from a series of images or videos.
- Object detection can be used to precisely monitor animal health and accurately diagnose a variety of medical conditions.

Edge devices

- Edge devices can perform onboard computations with built-in processors. Edge devices do not require internet connectivity, processes data locally, reduces latency, 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, embed on portable, stand-alone edge devices, and compare performance 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).

The authors can be contacted via email:
- Srikanth Aravamuthan (aravamuthan@wisc.edu)
- Dörte Döpfer (dopfer@wisc.edu)

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

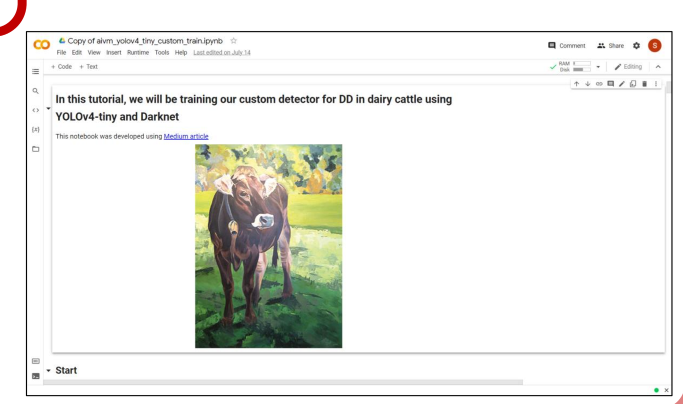
Dataset 1
- 2,227 JPG images
- 1,177 M0/M4H and 1,050 M2 class labels
- Single foot per image

Dataset 2
- 409 JPG images
- 240 M0, 17 M2, 51 M2P, 114 M4H, and 108 M4P class labels
- Multiple feet per image

All images were labeled in Python using LabelImg.

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 in Python using Google Colab on a 12GB NVIDIA Tesla K80 GPU.



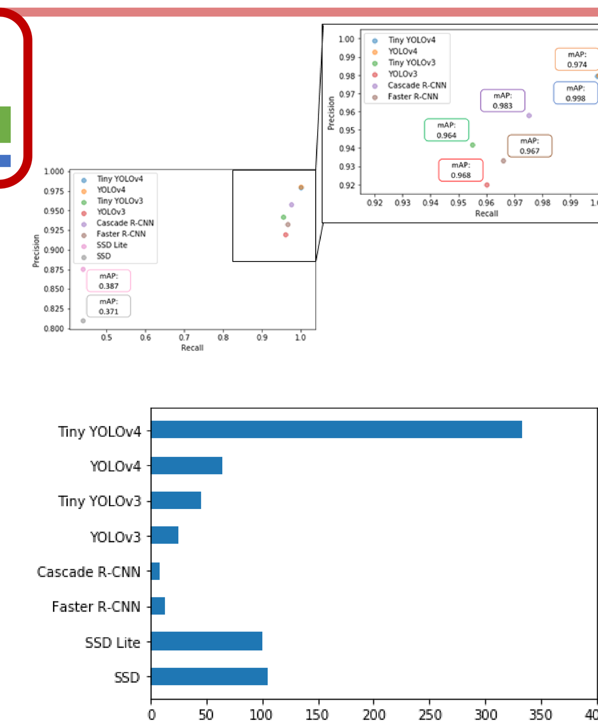


Figure 3. Performance of the eight CV algorithms (bottom-left) with inset of the top six CV model (top-right) for Dataset 1 (left panel).
Six of the eight CV models achieved an mAP between 0.964 to 0.998. Tiny YOLOv4 achieved the highest mAP of 0.998, whereas SSD and SSD Lite achieved the lowest mAP 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 2. Workflow for implementing an object detection model with custom data.

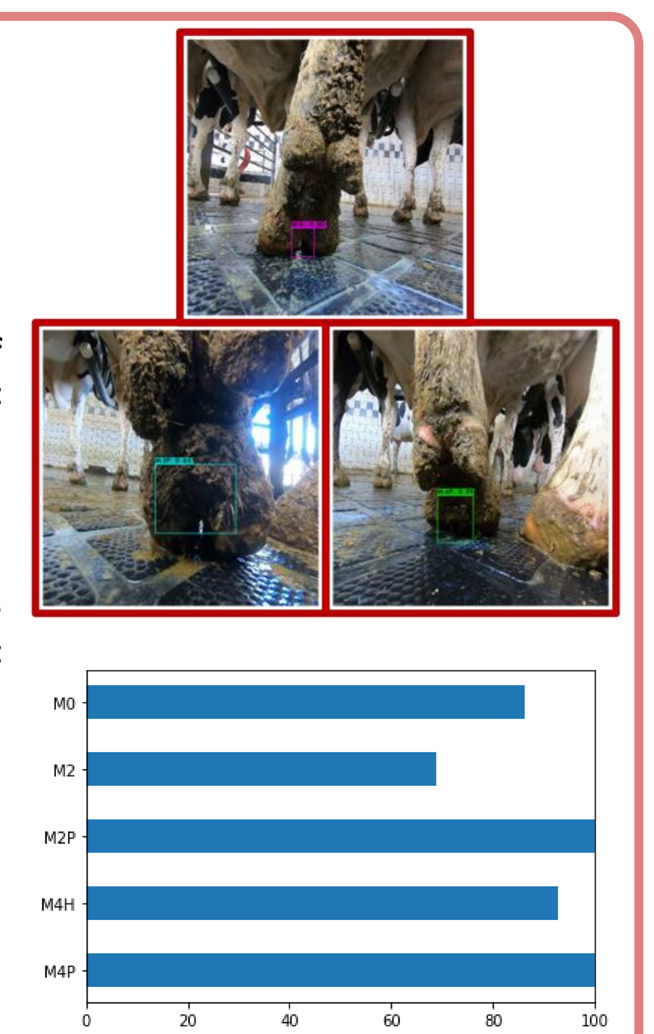


Figure 5. Bounding box predictions of M-stages by Tiny YOLOv4 for Dataset 2 (left panel).
Tiny YOLOv4 was able to detect all five class labels on images with an mAP of 0.895.
Figure 6. Average precision of the five M-stages by Tiny YOLOv4 for Dataset 2 (right panel).
Tiny YOLOv4 was able to detect M2P, M4H, and M4P lesions with a higher average precision compared to M2 lesions.

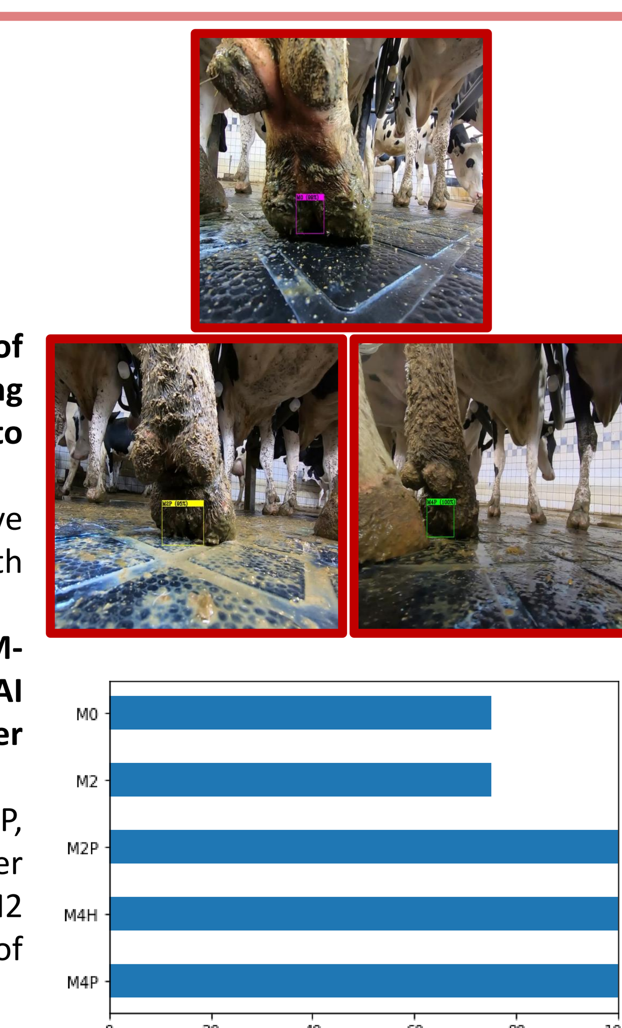


Figure 8. Bounding box predictions of M-stages by Tiny YOLOv4 using DepthAI on OAK-1 connected to Jetson Xavier NX (left panel).
Tiny YOLOv4 was able to detect all five class labels on video and webcam with a Cohen's kappa of 0.830.
Figure 9. Accuracy of the five M-stages by Tiny YOLOv4 using DepthAI on OAK-1 connected to Jetson Xavier NX (right panel).
Tiny YOLOv4 was able to detect M2P, M4H, and M4P lesions with a higher accuracy compared to M0 and M2 lesions with an overall accuracy of 0.873.

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 videos.
- Tiny YOLOv4 processed images at 40 FPS on an OAK-1 or OAK-D-Lite connected to a Jetson Xavier NX or Jetson Nano.
- The study is a step towards applying CV algorithms to veterinary medicine and implementing real-time DD detection on dairy farms.

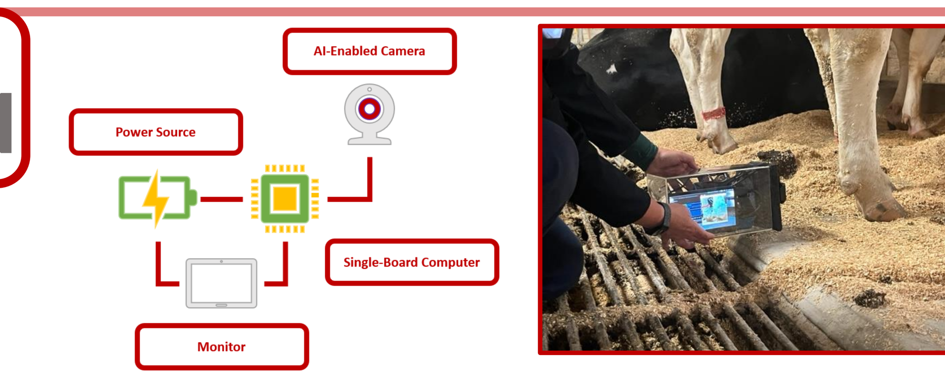


Figure 7. Implementation of Tiny YOLOv4 using DepthAI on OAK-1 connected to Jetson Xavier NX.
Schematic representation of edge device for deployment (left panel) and real-time detection of DD on a portable, self-contained edge device in action at 40 FPS (right panel).

SCAN ME

Videos 1-2. Implementation of M-stages by Tiny YOLOv4 using DepthAI on OAK-1 connected to Jetson Xavier NX.