Detection of collected debris during mechanical wild blueberry harvesting using convolutional neural networks

Anup K. Das[1], Qamar U. Zaman[1], Travis J. Esau[1], Aitazaz A. Farooque[2], Arnold W. Schumann[3]

[1]Dalhousie University, [2]University of Prince Edward Island, [3]University of Florida

Introduction

- The wild blueberry (*Vaccinium angustifolium* Ait.) is a naturally growing horticultural crop in Atlantic Provinces of Canada and Maine, USA.
- Canada produced around 101.95 million kg of berries in 2017, valued at $58.72 million
- Due to improved management practices, wild blueberry plant densities, plants heights and fruit yields have significantly increased
- Due to these augmented plant characteristics there is increased debris in the harvesters handling systems
- The field debris including weed, grass, wild blueberry leaf, wild blueberry stem and dirt are the major constraint for ensuring high fruit quality during harvesting
- Convolutional neural network (CNN) based debris detection systems can be a valuable addition in berry separation technology to improve quality of the fruit

Figure 1: Debris (weed, grass, leaves, stems, dirt) in side conveyor

Objectives

- Training and testing two CNNs for debris detection during mechanical wild blueberry harvesting
- Evaluation of two optimized CNNs based on debris detection accuracy

Methods

- The experimental images (~1000) were collected from two fields in central Nova Scotia using GoPro cameras mounted on the side and rear conveyors
- Debris classes (weed, grass, leaves, stems, dirt) were created and images were labelled using custom software.
- 90% of the images were used for training the CNN, and 10% were used for validation the model
- Two different neural networks (YOLOv3, YOLOv3-Tiny) were trained and validated.
- Networks were trained and tested on a GeForce RTX™ 2080 Ti @ 1665 MHz graphics processing unit (GPU) and an Intel® Core™ i5-4300U CPU @ 1.90 GHZ central processing unit-based computer
- The networks were evaluated based on detection accuracy (mAP)

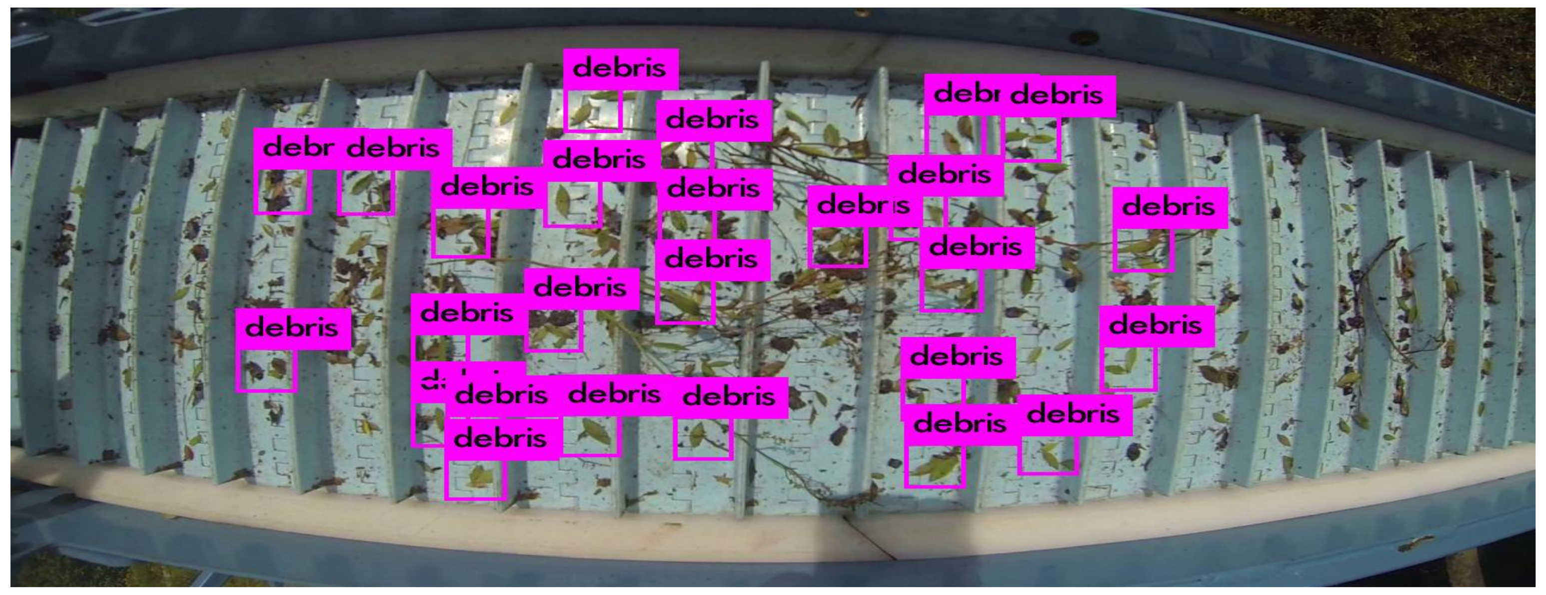
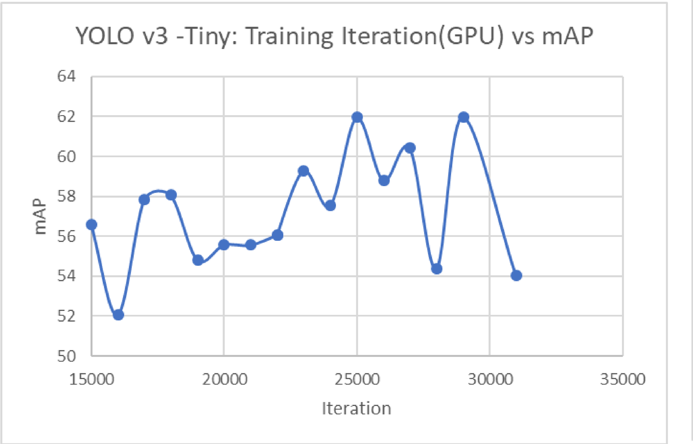


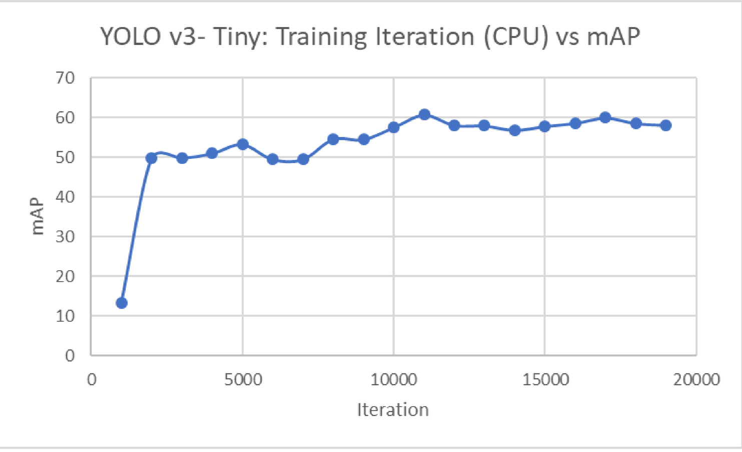
Figure 2: Debris detection using YOLOv3-Tiny

Figure 3: Debris detection using YOLOv3

Results

- The best overall mAP (68.08%) was achieved from the YOLOv3 network with F1 score of 0.67
- YOLOv3-Tiny also achieved mAP of 61.99% and 60.70% in GPU and CPU training respectively





- YOLOv3-Tiny took approximately 10 hours using a CPU and 1.5 hours in GPU to achieve lowest average error rate during training.
- YOLO v3 achieved highest mAP in 700 iterations, took less training time compared to YOLOv3-Tiny

Discussion and Conclusions

- YOLO v3 was able to detect debris more accurately than YOLOv3-Tiny in the testing dataset
- YOLOv3 achieved better mAP (68.08) with few training iterations than YOLOv3-Tiny
- GPU was more efficient for training the dataset than CPU
- In future, this model could be used for real time debris detection during mechanical wild blueberry harvesting.

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