ONTARIO PORK

Ontario Pork Research Final Report (21-06) Executive Summary

(Use the headings below to create an executive summary of the project with a maximum of 1 page double-spaced)

Reporting Date: December 20, 2023

Introduction: The existing approaches for evaluating pork meat quality and carcass traits face limitations such as high costs, substantial space requirements, invasive sampling, low throughput, and susceptibility to human error (Pomar & Marcoux, 2010). This underscores the necessity for alternative tools that can provide accurate measurements of desirable traits in the pork industry. The integration of Graphic Processing Unit (GPU) accelerated data science has ushered in enhanced methods for data analysis across various domains, facilitating innovative solutions that were previously unattainable. Data analytics encompasses 'machine learning,' which employs diverse techniques to construct models based on data. Among these techniques is 'deep learning,' an automated process that, however, demands significant computing power (GPUs) and substantial data volumes to train deep neural networks (Wynters, 2011). This training is essential for these networks to effectively perform tasks at a human-level and achieve accuracies beyond human capabilities. By leveraging deep learning technologies alongside extensive pork phenomics databases and image collections, a computer vision system was developed and assessed to autonomously identify various meat cuts using instance segmentation. Instance segmentation algorithms analyze images by classifying each pixel and at the same time distinguishing between different objects within the same class. With further development and larger datasets, the same deep learning approach will be able to quantify key quality traits in pork primal cuts, such as meat color, fat, and lean content, with a focus on high-throughput capabilities. The system, along with its data analysis models, will undergo ongoing testing and refinement to enhance performance, enabling its application in research and potentially in-line production.

Objectives:

1. Develop high-throughput computer vision system to efficiently measure pork meat quality and carcass primal cut traits.
2. Provide a platform using the resulting database and data analytics to develop precision farming technology.

Materials and Methods: A significant number of new digital images was generated during the duration of this project, contributing to the augmentation of the existing AAFC Phenomics program database and to the development of novel high-throughput approaches to automatically segment and analyze regions of interest from images of pork intact parts such as ham, shoulder and loins. Similarly, a number of deep learning approaches such as Mask R-CNN based on ResNet architectures were implemented and evaluated on the collected images. The models have the potential to process images in real-time and be integrated in computational pipelines that combine segmentation with image analyses such marbling estimation and scoring.

Results and Discussion: In summary, the project resulted in satisfying both objectives by augmenting the size of the existing AAFC phenomics database with more than 3,000 new images and developing a series of analytic and automated segmentation approaches for marbling and identification + separation of hams, shoulders and loins from background in digital images. The project explored the impact of various environment-, experimental- and sensor-based factors on the detection and scoring quality of intact pork products such as hams, shoulders, loins and bellies. The segmentation procedure includes deep learning modelling based on Mask R-CNN and two neural network architectures (ResNet 50 and 101), which proved to reach close to real-time FPS processing speeds.

Conclusions: Through this project, the existing pork phenomics database was expanded, establishing correlations between desirable meat quality traits, and creating a foundation for precision farming. This initiative produced an excellent technological starting point for innovative solutions that enhance research and production efficiency via the application of deep learning modelling for automatic instance segmentation of important meat part regions of interest and computer vision analytic approaches for uniform and automatic meat scoring, positioning the Canadian Pork industry at the forefront of advancements in research and sustainability.

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Ontario Pork Research Final Report (21-06)

(maximum of 6 pages double-spaced)

Date:

Introduction: Current methodologies employed for assessing pork meat quality and carcass traits face limitations, including high costs, extensive spatial requirements, invasive sampling, low throughput, and susceptibility to human error (Pomar and M. Marcoux, 2003). These limitations hinder our comprehensive understanding of factors influencing variability in pork meat quality and carcass traits, leading to inaccuracies in analyses and varying research outcomes. Such challenges may have adverse effects on the Ontario Pork Industry by impeding research into enhancing desirable pork quality and carcass traits through the manipulation of nutritional, environmental, and genetic factors. Furthermore, it could result in the use of imprecise phenotypes for genomic selection. This underscores the imperative for advanced tools capable of accurate trait measurement in the pork industry on a high-throughput scale.

Recent advancements in High-Performance Computing (HPC) using Graphic Processing Units (GPUs) have revolutionized data science, offering improved methods for data analysis across diverse fields. This technological progress has enabled innovative solutions previously deemed unattainable, such as autonomous self-driving vehicles. Applications of this technology are already being explored in agriculture, including autonomous vehicles for crop systems and real-time sensory data collection on livestock.

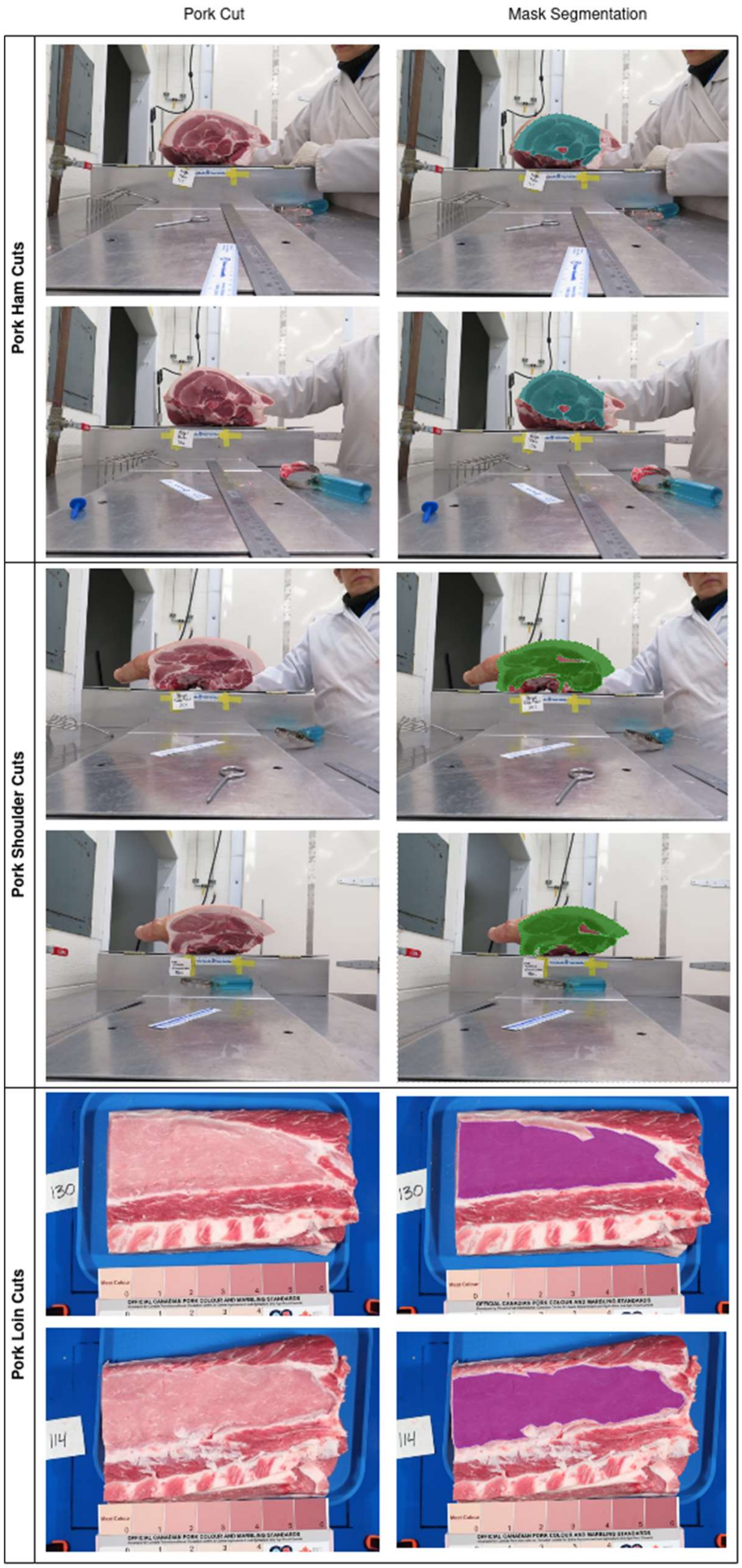
Three key elements have facilitated the realization of this project. Firstly, the utilization of high processing computing power through GPUs has enabled real-time data collection, analysis, and storage at a significantly higher throughput compared to CPUs. Secondly, the progress in data analytics applications, including machine learning, has allowed for the construction of complex models on data. Among these techniques is 'deep learning,' which automates the model-building process but requires substantial computing power (GPUs) and extensive data for training deep neural networks (Wynters, 2011) to perform tasks at a human-level and surpass human-level accuracies. By combining GPUs and data analytics, we can develop a computer vision system and test models capable of evaluating extensive data on meat quality and carcass traits. The third crucial element is the availability of data for training and optimizing a computer vision system. The Phenomics Program at the AAFC Lacombe Research Centre possesses a phenomics database with 15,588 images, which was significantly expanded with 3,000+ images during the execution of this project. This unique database amalgamates information from various Canadian pork projects since 2007, capturing images from different primal, sub-primal, and retail cuts. These include chops, loins, bellies, shoulders, butts, hanging hams, ham slices, and short hams, allowing analysis of lean color, marbling, lean and fat area, connective tissue, bone, blood spots, belly firmness, and dimensions. The database, available in JPEG and RAW formats, is continually expanding as the AAFC Phenomics program collects data from ongoing pork slaughters. The animals in these projects primarily consist of Canadian swine breeds, with 90% being Duroc x F1 (Large White x Pietrain), and the remaining 10% comprising crossbreds with breed compositions, including Iberian and Lacombe, to introduce variability. Notably, the database exclusively features images from Canadian pork cuts, facilitating the calibration of the computer vision system for Canadian pork measurements, rendering the research results particularly valuable for Canadian pork producers, packers, and researchers.

Leveraging this technology and the expanding AAFC pork phenomics database, a computer vision system powered by deep learning was created and evaluated to automatically detect the precise location of areas of interest in pork primal, sub-primal, and retail cuts present in digital images. The system is powered by a deep learning instance segmentation algorithm that has the potential to operate in real-time data analyses when deployed on GPUs and CPUs. Instance segmentation algorithms examine images by classifying individual pixels while simultaneously differentiating between distinct objects within the same category. This functionality would empower meat producers to automatically evaluate the quality of their products as they move through processing facilities. This represents a first step towards assessing quality traits such as lean color, marbling, lean and fat area, as well as the areas of other tissues (connective tissue, bone, blood spots), and dimensions, all achieved at a high-throughput level. The system and its accompanying data analysis models will undergo continuous testing and refinement to enhance performance, enabling optimal utilization in research and potentially in-line production.

This initiative will introduce potential future grading systems capable of rewarding producers for achieving high meat quality, ultimately enhancing Canadian pork products and bolstering the competitiveness of the Canadian pork international trade. Additionally, the outcomes may pave the way for the selection of traits specific to standards, rendering Canadian pork more attractive for export markets. Cooperative systems stand to benefit as well, using the developed system for prototype testing and data collection to assist producers. The impact extends beyond the Ontario Pork industry, as future research projects gain access to the pork phenomics database, facilitating a deeper understanding of pre- and post-mortem factors influencing pork quality and carcass traits. The identification of relationships between desirable meat quality and carcass traits will provide tools for commercial producers to precisely select for desirable traits, establishing a foundation for precision farming. In essence, this study will bring about innovative solutions to enhance research and production efficiency, positioning the Canadian Pork industry at the forefront of advancements in research and sustainability.

Objectives: (original objectives from project proposal)

1. *Develop high-throughput computer vision system to efficiently measure pork meat quality and carcass primal cut traits.*
2. *Provide a platform using the resulting database and data analytics to develop precision farming technology.*



Comparison of Pork Cut and Segmentation Ground Truth Mask

Figure 1. Image and mask pairs for ham, shoulder, and loin cuts. Masks for ham and shoulder cuts were segmented to cover the entirety of the meat cut. Loin masks were segmented for muscle segments of the cut.

Materials and Methods:

Data collection: The data was collected and annotated (Figure 1) by personnel from the Juarez Lab at the Lacombe Research and Development Centre, Agriculture and Agri-Food Canada, Lacombe, Alberta.

For image segmentation, a dataset of 1,949 red, blue and green (RGB) images with a 4,000 pixels x 3,000 pixels resolution representing pork cuts (ham, shoulder, loin), and corresponding annotation files produced with ImageJ were obtained. For each image we selected a corresponding annotation file representing the region of interest, containing a single binary polygonal mask. Each pixel within the polygonal mask is identified as belonging to the pork cut, and every pixel outside the polygonal mask was identified as belonging to the background. The annotations were created and formatted using ImageJ but were converted to the LabelMe format via a custom Python script. A subset of 1,342 images were selected for deep learning modeling, which included 852 ham cuts, 200 shoulder cuts and 290 loins. Image processing and modelling was performed on a desktop computer running Ubuntu Linux 22.04 and equipped with a single Nvidia GeForce RTX 3080 with 12 GB of memory. The computer processor was AMD Ryzen 9 5900X GPU @ 4.9 GHz with 32 GB of RAM. The programming was done using Python 3.7, TensorFlow 2.00, and Keras 2.3.1. The deep learning algorithm used in this study was Mask R-CNN (He et al., 2018) and a summary of the pipeline is provided in Figure 2.

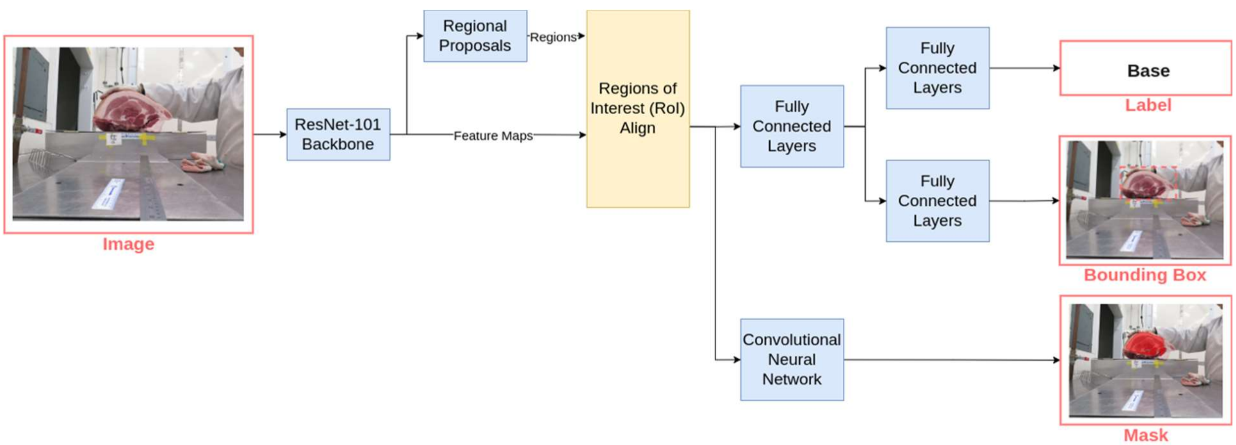


Figure 2. Mask-RCNN model architecture. Each blue box is a neural network. The architecture produces 3 outputs: the bounding box, the label, and the mask. For each output, Mask-RCNN allows multiple unique predictions for multi-object segmentation. For this project, each image contains only one ground truth segmentation, so we constrain the model to predict one label, one bounding box, and one mask.

We used the concept of transfer learning to speed-up model training. Model weights were initialized using two pre-trained model architectures (ResNet50 and ResNet101) on the MS-COCO dataset. The model was trained, validated and tested using an 80%-10%-10% split of the data. We explored different learning momentum values. The process was repeated three times and average precision, recall, Intersection over Union (IoU) and DICE scores were reported.

Results and Discussion:

Objective 1: The first component of this objective, namely the automatic segmentation of areas of interest from digital images representing pork cuts was accomplished using deep learning. The two Mask R-CNN model architectures (ResNet50 and ResNet 101) produced comparable results (Table 1) for correctly segmenting hams and shoulders with average IoU values around 0.88, DICE scores of 0.935, 0.95 precision and 0.92 recall. Sample results are presented in Figure 3.

Table 1. Whole-cut segmentation results (IoU, DICE, Precision, Recall and Accuracy) on the test set for the two models.

Backbone Model	Learning Momentum	IoU	DICE	Accuracy	Precision	Recall
Resnet-50	Small (0.85)	0.877	0.928	0.995	0.939	**0.931**
	Medium (0.90)	**0.881**	0.929	**0.996**	0.959	0.906
	Large (0.95)	**0.881**	0.932	**0.996**	0.952	0.919
Resnet-101	Small (0.85)	0.876	0.932	0.995	0.961	0.907
	Medium (0.90)	0.875	0.939	**0.996**	**0.963**	0.921
	Large (0.95)	**0.881**	**0.941**	**0.996**	**0.963**	0.923

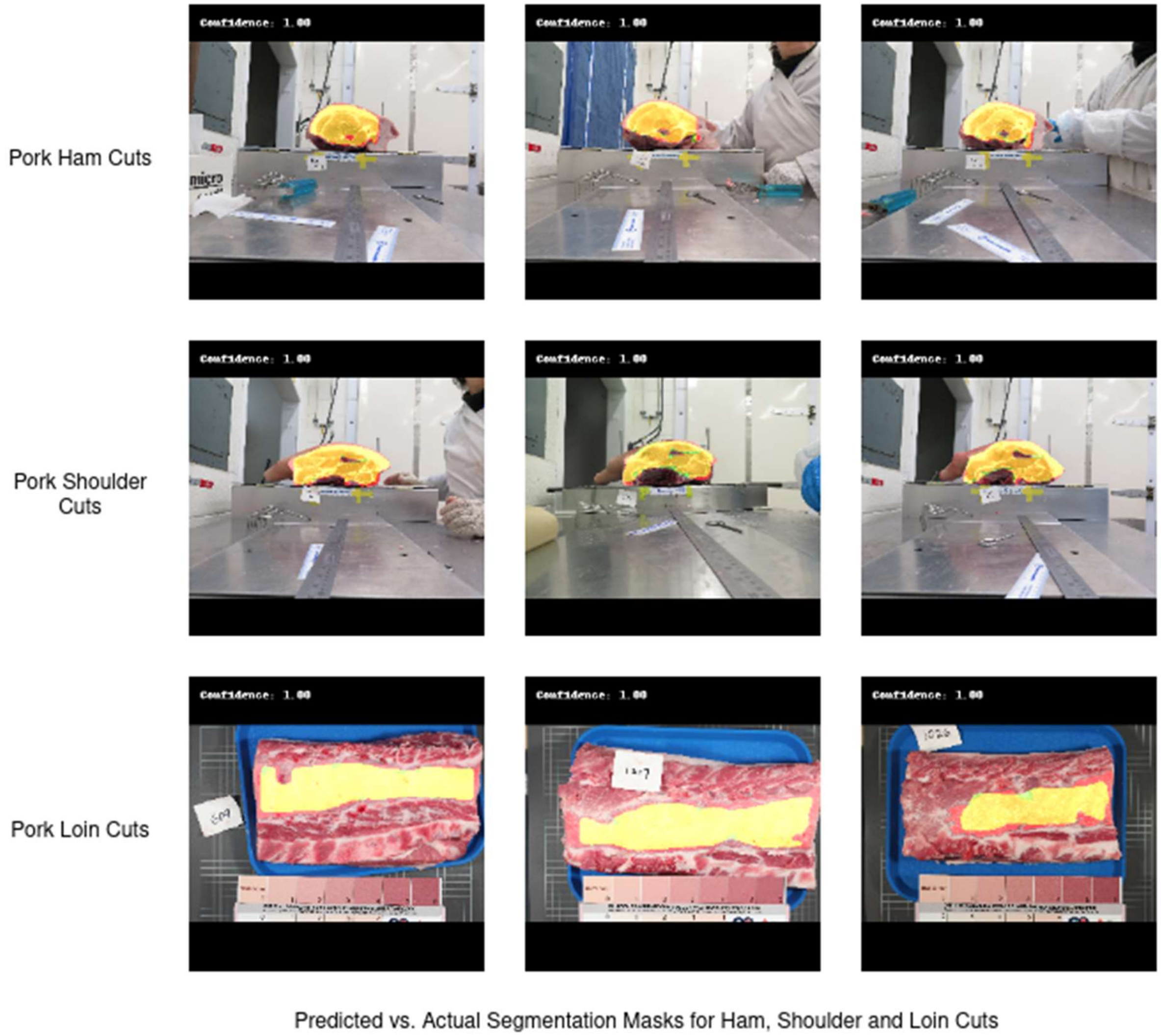


Figure 3. Predicted and ground truth overlap for ham, shoulder, and loin cuts. The red mask is the ground truth, the green is the model prediction mask, and the yellow mask segment shows the area of overlap between the prediction and ground truth masks. The model that produced the segmentations was trained with a Resnet-101 backbone and a large (0.95) learning rate.

The segmentation of the lean part of loins proved to be slightly more challenging. The two model architectures correctly segmented the lean part of the loin with average IoU values around 0.82, DICE scores of 0.93, 0.93 precision and 0.87 recall (Table 2).

Table 2. Muscle-cut segmentation results (IoU, DICE, Precision, Recall and Accuracy) on the test set for the two models.

Backbone Model	Learning Momentum	IoU	DICE	Accuracy	Precision	Recall
Resnet-50	Small (0.85)	0.802	0.891	0.984	0.919	0.861
	Medium (0.90)	0.822	0.902	0.984	**0.942**	0.874
	Large (0.95)	0.832	0.904	0.983	0.934	0.879

Resnet-101	Small (0.85)	0.806	0.889	0.983	0.926	0.862
	Medium (0.90)	0.832	0.907	0.979	0.929	0.883
	Large (0.95)	**0.844**	**0.913**	**0.988**	0.937	**0.884**

No significant advantage was provided by using the more complex network architecture of ResNet101, and thus we recommend the use of the more computationally efficient ResNet50 for this task. We have also investigated the practicality and potential utilization in real-time applications of the trained models in terms of execution speeds using either a GPU or a CPU (Table 3).

Table 3. Number of frames-per-second and seconds-per-image for the models considered in this work.

Computer Architecture	Task Type	Mask-RCNN Backbone	Maximum Frames-per-Second (FPS)	Seconds-per-Image
GPU	Whole-Cut Segmentation	Resnet-50	**23.40**	**0.04273**
		Resnet-101	19.81	0.05046
	Muscle-Cut Segmentation	Resnet-50	8.93	0.11193
		Resnet-101	8.04	0.12436
CPU	Whole-Cut Segmentation	Resnet-50	7.71	0.12976
		Resnet-101	6.16	0.16240
	Muscle-Cut Segmentation	Resnet-50	6.38	0.14623
		Resnet-101	5.30	0.18856

The GPU executions achieved processing speeds of up to 23.40 Frames-Per-Second (FPS) for the segmenting ham and shoulder cuts and up to 8.9 FPS for loins using a Resnet-50 backbone. This frame rate is comparable to real-time video and proves to be an effective real time segmentation mechanism. The CPU executions achieved processing speeds of up to 7.7 FPS for hams and shoulder cuts and up to 6.4 FPS for loins.

The second component of this objective included the development of approaches for measurement of marbling in the intact pork loin. A method for image analysis aimed at identifying marbling on exposed, boneless pork loin surfaces was developed to address the challenge of inconsistent lean color. When comparing results obtained from RAW and JPEG images of the mid-loin pork chop, it was observed that, except at very high marbling levels, the estimation of %IMF (intramuscular fat) demonstrated similarity with both image types (R2 = 0.72 and 0.74, respectively). Marbling calculated from JPEGs exhibited a positive correlation with %IMF, but the correlation diverged as %IMF increased. Assessments of %IMF at the mid-loin chop from JPEGs of external loin sites indicated that marbling on the posterior face had the strongest correlation ($r = 0.72$, $P < 0.0001$), followed by the ventral surface ($r = 0.62$–0.64, $P < 0.0001$), and the anterior face (r =

0.56, P < 0.0001). Considering the importance of computing speed for online applications, this study suggested that an image capture system could be simplified to capture a cyan-filtered monochrome JPEG image for subsequent analysis. The image segmentation approach combined with the two image analyses approaches will require additional integration work and could lead to one-of-a-kind solution for automatic evaluation of meat products directly on an industrial setting.
Objective 2: Significant effort was made to explore and experiment with different camera technologies and image processing technologies to acquire high quality digital images that are easier to process and that can lead to better results during the analytic process. These strategies aimed to address commonly occurring issues such as specular reflectance on the meat surface, variable depth of field, variable image capture speed, filtering (green filters perform best), exposure settings to control pixel saturation levels, etc. Code has been developed that has real-time capabilities and can be integrated into a computational platform for precision meat quality assessment in industrial settings. The integration of the resulting technologies is going to be considered in the next stage of the larger initiative and we are currently exploring way to achieve this with minimum programming efforts and ideally by engaging external partners.
Conclusions: This project played a pivotal role in expanding the current pork phenomics database, fostering connections between sought-after meat quality traits, and laying the groundwork for precision farming. The initiative provided a robust technological foundation for cutting-edge solutions that improve research and production efficiency. This involved the implementation of deep learning models for the automatic instance segmentation of crucial meat part regions of interest and computer vision analytics for consistent and automated meat scoring. As a result, the Canadian Pork industry is positioned at the forefront of progress in research and sustainability.

References:

He, K., G. Gkioxari, P. Dollár, and R. Girshick. 2018. Mask R-CNN. doi:10.48550/arXiv.1703.06870. Available from: http://arxiv.org/abs/1703.06870

Pomar and M. Marcoux, C. 2003. Comparing the Canadian pork lean yields and grading indexes predicted from grading methods based on Destron and Hennessy probe measurements. Can. J. Anim. Sci. 83:451–458. doi:10.4141/A02-107.

Wynters, E. 2011. Parallel processing on NVIDIA graphics processing units using CUDA. J. Comput. Sci. Coll. 26:58–66.

Knowledge Transfer:

Highlight any communications of the research to date

- Presentation, poster or abstract from a scientific or industry meeting (please provide a copy or the link):
  Vinden, N. (2023). A Mask-RCNN Approach to Segmenting Pork Cuts. AAFC-UofG collaborators meeting, December 2023.
- Popular Press Articles and communications:
  Vinden, N., Uttaro, B., Juárez, M. & Tulpan, D. (in preparation). A Deep Learning Approach for Automatic Pork Cuts Segmentation.