Proceedings of the Canadian Society for Mechanical Engineering International Congress 2021
CSME Congress 2021
June 27-30, 2021, Charlottetown, PE, Canada

Parameters Influencing Hair Fescue and Sheep Sorrel Identification in Wild Blueberry Fields Using Convolutional Neural Networks

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Abstract— Broadcast applications of liquid herbicides are used to manage weeds such as hair fescue (*Festuca filiformis* Pourr.) and sheep sorrel (*Rumex acetosella* L.) in wild blueberry (*Vaccinium angustifolium* Ait.) fields. Weeds typically grow in patches of the fields, consequently, herbicide is wasted on areas of the field without weed cover. Application efficiency can be optimized by employing a smart sprayer which uses machine vision to identify areas of the field containing the target weeds in real-time. The YOLOv3-Tiny convolutional neural network (CNN) was trained to detect hair fescue and sheep sorrel using 1280x720 resolution images captured in 58 wild blueberry fields throughout Nova Scotia, Canada. The trained CNN detected at least one target weed per validation image with F_1-scores of 0.97 for hair fescue and 0.90 for sheep sorrel at a network resolution of 1280x736. An evaluation was performed at a commercial wild blueberry field in Debert, Nova Scotia, to examine the effects of camera selection and target distance on detection accuracy. A Logitech c920 webcam, an LG G6 smartphone, and a Canon T6 DSLR camera were used to capture colour images at distances of 0.57 m, 0.98 m, and 1.29 m from target weeds. Test plots were selected at randomly spaced intervals along an inverted "W" pattern in the field. Mean F_1-scores for each combination of camera and image height were analyzed in a 3x3 factorial arrangement for hair fescue and a 3x2 factorial arrangement for sheep sorrel. The peak F_1-score for detection of at least one hair fescue plant, 0.97, was achieved with images captured with the LG G6 smartphone at a height of 0.98 m. Images captured with the LG G6 smartphone and Canon T6 DSLR camera at 0.98 m each achieved an F_1-score of 0.82 for detection of at least one sheep sorrel plant per image. Sheep sorrel was only detected by the CNN in images from the Logitech c920 camera using 3 of 9 parameter combinations in the analysis. Future work will examine images from two additional fields tested under similar conditions. Additionally, the CNN will be used to control herbicide applications after integration with a real-time smart sprayer. A web-based application will be developed to detect target weeds using the CNN and provide wild blueberry growers with site-specific information to aid management decisions. Using a CNN to detect weeds will improve traditional management techniques and create cost-savings and greater sustainability for wild blueberry growers.

Keywords—Deep learning; artificial intelligence; machine vision; precision agriculture; weed detection

I. INTRODUCTION

Wild blueberries (*Vaccinium angustifolium* Ait.) are a perennial, economically important crop native to northeastern North America. Commercial management typically occurs in a two-year cycle with the fruit buds beginning to grow from August to October in the non-bearing (sprout) year, then lie dormant through the winter [1]. The wild blueberry plants continue growing into the bearing (crop) year, and the fruit is harvested in August when 90% of the berries are ripe [2]. The growth cycle is restarted after the harvest, as the bare branches are pruned by flail mowing or burning [1].

Broadcast applications of liquid herbicides are typically used to manage more than 100 unique species of weeds, a major yield-limiting factor in wild blueberry production [3], [4]. In the most recent weed survey, sheep sorrel (*Rumex acetosella* L.) and hair fescue (*Festuca filiformis* Pourr.) ranked as the first and fourth most common weeds in Nova Scotia wild blueberry fields [5]. Hair fescue grows as a tufted grass and is recognizable by its thin green- and tan-coloured blades (Figure 1) [6]. Sheep sorrel is characterized by its green or red leaves which are small, round, and arrow-shaped (Figure 2). The survey found that hair fescue and sheep sorrel had field uniformities of 25% and 63%, respectively [5]. The intermittent nature of these weeds presents an opportunity for increased herbicide application efficiency using a smart variable-rate sprayer. Smart sprayers utilize sensors and high-speed computer inferencing to select which areas of a field to apply

Funding for this research was generously provided by the Natural Sciences and Engineering Research Council of Canada Discovery Grants Program (RGPIN-06295-2019), Doug Bragg Enterprises, Ltd, and New Brunswick Canadian Agricultural Partnership (CAP).

Figure 1. A hair fescue tuft growing in a sprout-year wild blueberry field in spring 2019 [6]. The wild blueberry branches behind the tuft have been pruned through flail mowing.

agrochemicals, limiting the total volume needed for management [7]–[13].

Recent smart sprayers for wild blueberry management have relied on red-green-blue (RGB) image data from cameras to detect foliage [7]–[11]. A smart sprayer relying on green colour segmentation could successfully isolate green foliage from blueberry branches and bare ground [7]–[9]. This resulted in herbicide savings of up to 78.5% [9], but the algorithm could not discriminate between different weed species containing green. Another imaging system relying on colour co-occurrence matrices was created to detect goldenrod (*Solidago* spp.) in wild blueberry fields, but could not be easily adapted to other weeds [10], [11]. These smart sprayers have typically attached cameras 1.1 m [7], [8] to 1.2 m [9]–[11] from the ground on the applicator boom ahead of the spray nozzles. This boom height is higher than smart sprayers in other cropping systems [12]–[15], but is necessary due to the highly variable topography of wild blueberry fields (Figure 3).

Figure 2. Sheep sorrel leaves growing in a sprout-year wild blueberry field in spring 2019 [6]. The wild blueberry branches intermingled with the leaves have been pruned through flail mowing.

Deep learning convolutional neural networks (CNNs) are an image processing technique which has been gaining popularity for agricultural applications in recent years [16]. Datasets with thousands of images labelled or sorted according to their classification are used to train a CNN to classify new, unlabeled images through backpropagation [17]. CNNs provide an opportunity for high-speed, automatic inferencing of field conditions using images from RGB cameras [18], [19]. In the wild blueberry cropping system, Schumann et al. [20] trained four CNNs to detect and classify fruit ripeness stages and provide yield prediction. CNNs have been used to detect weeds in other cropping systems such as potatoes [21], strawberries [22], and various Florida vegetables [23]. Hennessy et al. [24] trained six CNNs for detecting hair fescue and sheep sorrel using images from 58 wild blueberry fields in Nova Scotia, Canada. Training images were captured at three heights (0.52 ± 0.04 m, 0.99 ± 0.09 m, and 1.35 ± 0.07 m), corresponding with the possible range of image capture heights on a smart sprayer. The CNNs achieved F_1-scores [25] of up to 0.97 and 0.90 for detecting at least one instance of hair fescue and sheep sorrel in an image, respectively. The study concluded that the YOLOv3-Tiny CNN [26] had an appropriate balance between identification accuracy and processing speed and should be investigated further for controlling herbicide applications from a smart sprayer.

This study examined the use of YOLOv3-Tiny, with the trained weights from [24], to detect instances of hair fescue and sheep sorrel in images captured from a wild blueberry field in Debert, Nova Scotia. Images were captured using varying combinations of three cameras and three image heights at randomly spaced intervals along an inverted "W" path [4], [27], [28] through the field. The mean F_1-scores for hair fescue detection were analyzed in a 3x3 factorial arrangement. The mean F_1-scores for sheep sorrel used results from two of three cameras and were analyzed in a 3x2 arrangement. This paper contributes information regarding optimal image capture distances and recommendations towards effective camera selection for accurate weed detection.

TABLE I. NUMBER OF TARGET AND NON-TARGET PLOTS USED TO COLLECT IMAGES FOR TESTING THE WEED-DETECTION CNNS.

Target	**Height (m)**			**Total**
	0.57	***0.98***	***1.29***	
Hair Fescue	5	5	5	15
Not Hair Fescue	4	4	6	14
Sheep Sorrel	3	3	3	9
Not Sheep Sorrel	6	6	8	20

Figure 3. An example of the topography seen in many wild blueberry fields [6]. This picture was captured in Murray Siding, NS (45.3654°N, 63.2118°W) on October 9, 2020, prior to pruning. The leaves on the wild blueberry plants have turned from green to red with the change in season.

II. Materials and Methods

A. Field Image Collection

Images were collected in a sprout-year field in Debert, Nova Scotia (45.4265°N, 63.4826°W) on three dates corresponding to typical herbicide application timing: May 6, May 14, and May 25, 2020. Test plots were selected by walking an inverted "W" pattern through the field [4], [27], [28]. The starting point of the path was selected by walking 10 paces along the edge of the field, then 10 paces into the field. Test plots were selected at random intervals from 5 to 10 paces along the "W" and randomly assigned an imaging height of 0.57 m, 0.98 m, or 1.29 m. This process continued until at least three target and non-target test plots were selected for each weed at each imaging height. A resulting count of 29 test plots were used for image collection (Table I).

A Canon EOS Rebel T6 DSLR camera ("Canon T6"), an LG G6-H873 smartphone ("LG G6"), and a Logitech c920 HD Pro USB 2.0 webcam ("Logitech c920") were used to capture images at each test plot. The Logitech c920 was selected for its low cost and successful deployment in smart variable-rate sprayers developed by [12] and [13]. The Logitech c920 was mounted to a tripod and connected to a USB 3.1 port on an MSI workstation laptop (WS65 9TM-1410CA, Micro-Star International Co., Ltd) with an Nvidia Quadro RTX 5000 graphics processing unit (GPU) via a 2 m USB 3.0 extension cable. Images were captured at 1920x1080 resolution in Logitech Capture software. The image sharpness was reduced from the default 128 to 95 to prevent image tearing and artifacts (Figure 4). The autofocus function did not properly focus on the

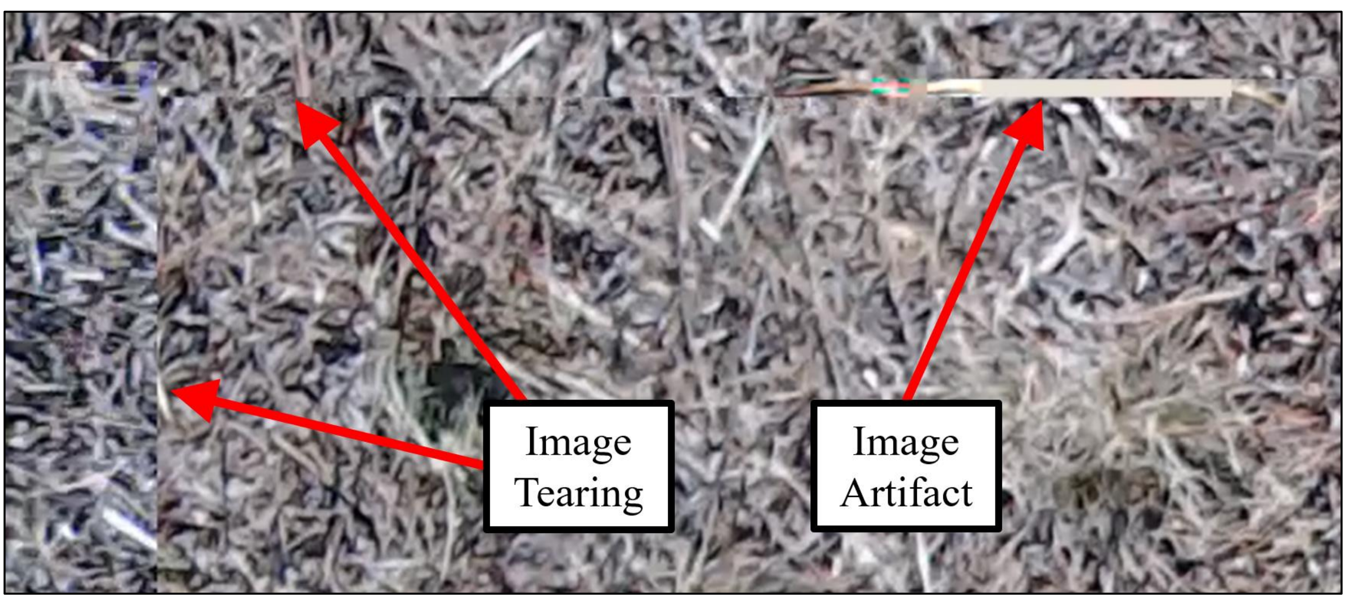

Figure 4. Tearing and artifacts present in images from the Logitech c920 camera when the default sharpeness setting was used [6].

targets, so manual focus was used. Eight Logitech c920 cameras were tested and all exhibited the same behaviour when used in the field but functioned normally when used indoors. The Canon T6 and LG G6 cameras were used to capture images in the same orientation with their respective lenses placed directly next to the lens of the Logitech camera. Images were captured with the Canon T6 and LG G6 using autofocus and without zoom, at resolutions of 5184x3456 and 4160x3120, respectively. These two cameras were selected for their subjectively clearer images and greater colour depth.

B. Image Processing

The field images were organized by date, camera, height, and target weeds on the MSI laptop for analysis. The YOLOv3-Tiny CNN running on the Darknet framework [29] with an internal resolution of 1280x736, detection threshold of 0.15, and the trained weights from [24] was used to detect hair fescue and sheep sorrel in the field images. The results of each combination of camera, lens height, and date were evaluated on their effectiveness of detecting at least one target weed per image using the precision, recall, and F_1-score metrics [25]. These scores are calculated based on the number of true positive (*tp*), false positive (*fp*), and false negative (*fn*) detection of targets. Precision is ratio of true positives to all detections:

$$Pr = \frac{tp}{tp + fp} \tag{1}$$

Recall is the ratio of true positives to all actual targets:

$$Re = \frac{tp}{tp + fn} \tag{2}$$

F_1-score is the harmonic mean of precision and recall:

$$F_1 = 2 \cdot \frac{Pr \cdot Re}{Pr + Re} \tag{3}$$

C. Experimental Design

The F_1-score for detection of at least one target weed per image was calculated for each combination of date, camera, and lens height. An analysis of variance was performed in Minitab 19 to determine the significant main and interaction effects. For hair fescue, the main effects of camera selection ($p = 0.011$) and lens height ($p = 0.018$), and the interaction between the two ($p = 0.033$) were significant. For sheep sorrel, the only significant effect was lens height ($p = 0.006$). The camera selection and lens height are important considerations for development of a smart sprayer, so they were chosen for further analysis. The mean F_1-score for hair fescue detection with each combination of camera and lens height was analyzed using a randomized complete block design in a 3x3 factorial arrangement. The CNN did not detect any instances of sheep sorrel in images from the Logitech c920 in 6 of 9 combinations of date and lens height, making the F_1-score incalculable. For sheep sorrel detection, the results from the Logitech c920 camera were omitted and the design was modified to a 3x2 factorial arrangement. Means comparisons were generated using Tukey's pairwise method.

III. Results and Discussion

A. Target Weed Detecion Results with Each Camera and Image Height

For hair fescue detection, the camera producing the highest F_1-score was different at each image capture height (Table II). At 0.57 m, the Canon T6 produced the greatest F_1-score (0.74); however, this was not significantly different than the F_1-scores from images captured with the LG G6 (0.67) and Logitech c920 (0.59). At 0.98 m, the LG G6 produced the highest-scoring images of the entire test, with a mean F_1-score of 0.97. Images from the Canon T6 at this height were the second highest scoring (0.82), while images from the Logitech produced a significantly lower F_1-score (0.60). At 1.29 m, the Logitech c920 images had the highest F_1-score (0.82), but the F_1-scores from the Canon T6 images (0.80) and LG G6 images (0.81) were not significantly different. For sheep sorrel detection, images from the Canon T6 and LG G6 both produced an average F_1-score of 0.43 at the 0.57 m height. Images captured at 0.98 m produced the highest F_1-scores for both cameras. The Canon T6 images (0.82) produced greater F_1-scores than the LG G6 (0.77), but the difference between the two was not significant. At 1.29 m, images from the LG G6 produced and F_1-score of 0.40, while images from the Canon T6 produced an F_1-score of 0.35.

TABLE II. MEAN F_1-SCORES FOR DETECTION OF AT LEAST ONE HAIR FESCUE OR SHEEP SORREL PLANT PER IMAGE USING VARIOUS LENS HEIGHTS AND CAMERAS

Height (m)	**Camera**	**F_1-score**			
		Hair Fescue		***Sheep Sorrel***	
0.57	Canon T6	0.74	AB^	0.43	AB^
0.57	LG G6	0.67	B	0.43	AB
0.57	Logitech c920	0.59	B		
0.98	Canon T6	0.82	AB	0.82	A
0.98	LG G6	0.97	A	0.77	A
0.98	Logitech c920	0.60	B		
1.29	Canon T6	0.80	AB	0.35	B
1.29	LG G6	0.81	AB	0.40	AB
1.29	Logitech c920	0.82	AB		

^Means within the same column followed by the same letter(s) for each weed are not significantly different based on Tukey's means comparison at $\alpha = 0.05$.

For both weeds, the peak F_1-scores were achieved with images captured at 0.98 m. This may be a result of bias in the training dataset, as 70% of the images were captured at 0.99 ± 0.09 m [24]. The lowest F_1-scores for sheep sorrel were produced at 1.29 m. At this distance, there may not have been enough pixels at the 1280x736 processing resolution to adequately capture the features of the small sheep sorrel leaves. Overall, the F_1-scores for detecting at least one hair fescue or sheep sorrel plant per image in this study were lower than the F_1-scores produced by [24]. A possible reason for this could be from bias in the original dataset. Training images were collected by walking throughout the fields without a defined random

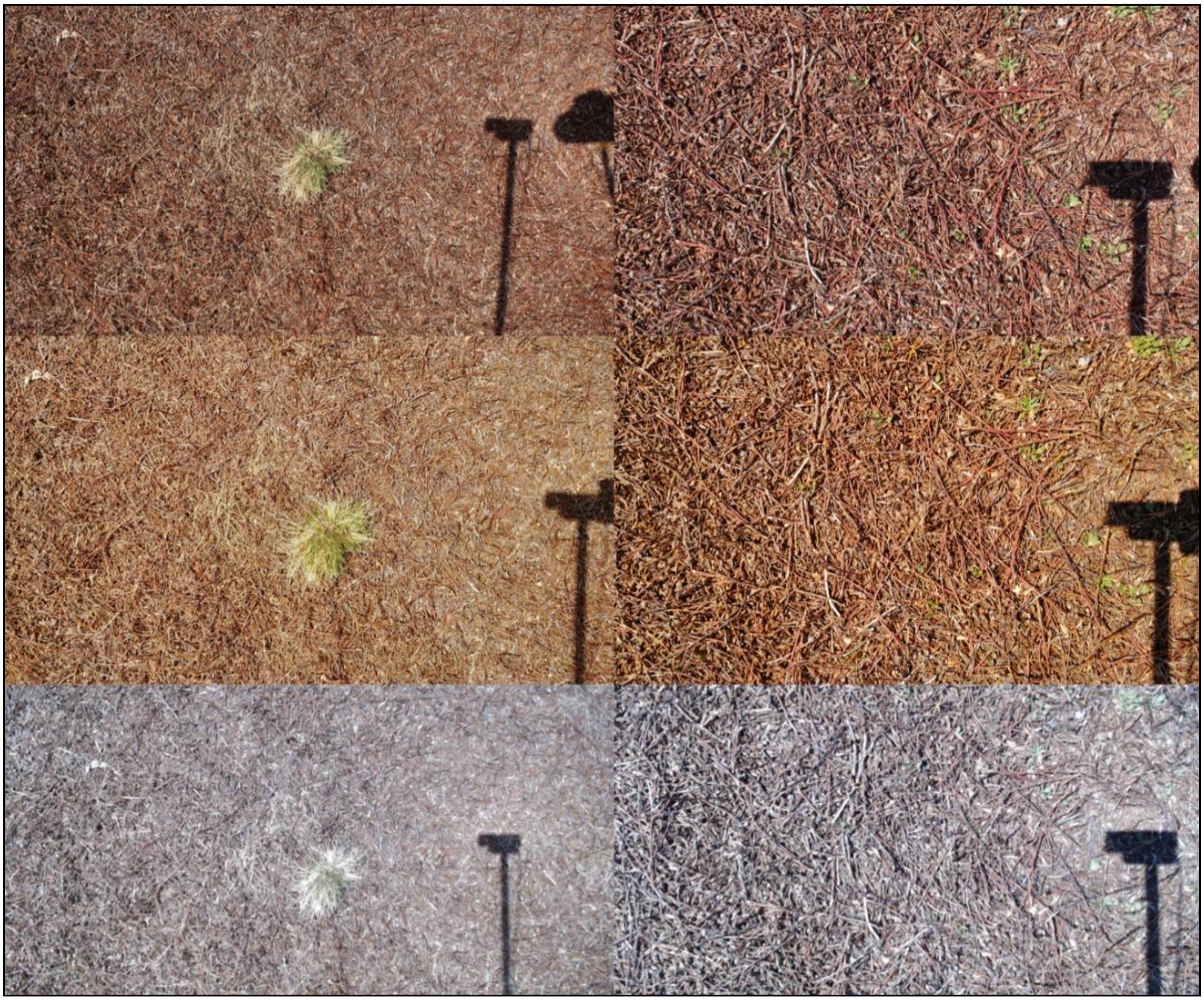

Figure 5. Comparison of images captured with the Canon T6 (top row), LG G6 (middle row) and Logitech c920 (bottom row) cameras on May 6, 2020 [6]. Images in the left column contain a hair fescue tuft captured at 0.98 and images in the right column contain sheep sorrel captured at 0.57 m.

sampling method. The personnel capturing the images may have been biased towards weed instances that were easier to see, unintentionally ignoring hair fescue and sheep sorrel plants that were more difficult to see.

One or more instances of sheep sorrel were detected in some images from the Logitech c920 on May 14 and May 25. The peak F_1-score for these scenarios was 0.33 (Table III).

TABLE III. F_1-SCORES FOR DETECTION OF AT LEAST ONE SHEEP SORREL PLANT PER IMAGE USING THE LOGITECH C920 CAMERA

Date	Height (m)	F_1-score
May 14	0.57	0.29
	1.29	0.33
May 25	0.57	0.33

B. *Image Quality and Errors with the Logitech c920 Camera*

Considering that 6 of 9 parameter combinations of date and height did not generate any true positive detections, the Logitech c920 was not a viable option for detecting sheep sorrel. The inability of the CNN to detect sheep sorrel in images from the Logitech c920 may have been due to washed-out, lower-quality images compared to the images captured with the Canon T6 and LG G6 (Figure 5). Preprocessing images from the Logitech c920 to accentuate the green hues may improve detection accuracy detection accuracy but would do so at the expense of processing speed. The reduced sharpness setting used to correct the image errors in Figure 4 may have reduced the image clarity, resulting in lower F_1-scores.

IV. CONCLUSIONS

The F_1-scores produced in this experiment were lower than the F_1-scores produced by [24], which may be the result of bias in the original training dataset. A lens height of 0.98 m produced the best results for hair fescue and sheep sorrel. The Logitech c920 camera was not viable for sheep sorrel detection, as 6 of 9 combinations of date and height resulted in zero true positive detections. This may have been due to either lower quality images compared to the Canon T6 and LG G6. Preprocessing images to accentuate the green colours may cause the sheep sorrel to be more visible, potentially improving detection results. Future work will involve further verification using images from two additional fields. Additionally, a CNN will be used to selectively spray herbicide from a smart sprayer. The results of the LG G6 images indicate that the quality of smartphone pictures is adequate for identifying hair fescue and sheep sorrel with a CNN. A web-based application will be developed to detect target weeds in smartphone images using a CNN and provide growers with site-specific information for management decisions. Using a CNN to detect weeds will improve management techniques in the wild blueberry industry and create cost-savings for growers.

Acknowledgments

The authors would like to thank Dr. Scott White for helping with field selection for development of the image dataset and the wild blueberry growers in Nova Scotia for use of their fields during image collection. Also, the authors would like to acknowledge the efforts of the mechanized systems and precision agriculture research teams at Dalhousie's Faculty of Agriculture.

References

[1] I. V. Hall, L. E. Aalders, N. L. Nickerson, and S. P. Vander Kloet, "The biological flora of Canada 1. Vaccinium angustifolium Ait., sweet lowbush blueberry," *Can. Field-Naturalist*, vol. 93, pp. 415–430, 1979.

[2] A. A. Farooque, Q. U. Zaman, D. Groulx, A. W. Schumann, D. E. Yarborough, and T. Nguyen-Quang, "Effect of ground speed and header revolutions on the picking efficiency of a commercial wild blueberry harvester," *Appl. Eng. Agric.*, vol. 30, no. 4, pp. 535–546, 2014.

[3] K. I. N. Jensen and D. E. Yarborough, "An overview of weed management in the wild lowbush blueberry - Past and present," *Small Fruits Rev.*, vol. 3, no. 3–4, pp. 229–255, 2004.

[4] K. V. McCully, M. G. Sampson, and A. K. Watson, "Weed survey of Nova Scotia lowbush blueberry (Vaccinium angustifolium) fields," *Weed Sci.*, vol. 39, no. 2, pp. 180–185, 1991.

[5] S. N. White, "Final weed survey update and research progress on priority weed species in wild blueberry," in *Wild Blueberry Producers Association of Nova Scotia Annual General Meeting*, 2019.

[6] P. J. Hennessy, "Convolutional Neural Networks for Real-Time Weed Identification in Wild Blueberry Production," M.Sc. Thesis, Dalhousie University, 2020.

[7] T. Esau, Q. U. Zaman, Y. K. Chang, D. Groulx, A. W. Schumann, and A. A. Farooque, "Prototype variable rate sprayer for spot-application of agrochemicals in wild blueberry," *Appl. Eng. Agric.*, vol. 30, no. 5, pp. 717–725, 2014.

[8] T. Esau *et al.*, "Economic analysis for smart sprayer application in wild blueberry fields," *Precis. Agric.*, vol. 17, no. 6, pp. 753–765, 2016.

[9] T. Esau, Q. Zaman, D. Groulx, A. Farooque, A. Schumann, and Y. Chang, "Machine vision smart sprayer for spot-application of agrochemical in wild blueberry fields," *Precis. Agric.*, vol. 19, no. 4, pp. 770–788, 2018.

[10] T. U. Rehman, Q. U. Zaman, Y. K. Chang, A. W. Schumann, K. W. Corscadden, and T. Esau, "Optimising the parameters influencing performance and weed (goldenrod) identification accuracy of colour co-occurrence matrices," *Biosyst. Eng.*, vol. 170, pp. 85–95, 2018.

[11] T. U. Rehman, Q. U. Zaman, Y. K. Chang, A. W. Schumann, and K. W. Corscadden, "Development and field evaluation of a machine vision based in-season weed detection system for wild blueberry," *Comput. Electron. Agric.*, vol. 162, no. July 2018, pp. 1–13, 2019.

[12] N. Hussain *et al.*, "Design and development of a smart variable rate sprayer using deep learning," *Remote Sens.*, vol. 12, no. 24, pp. 1–17, 2020.

[13] V. Partel, S. C. Kakarla, and Y. Ampatzidis, "Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence," *Comput. Electron. Agric.*, vol. 157, no. December 2018, pp. 339–350, 2019.

[14] Trimble Inc., "WeedSeeker 2 spot spray system," 2020. [Online]. Available: https://agriculture.trimble.com/product/weedseeker-2-spot-spray-system/. [Accessed: 17-Oct-2020].

[15] Blue River Technologies, "See & spray agricultural machines," 2018. [Online]. Available: http://www.bluerivertechnology.com/. [Accessed: 17-Oct-2020].

[16] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Comput. Electron. Agric.*, vol. 147, no. February, pp. 70–90, 2018.

[17] D. Rumelhart, G. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, pp. 533–536, 1986.

[18] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*, 1st ed. Cambridge: The MIT Press, 2016.

[19] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[20] A. W. Schumann, N. S. Mood, P. D. K. Mungofa, C. MacEachern, Q. U. Zaman, and T. Esau, "Detection of three fruit maturity stages in wild blueberry fields using deep learning artificial neural networks," in *2019 ASABE Annual International Meeting*, 2019.

[21] N. Hussain, A. A. Farooque, A. W. Schumann, and F. Abbas, "Application of deep learning to detect Lamb's quarters (Chenopodium album L .) in potato fields of Atlantic Canada," *Comput. Electron. Agric.*, vol. 182, no. March, p. 106040, 2021.

[22] S. M. Sharpe, A. W. Schumann, and N. S. Boyd, "Detection of Carolina geranium (Geranium carolinianum) growing in competition with strawberry using convolutional neural networks," *Weed Sci.*, vol. 67, no. 2, pp. 239–245, 2019.

[23] S. M. Sharpe, A. W. Schumann, J. Yu, and N. S. Boyd, "Vegetation detection and discrimination within vegetable plasticulture row-middles using a convolutional neural network," *Precis. Agric.*, vol. 21, pp. 264–277, 2020.

[24] P. J. Hennessy, T. J. Esau, A. A. Farooque, A. W. Schumann, Q. U. Zaman, and K. W. Corscadden, "Hair Fescue and Sheep Sorrel Identification Using Deep Learning in Wild Blueberry Production," *Remote Sens.*, vol. 13, no. 5, p. 943, 2021.

[25] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Inf. Process. Manag.*, vol. 45, no. 4, pp. 427–437, 2009.

[26] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," *arXiv*, 2018.

[27] A. G. Thomas, "Weed survey system used in saskatchewan for cereal and oilseed crops," *Weed Sci.*, vol. 33, pp. 34–43, 1985.

[28] A. Hughes, S. N. White, N. S. Boyd, P. Hildebrand, and C. G. Cutler, "Red sorrel management and potential effect of red sorrel pollen on Botrytis cinerea spore germination and infection of lowbush blueberry (Vaccinium angustifolium Ait.) flowers," *Can. J. Plant Sci.*, vol. 96, no. 4, pp. 590–596, 2016.

[29] J. Redmon, A. Bochkovskiy, and S. Sinigardi, "Darknet: YOLOv3 - Neural network for object detection," *GitHub Repository*, 2020. [Online]. Available: https://github.com/AlexeyAB/darknet. [Accessed: 20-Jan-2020].