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Evaluation of cameras and image distance for CNN-based weed detection in wild blueberry

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ABSTRACT

Agricultural herbicide application efficiency can be improved using smart sprayers which provide site-specific, rather than broadcast, applications of agrochemicals. The YOLOv3-Tiny convolutional neural network (CNN) was trained to detect two weeds, hair fescue and sheep sorrel, in images captured from wild blueberry fields throughout Nova Scotia, Canada. An evaluation was performed in three commercial wild blueberry fields in Nova Scotia to examine the effects of camera selection and target distance on detection accuracy. A Canon T6 DSLR camera, an LG G6 smartphone, and a Logitech c920 webcam were used to capture RGB images at varying distances from target weeds. Mean F_1-scores for each combination of camera and image height were analysed in a 3×3 factorial arrangement for hair fescue and a 3×2 factorial arrangement for sheep sorrel. Images captured from 0.98 m with the LG G6 and Canon T6 produced F_1-scores of up to 0.97 for detection of at least one hair fescue tuft. Images captured with the LG G6 and Canon T6 DSLR from 0.57 m achieved F_1-scores of 0.94 and 0.93, respectively, for detection of at least one sheep sorrel plant per image. Sheep sorrel was undetectable in images from the Logitech c920 under 19 of 27 parameter combinations. Future work will involve using the CNN to control herbicide applications with a real-time smart sprayer. Additionally, the CNN will be used in a web-based application to detect target weeds and provide site-specific information to aid management decisions. Using a CNN to detect weeds will create improvements in management techniques, resulting in cost-savings and greater sustainability for the wild blueberry industry.

1. Introduction

1.1. Wild blueberry cropping system

Wild blueberries (*Vaccinium angustifolium* Ait.) are a perennial crop native to northeastern North America. The plants spread through rhizomes [1] and grow to a stem height of 5 to 30 cm [2]. Commercial production occurs in a two-year cycle, during which the plants are pruned by flail mowing or burning after the harvesting period in August and September of the second (crop) year. During the first (sprout) year after pruning, plant growth begins, and berry buds begin to regrow in August [1]. The plants lay dormant through the winter, and growth continues during the crop year [1]. Harvest begins when approximately 90% of the berries are ripe [2]. Wild blueberries were harvested with a hand rake prior to the introduction of a viable mechanical harvester by Doug Bragg in 1981 [3,4]. Better management practices, including development of the mechanical harvester, resulted in the wild blueberry industry expanding in Canada [2,5,6].

1.2. Weed management practices

Weeds in wild blueberry production limit yield [7–9], interfere with harvesting equipment [10], and reduce berry quality [11,10]. Weeds in other cropping systems can be managed using tillage, crop rotation, and hand weeding [12]. Tillage and crop rotation are not viable for the wild blueberry industry due to the perennial and rhizomatous nature of the crop [1]. Hand weeding is prohibitively expensive due to labour costs [13], so a uniform application of liquid herbicides is typically used to manage weeds in wild blueberry fields [7,11]. Hair fescue (*Festuca filiformis* Pourr.) is the fourth most common weed in Nova Scotia wild blueberry fields with an adjusted frequency and occurrence uniformity of 74.55% and 37.37% respectively [14]. Hair fescue grows in tufts and is characterized by thin, green and tan coloured blades (Fig. 1). The occur-

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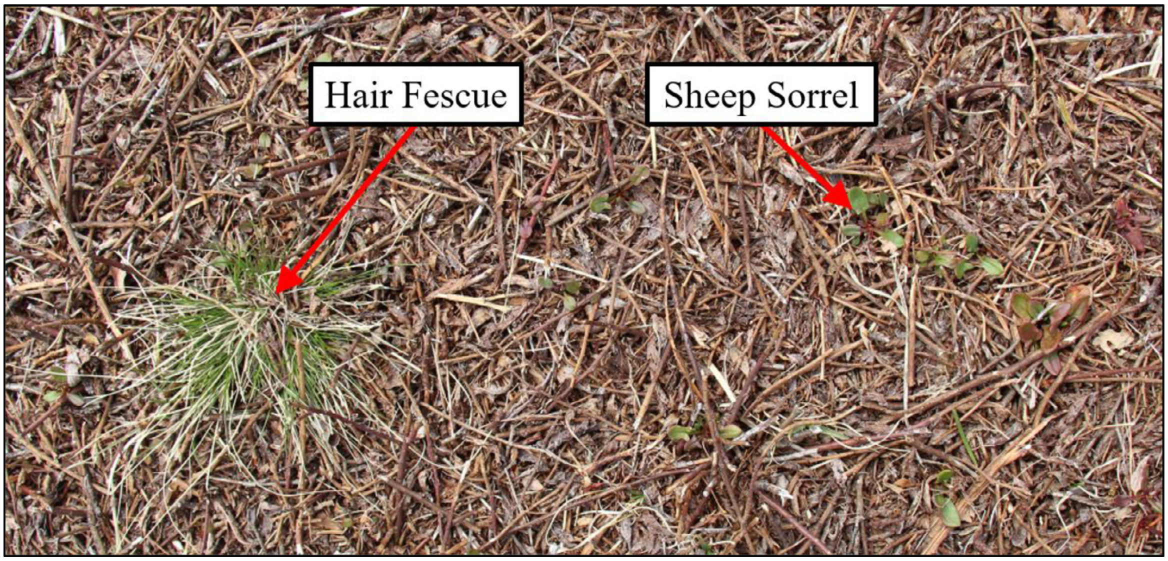

Fig. 1. Hair fescue and sheep sorrel growing in a spout-year wild blueberry field during spring 2019 in Nova Scotia. The hair fescue tuft is characterized by its thin, green blades, while the sheep sorrel plants are characterized by their green and red narrow-shaped leaves.

rence uniformity of 37.37% indicates that hair fescue grows in patches of wild blueberry fields, rather than uniformly throughout each field. Hexazinone was commonly used to manage hair fescue until resistance developed from repeated applications [7]. Hair fescue in wild blueberry fields is currently best managed with pronamide [15], which costs more than double the cost of hexazinone to spray on wild blueberry fields [16]. Sheep sorrel (*Rumex acetosella* L.) is the most common weed in Nova Scotia wild blueberry fields with an adjusted frequency and occurrence uniformity of 97.58% and 64.44%, respectively [14]. It is visually recognizable by its small, round arrow-shaped leaves which are green or red in colour (Fig. 1). The measured uniformity of 64.44% stipulates that there are substantial sections of the fields which do not contain sheep sorrel. Pollen from sheep sorrel plants may increase the likelihood of botrytis blight (*Botrytis cinerea*) disease on wild blueberry leaves [17], which can spread to the fruit buds if left unmanaged [18]. Sheep sorrel has been managed using hexazinone [7,19] and pronamide [17] with mixed results. Spring applications of sulfentrazone have shown a reduction in sheep sorrel seedlings, indicating that this may be an effective future management option [20]. Due to the intermittent nature of hair fescue and sheep sorrel in wild blueberry fields, spot application using a smart sprayer would reduce the overall volume of herbicide needed to manage these weeds.

Smart sprayers limit agrochemical application volume by only applying on areas of the field with weed cover [21–27]. Esau et al. [23] developed a spot targeting system based on green colour segmentation to detect weeds in wild blueberry fields. When used on a smart sprayer with cameras 1.2 m from the ground, the system resulted in 44.5% reduction in agrochemical usage compared to a broadcast sprayer [21]. Further developments with this smart sprayer resulted in herbicide savings of up to 78.5% [22]. However, this system was limited by its inability to discriminate between different weeds of the same colour. Commercial smart sprayers GreenSeeker and WeedSeeker[1] available in other cropping systems also work based on green colour detection. Colour co-occurrence matrices were used for real-time targeting of goldenrod (*Solidago* spp.) in wild blueberry fields [25,26]. This method reduced agrochemical usage by up to 60.58% [25] but had to be designed specifically for goldenrod and was not easily transferable to other weeds.

[1] Trimble Inc., Sunnyvale, CA, USA.

1.3. Convolutional neural networks in agriculture

Convolutional neural networks (CNNs) are an advanced form of machine vision which can successfully classify images or objects within an image [28]. They are trained using datasets with thousands of labelled pictures of the desired target. CNNs intelligently identify visual features and find patterns associated with the target using backpropagation of errors [29] and iterative optimization algorithms based on gradient descent [30]. Beyond dataset preparation, this training requires minimal input from the user, making CNNs easily adaptable for new targets. Images are typically processed at resolutions from 224 × 224 [31–33] to 608 × 608 [34,35], but this can be increased to improve clarity of visual features [36,33]. CNNs have been used in agriculture for detecting weeds [37–41], detecting plant diseases [42,43], monitoring plant growth and ripeness [44,36,45], and monitoring livestock [46,47].

Hennessy et al. [37] trained six CNNs using the Darknet framework [48] to identify hair fescue and sheep sorrel in images of wild blueberry fields. The training image dataset was collected in April and May 2019 using eight different cameras. The study concluded that the YOLOv3-Tiny CNN [34] was highly effective for detecting these weeds in wild blueberry fields, and was a promising option for controlling spray applications from a smart sprayer. The processing resolution of YOLOv3-Tiny was increased from 416 × 416 to four resolutions ranging from 864 × 480 to 1280 × 736 [37]. The accuracy of the CNN was tested with detection thresholds of 0.15 and 0.25. F_1-scores [49] for detection of at least one weed instance per image with YOLOv3-Tiny ranged from 0.94 to 0.97 for hair fescue and 0.87 to 0.90 for sheep sorrel. A key limitation of this study was potential bias in the training dataset. Image collection for the training dataset lacked structured rules for sampling locations. Personnel therefore may have been more inclined to capture images of weeds which were more visible, omitting targets which were more difficult to see.

1.4. Contributions of this paper

This study used YOLOv3-Tiny to detect hair fescue and sheep sorrel in images captured at distances of 0.57 m, 0.98 m, and 1.29 m from target weeds with three digital colour cameras in wild blueberry fields in Nova Scotia, Canada. Images were captured in three commercial wild blueberry fields on three dates in May 2020 during the herbicide application timing interval. Image capture locations were selected by walk-

Table 1
Number of target and non-target images collected for hair fescue and sheep sorrel. The images were captured three separate times on May 6, May 14, and May 25, 2020.

Field	Target	Height			Total
		0.57 m	0.98 m	1.29 m	
Debert	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
Folly Mountain	Hair Fescue	3	5	3	11
	Not Hair Fescue	5	3	4	12
	Sheep Sorrel	4	4	4	12
	Not Sheep Sorrel	4	4	3	11
Portapique	Hair Fescue	6	4	7	17
	Not Hair Fescue	6	4	4	14
	Sheep Sorrel	8	4	5	17
	Not Sheep Sorrel	4	4	6	14

ing an inverted "W" pattern through each field [17,14,11,50]. The F_1-scores for detection of the two weeds using combinations of camera and capture distance were compared. The results of this study provide valuable information for selecting cameras and spray boom height on smart sprayers. Using a CNN to control herbicide applications from a smart sprayer can reduce the volume of agrochemicals needed for field management.

2. Materials and methods

2.1. Field image collection

Images were captured on May 6, May 14, and May 25, 2020, in sprout year wild blueberry fields. The three dates were selected to correspond with the range of dates wild blueberry growers typically apply herbicides in the spring. Images were collected from three fields in Debert (45.4265°N, 63.4826°W), Folly Mountain (45.4829°N, 63.5755°W), and Portapique (45.4054°N, 63.6706°W), Nova Scotia from 9:00 am to 3:00 pm each day. Test sites were selected in each field by walking an inverted "W" pattern [17,14,11,50]. The starting point was selected by walking 10 paces along the edge of the field, then 10 paces into the field, perpendicular to the original direction. Test plots were marked with flags along the "W" and randomly determined intervals of 5 to 10 paces created using Minitab 19.[2] Images were captured at each test plot at one of three possible heights, 0.57 m, 0.98 m, or 1.29 m, to account for variations in sprayer boom height. The 0.98 m and 1.29 m image heights did not vary significantly from image capture heights used by Hennessy et al. [37] to develop the CNN training dataset (0.99 ± 0.09 m, 1.35 ± 0.07 m), while the 0.57 m height was significantly different (0.52 ± 0.04 m). The selected height for each test plot was also randomly determined with Minitab 19. This process was repeated until there were at least three target and three non-target plots at each height in each field for hair fescue and sheep sorrel (Table 1). A total of 83 plots were used: 29 at the Debert field, 23 at the Folly Mountain field, and 31 at the Portapique field.

Three cameras were used to take images at each test plot. A Logitech c920 USB 2.0 webcam[3] was attached to a tripod using an extension arm with the camera lens pointed toward the ground (Fig. 2). The camera was connected to USB 3.1 port on an MSI Workstation laptop[4] through a 2 m USB 3.0 extension cable,[5] and images were saved using Logitech Capture at 1920 × 1080 resolution. All image settings in Logitech Capture except sharpness were left at their default values. Sharpness was reduced from 128 to 95 to prevent image tearing and artifacts (Fig. 3). The c920's autofocus sporadically changed the focus setting, so a manual focus of infinity was used. This camera was selected for being a low-cost consumer camera which easily interfaces with Windows[6] and had been previously used in a smart sprayer [51]. Eight Logitech c920 cameras were tested to make sure that the image glitches and sporadic autofocus changes were not limited to a single faulty model. All eight Logitech c920 cameras exhibited similar behaviour. A Canon T6 DSLR camera[7] and an LG G6 smartphone[8] were used to capture images in the same orientation with their respective lenses placed directly next to the lens of the Logitech camera (Fig. 2). These cameras were selected for their subjectively clearer images and greater colour depth compared to the Logitech c920. The Canon T6 and LG G6 captured images at resolutions of 5184 × 3456 and 4160 × 3120, respectively. Images were captured with the Canon T6 and LG G6 using autofocus and without zoom. The standard lens on the LG G6, rather than the ultrawide lens, was used to capture images.

2.2. Target dimension measurements

A sample of hair fescue and sheep sorrel dimensions were measured in the Debert field on May 1, 2020 at the sampling plots along the "W" pattern. Measurements were recorded from up to three instances of each weed at each test location, pending availability, resulting in 25 measurements for hair fescue and 24 measurements for sheep sorrel. A ruler was used to measure the length and width of each weed from a top-down perspective. The length was defined as the largest horizontal dimension of the weed and the width was defined as the widest measurement perpendicular to the length measurement (Fig. 4). To understand the field of view (FOV) of the images, a measuring tape was placed on the ground underneath the Logitech c920 camera to measure the physical image size at each of the three heights. These measurements aided interpretation of the detection results from the CNN.

2.3. Image processing

The field images were organized by date, field, camera, height, and targets on the MSI Workstation Laptop with an Intel Core i9–9980H central processing unit (CPU)[9] and an Nvidia RTX Quadro 5000 graphics processing unit (GPU)[10] for analysis. The YOLOv3-Tiny CNN running on the Darknet framework with the trained weights from Hennessy et al. [37] was used to detect hair fescue and sheep sorrel in the field images. The images were initially run as entire batches to determine the optimal image resolution and detection threshold for detection of the two weeds. The internal network resolutions tested were 1280 × 736 and 864 × 480, with an initial detection threshold of 0.15. The results of each resolution and threshold combination were evaluated on their effectiveness of detecting at least one target weed per image using the precision, recall, and F_1-score metrics [49]. 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:

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

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

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

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

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

2 Minitab, LLC, State College, PA, USA
3 Logitech International S.A., Lausanne, Switzerland
4 WS65 9TM-1410CA, Micro-Star International Co., Ltd, New Taipei, Taiwan
5 AmazonBasics HL-007250, Amazon.com, Inc., Seattle, WA, USA
6 Microsoft Corporation, Redmond, WA, USA
7 EOS Rebel T6, Canon Inc., Tokyo, Japan
8 G6-H873, LG Electronics Inc., Seoul, South Korea
9 Intel Corporation, Santa Clara, California, USA
10 Nvidia Corporation, Santa Clara, California, USA

Fig. 2. Field experimental setup showing image capture in the Portapique field on May 25, 2020. A tripod with an extension arm was used to hold the Logitech c920 camera at a position of 0.98 m between the lens and the ground while the laptop captured the image (L). The Canon T6 camera was held with the lens directly beside the Logitech c920 at the same height for image capture (R).

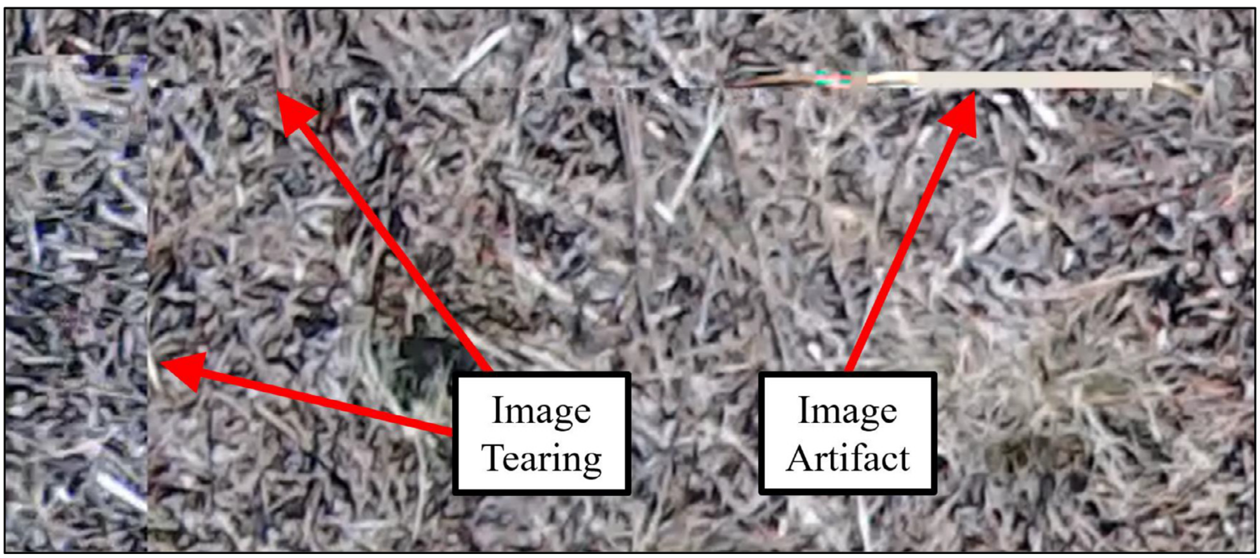

Fig. 3. Examples of image tearing and artifacts seen in the Logitech c920 images when the default sharpness setting was used.

The precision was observed to be higher than the recall in all cases at the threshold of 0.15, so two lower detection thresholds, 0.10 and 0.05, were also tested. Lowering the threshold increases the number of true and false positive detections, thus lowering precision and increasing recall. A resolution of 1280 × 736 and threshold of 0.05 produced the highest F_1-score for both weeds and was used for the rest of the analysis.

2.4. Experimental design

Field images were tested for detecting hair fescue and sheep sorrel with the YOLOv3-Tiny CNN using the Darknet framework and trained weights from Hennessy et al. [37]. The F_1-score for detection of at least one target weed per image was calculated for each combination of date, field, camera, and lens height. An analysis of variance was done using Minitab 19 to determine the significant main and interaction effects. The main effects of camera selection, image height, and field, and the three-way interaction between these effects were significant for hair fescue. Further analysis for hair fescue was done in a 3 × 3 factorial arrangement of lens height (0.57 m, 0.98 m, 1.29 m) and camera (Canon T6, LG G6, Logitech c920) in a randomized complete block design for each field. The mean F_1-score for interaction effect of camera and lens height in each field was calculated and the mean comparisons were performed with Tukey's pairwise method in Minitab 19. The analysis for sheep sorrel was done in a 3 × 2 factorial arrangement with the same three lens heights but omitted the results from the Logitech c920 camera due to insufficient data from this camera.

3. Results and discussion

3.1. Optimal image resolution and detection threshold

F_1-scores for detection of at least one hair fescue plant per image varied between 0.80 and 0.81 when changing the detection threshold and resolution (Table 2). The highest precision score (0.85) was produced at 1280 × 736 resolution at the threshold of 0.15, while the lowest precision score (0.78) was produced with both resolutions at the 0.05 threshold. Recall peaked (0.85) at 1280 × 736 resolution and 0.05 threshold, although it only decreased by 0.01 when the resolution was changed to 864 × 480. The general trend for both target weeds was that decreasing the threshold increased the recall at the expense of precision. The key factor for sheep sorrel detection was maximizing the resolu-

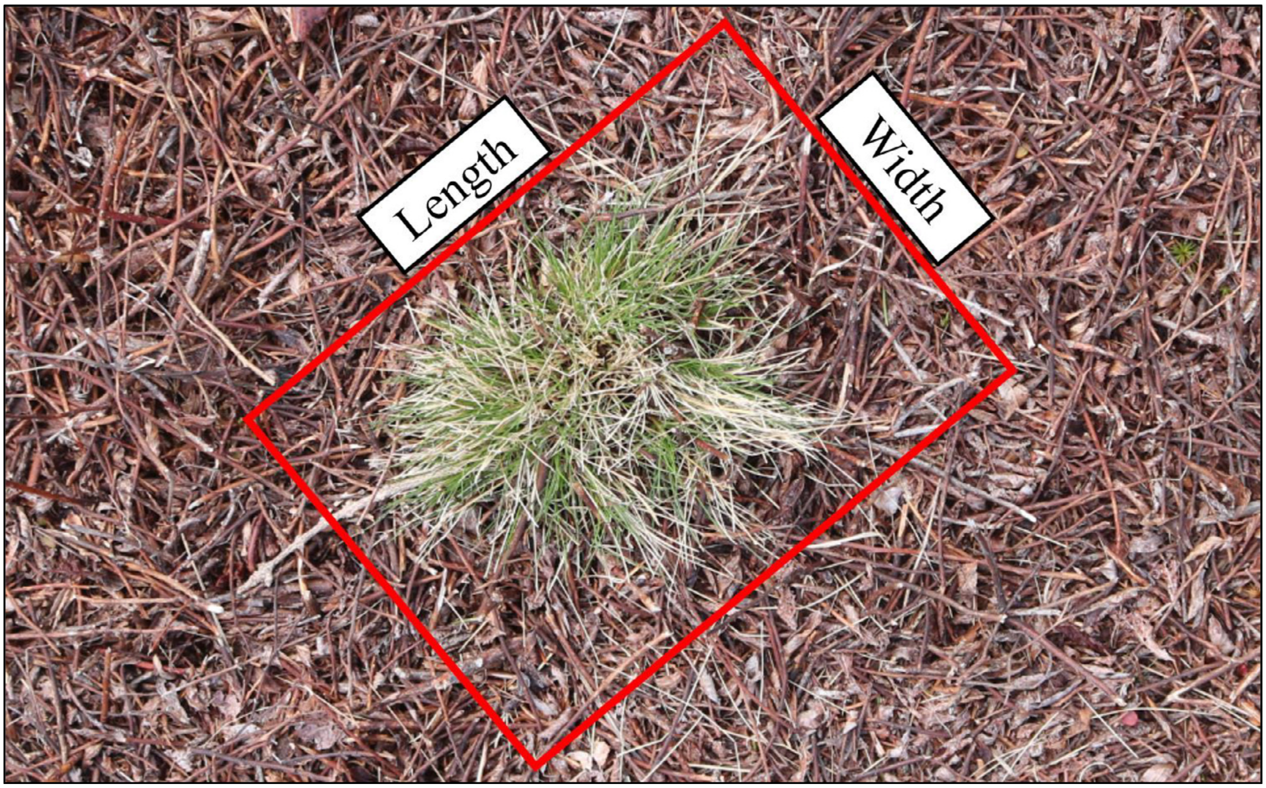

Fig. 4. Example of the measurement method for a hair fescue tuft, with the red bounding box showing the length and width of the tuft. The base image was captured on April 26, 2019 with the Canon T6 camera at a sprout-year field in Debert, NS (45.4381°N, 63.4534°W). The image also shows branches and leaves from wild blueberry plants after mechanical flail mowing.

Table 2
Precision, recall, and F_1-scores for detection of at least one hair fescue or sheep sorrel target per image at varying detection threshold and resolution.

Threshold	Resolution	Hair Fescue			Sheep Sorrel		
		Precision	Recall	F_1-Score	Precision	Recall	F_1-Score
0.05	864×480	0.78	0.84	0.81	0.72	0.57	0.63
	1280×736	0.78	0.85	0.81	0.68	0.66	0.67
0.10	864×480	0.81	0.79	0.80	0.73	0.48	0.58
	1280×736	0.84	0.79	0.81	0.71	0.59	0.65
0.15	864×480	0.85	0.75	0.80	0.74	0.40	0.52
	1280×736	0.89	0.74	0.80	0.76	0.53	0.63

tion. The networks were trained at 1280 × 736 resolution, which may have influenced the results. The F_1-scores for sheep sorrel were higher at 1280 × 736 than 864 × 480 by an average of 0.07, with the peak F_1-score (0.67) being produced at 0.05 detection threshold. A resolution of 1280 × 736 and a detection threshold of 0.05 was determined to be the optimal parameter combination for both weeds. The peak F_1-scores in this test were lower than the F_1-scores produced by Hennessy et al. [37] for hair fescue (0.97) and sheep sorrel (0.90). The effects of camera selection are examined in this study, but another factor which influenced results may have been the training dataset. The images were collected by personnel walking through fields and manually scouting for target weeds. The personnel could have been more inclined to walk towards larger, more visible weeds when creating the training dataset. The “W” sampling method used in this study has less bias and should produce a better representation of the hair fescue and sheep sorrel present in wild blueberry fields used.

3.2. Measurement of hair fescue and sheep sorrel targets

The mean length and width of hair fescue tufts at the Debert site were 54.6 ± 15.9 mm and 42.6 ± 13.3 mm, respectively (Table 3). The mean length and width of sheep sorrel were much smaller, at 11.0 ± 1.7 mm and 6.0 ± 0.9 mm, respectively. The 95% C.I. for the hair fescue measurements were much larger than for the sheep sorrel measurements, indicating more variability in the size of hair fescue tufts. The physical measurement represented by an individual pixel varied from 0.60 mm to 1.35 mm for 1280 × 736 images, and 0.89 mm to 2.00 mm for 864 × 480 images (Table 4). At both resolutions, the finer features of sheep sorrel may not be clear at higher image heights. With pixel sizes of 1.35 mm and 2.00 mm, the average width of a sheep sorrel leaf in an image was 4 and 3 pixels, respectively. Higher resolutions may be necessary for ac-

Table 3
Mean measurements of hair fescue and sheep sorrel plants at the Debert Site on May 1, 2020.

Target Weed	Dimension	Mean Measurement (mm)
Hair Fescue	Length	54.6 ± 15.9
	Width	42.6 ± 13.3
Sheep Sorrel	Length	11.0 ± 1.7
	Width	6.0 ± 0.9

Table 4
FOV of the Logitech c920 camera at each tested image height. The size of the field represented by each pixel at 1280×736 and 864×480 resolution was calculated based on the FOV. .

Height (m)	FOV (m)		Pixel Size, 1280 × 736 (mm)	Pixel Size, 864 × 480 (mm)
	Length	Width		
0.57	0.77	0.43	0.60	0.89
0.98	1.30	0.73	1.02	1.51
1.29	1.72	0.97	1.35	2.00

Table 5
Effect of lens height and camera selection on mean F_1-score for detection of hair fescue plants using the YOLOv3-Tiny weights trained by Hennessy et al. [13]. Test images were captured in Nova Scotia on May 6, May 14, and May 25, 2020.

Height (m)	Camera	Field Debert		Folly Mountain		Portapique	
0.57	Canon T6	0.74	CD^	0.70	CD	0.84	ABCD
0.57	LG G6	0.67	CD	0.72	CD	0.84	ABCD
0.57	Logitech c920	0.61	D	0.75	BCD	0.77	ABCD
0.98	Canon T6	0.82	ABCD	0.97	A	0.83	ABCD
0.98	LG G6	0.97	A	0.97	A	0.77	ABCD
0.98	Logitech c920	0.63	D	0.96	AB	0.78	ABCD
1.29	Canon T6	0.80	ABCD	0.72	CD	0.86	ABCD
1.29	LG G6	0.81	ABCD	0.79	ABCD	0.92	ABC
1.29	Logitech c920	0.82	ABCD	0.76	ABCD	0.89	ABCD

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

curate detection of sheep sorrel. Additionally, dust or dirt on the camera lens may negatively impact the results, particularly for images captured with the LG G6 and Logitech c920 which have smaller lenses than the Canon T6. Interference from dust was not noticeable in any images captured for this study but may cause limitations when this system is deployed in a commercial environment.

3.3. Effects of camera selection and image height

For hair fescue detection, the main effects of camera selection, image height, and field selection, the two-way interaction effect between image height and field, and the three-way interaction effect between camera selection, image height, and field were significant ($p < 0.05$). The main effect of day, the two-way interaction effects between day and camera, day and height, day and field, camera and height, camera and field, and the three-way interaction between day, camera, and height were not significant. Tukey's pairwise comparison for interaction between image height and camera selection showed that the best option for the Debert field was the LG G6 at 0.98 m (F_1-score = 0.97) (Table 5). The Canon T6 at 0.98 m (F_1-score = 0.82) was the second-best option for this field but was not significantly different from any lesser performing combinations. In the Folly Mountain field, the best detection results came from images captured at 0.98 m with the Canon T6 and LG G6 cameras (F_1-score = 0.97). The images from the LG G6 at 1.29 m produced the best detection in the Portapique field (F_1-score = 0.92), but they were not significantly different from detection results from all other combinations in this field. The only scenario where camera selection produced significantly different results was in the Debert field at a height of 0.98 m. The LG G6 performed the best (F_1-score = 0.97), followed by the Canon T6 (F_1-score = 0.82), and the Logitech c920 (F_1-score = 0.63). The LG G6 and Logitech c920 cameras varied significantly from each other, but not from the Canon T6. Approximately 70% of the images in the original training dataset were captured at 0.99 ± 0.09 m,

Table 6
Sheep sorrel detection results from YOLOv3-Tiny on images captured with the Logitech c920 camera at three wild blueberry fields in Nova Scotia.

Date	Field	Height (m)	F_1-Score
06-May	Portapique	0.57	0.22
		1.29	0.44
14-May	Debert	0.57	0.29
		1.29	0.33
	Folly Mountain	0.78	0.33
	Portapique	0.57	0.22
		1.29	0.44
25-May	Debert	0.57	0.33

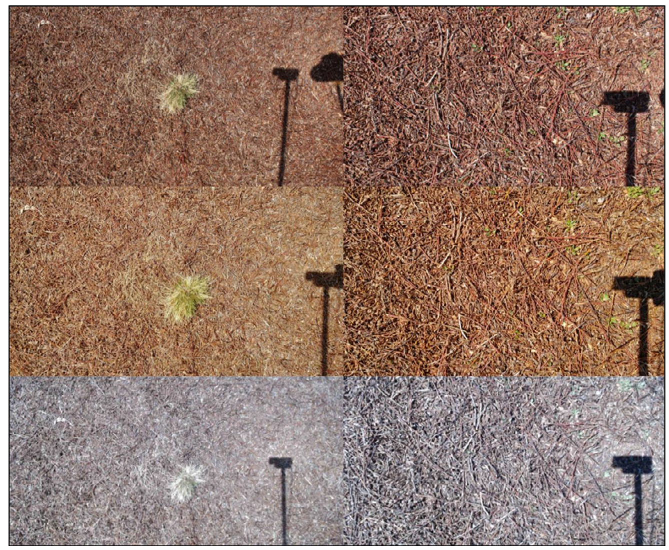

Fig. 5. Sample of field images captured in the Folly Mountain field on May 6th, 2020. Pictures in the left column were captured at a height of 0.98 m and have a hair fescue tuft in the centre of the image. Pictures in the right column were captured at 0.57 m and have sheep sorrel leaves dispersed throughout the images. Images in the top row were captured with the Canon T6 camera, the middle row were captured with the LG G6 smartphone, and the bottom row were captured with the Logitech c920.

which may have contributed to the high level of accuracy at the 0.98 m height.

During calculation of F_1-scores for sheep sorrel detection, 19 of 27 combinations of height, date, and field for images captured with the Logitech c920 did not return a result. There were zero true positive detections in these scenarios, thus creating precision and recall scores of zero, which resulted in the F_1-scores being incalculable due to a division by zero. The maximum average F_1-score from images captured with the Logitech c920 camera was 0.44 (Table 6). The features in images captured with the Logitech c920 were blurrier due to the reduced sharpness, and there was less contrast between colours (Fig. 5). Preprocessing images from the Logitech c920 to accentuate green hues may improve results for sheep sorrel and hair fescue detection but would likely have a negative impact on processing speed. The Canon T6 and LG G6 cameras were used to collect training images, while the Logitech c920 was not used. This may have resulted in the CNN being more biased towards detecting weed instances in the Canon T6 and LG G6 images.

Significant effects ($p < 0.05$) for sheep sorrel detection were the main effects of image height and field, and the two-way interaction between field and image height. The main effect of camera, the two-way interaction effects between day and camera, day and height, day and field, camera and height, camera and field, and all three-way interaction effects were not significant. The best height for capturing images in the

Table 7
Effect of lens height and camera selection on mean F_1-score for detection of sheep sorrel plants using the YOLOv3-Tiny weights trained by Hennessy et al. [13]. Test images were captured in Nova Scotia on May 6, May 14, and May 25, 2020.

Height (m)	Camera	Field Debert		Folly Mountain		Portapique	
0.57	Canon T6	0.43	BCˆ	0.93	A	0.88	AB
0.57	LG G6	0.43	BC	0.94	A	0.83	ABC
0.98	Canon T6	0.83	ABC	0.83	ABC	0.76	ABC
0.98	LG G6	0.83	ABC	0.72	ABC	0.75	ABC
1.29	Canon T6	0.36	C	0.89	AB	0.65	ABC
1.29	LG G6	0.41	BC	0.83	ABC	0.72	ABC

ˆMeans followed by the same letter(s) are not significantly different based on Tukey's means comparison at $\alpha = 0.05$.

Debert field was 0.98 m, with images from both cameras producing an F_1-score of 0.83 (Table 7). The other combinations of camera and image height did not vary significantly. In the Folly Mountain field, the best detection results were produced with images captured at 0.57 m with both cameras (F_1-score = 0.94, 0.93), but other combinations were not significantly different. Similar results were produced with images from the Portapique field, with images captured at 0.57 m using both cameras producing the best results (F_1-score = 0.88, 83), while the results at other heights were not significantly different. The small size of the sheep sorrel leaves may be contributing to the reduced accuracy in images captured from higher positions.

4. Conclusions

The higher resolution, 1280 × 736, with the lowest threshold, 0.05, produced the best results for detecting sheep sorrel with the YOLOv3-Tiny CNN producing a peak F_1-score of 0.67 across all images captured in three fields in Nova Scotia. These parameters had little effect on the F_1-scores for hair fescue detection, which were consistently 0.80 or 0.81. These results were lower than the validation scores produced when the networks were trained, which may be the result of bias in the original image dataset. The small size of sheep sorrel leaves indicates the higher resolution may have been necessary to adequately represent their visual features. Camera selection had minimal effect on hair fescue detection except in the Debert field at a height of 0.98 m. The Logitech c920 camera was not viable for sheep sorrel detection, as 19 of 27 parameter combinations resulted in zero detections. This may have been due to either lower quality images compared to the Canon T6 and LG G6 or because images from the Logitech c920 were not used to train the CNN. A lens height of 0.57 m produced the best results for sheep sorrel in two out of three fields. Preprocessing images to accentuate the green colours may cause the sheep sorrel to be more visible, potentially improving detection results. This would add another step to image processing, potentially reducing processing speed. Results from the LG G6 camera indicate that the quality of smartphone pictures is adequate for identifying hair fescue and sheep sorrel in field images. Future work should involve selecting a high-quality camera for use on a smart sprayer and collecting an unbiased image dataset for retraining the CNNs. Preprocessing techniques should also be examined for their effect on CNN accuracy and their impact on processing speed. Additionally, the CNNs should be tested for use in real-time on a smartphone app or web browser, to allow wild blueberry growers to identify hair fescue and sheep sorrel in their fields. Considerations regarding the effect of dust and dirt accumulation on camera lenses should be made in future studies. Using a CNN to target hair fescue, sheep sorrel, and other weeds in wild blueberry fields on a smart sprayer can reduce herbicide use and create cost-savings for growers.

Declaration of Competing Interest

The authors declare no conflict of interest with this research paper.

CRediT authorship contribution statement

Patrick J. Hennessy: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Supervision, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Travis J. Esau:** Conceptualization, Methodology, Validation, Resources, Supervision, Visualization, Writing – review & editing, Project administration, Funding acquisition. **Arnold W. Schumann:** Methodology, Validation, Resources, Writing – review & editing, Supervision. **Qamar U. Zaman:** Validation, Resources, Writing – review & editing. **Kenneth W. Corscadden:** Validation, Writing – review & editing, Supervision, Funding acquisition. **Aitazaz A. Farooque:** Validation, Writing – review & editing, Supervision, Resources.

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