Using photographs and deep neural networks to understand flowering phenology and diversity in mountain meadows

Aji John [1,*], Elli J. Theobald [1], Nicoleta Cristea [2,3], Amanda Tan [3] and Janneke Hille Ris Lambers [1,4]

[1]Department of Biology, University of Washington, Seattle, WA 98195, USA.
[2]Department of Civil and Environmental Engineering, University of Washington, Seattle, WA 98195, USA.
[3]eScience Institute, University of Washington, Seattle, WA 98195, USA.
[4]Plant Ecology, Institute of Integrative Biology, D-USYS, ETH Zürich, 8092 Zürich, Switzerland.

*Corresponding author – ajijohn@uw.edu

ABSTRACT

Mountain meadows are an essential part of the alpine-subalpine ecosystem; they provide ecosystem services like pollination and nutrient recycling and are home to diverse plant communities. Changes in climate affect the meadow ecology on multiple levels, altering growing season dynamics and water availability, and tracking the effects of climate change on meadow diversity is critical to conservation efforts. Here, we explore how to combine crowd sourced camera images with machine learning to quantity flowering species richness across a range of elevations in alpine meadows located in Mt Rainier National Park, Washington, USA. We employed three machine learning techniques (Mask R-CNN, RetinaNet and YOLO) to detect wildflower species in images taken during two flowering seasons. We demonstrate that deep learning techniques can detect multiple species, providing information on flowering richness in photographed meadows. The results indicate higher richness just above the tree line for most of the species, which is comparable with patterns found using field studies. We found that the two-stage detector Mask R-CNN was more accurate than single-stage detectors like RetinaNet and YOLO, with the Mask R-CNN network performing best overall with mean average precision (mAP) of 0.67 followed by RetinaNet (0.5) and YOLO (0.4). We also show that detection is possible even when pictures are interspersed with complex backgrounds and are not in focus. We expect this approach can be used to address many ecological questions that benefit from automated flower detection, like studies of flowering phenology or floral resources, and that this approach can therefore complement a wide range of ecological approaches (e.g., field observations, experiments, community science, etc.). In all, our study suggests that ecological metrics like floral richness can be efficiently monitored by

combining machine learning with easily accessible publicly curated datasets (e.g., Flickr, iNaturalist).

Keywords: Alpine wildflowers; convolutional neural net, climate-change, phenology.

1. INTRODUCTION

Alpine environments harbor a wide diversity of plant and animal species, but are also uniquely susceptible to climate change (Ganjurjav et al., 2016; Steinbauer et al., 2018). Species in alpine meadows are limited by a short growing window that is driven by late snowmelt (Cardinale et al., 2007) which can make them prone to a warming climate (Inouye, 2008). Floral richness is one measure that provides an important yardstick on the fitness of Alpine wildflowers, as meadow species are generally perennial (Roslin et al., 2021). Furthermore, flowers are good indicators for measuring the effects of climate change (Dreyer et al., 2006; Gallagher et al., 2009; Miller-Rushing et al., 2008; Rawal et al., 2015).

Phenological shifts in flowering could have drastic impacts to flora and fauna (Anthelme & Dangles, 2012; Gottfried et al., 2012). For example, pollination might be at risk if pollinators emerge after peak flowering or earlier before the onset of flowering (Inouye, 2008; Ogilvie et al., 2017). Furthermore, the experience of human visitors who visit to enjoy the wildflower displays could be at risk after these mismatches (Breckheimer et al., 2020; Hille Ris Lambers et al., 2021). An extremely warm year might hasten flowering and make flowers susceptible to frost damage (Klein et al., 2018). On other hand, in a year with late snowmelt (i.e., after an extremely snowy winter or an unusually chilly spring), flowering might get delayed, resulting in pollinator mismatch (Vorkauf et al., 2021). Hence, evaluating patterns of floral richness spatiotemporally is important for understanding the factors driving meadow species reproductive life cycle (Inouye et al., 2003).

Traditionally, wildflower richness and phenology has been studied labor-intensive and time-consuming field observations. Detecting flowers from pictures taken in natural settings (such as alpine meadows) could provide a solution, but is a complex task that recent developments in computer vision algorithms may aid in. Isolating flowers in a picture of a typical mountain meadow is challenging because of the diversity of meadow species, the wide range of floral structures, and because of the backgrounds in which the flowers exist (like leaves, trees, rocks etc.). Flowers are inherently complex because of extraordinary diversity of floral morphologies resulting from eco-evolutionary dynamics (Moyroud & Glover, 2017). However, machine learning (ML) vision-based algorithms show promise in detecting life stages or phenologies (e.g., identifying blooming), and in-depth evaluation of a single phenological stage for particular species has been successful (e.g. fruit maturity in passion fruit (Tu et al., 2018), strawberries (Chen et al., 2019) and tomatoes (Wan et al., 2018); ripeness in papayas (Santos Pereira et al., 2018), and flowering in cotton plants (Jiang et al., 2020)). ML approaches have also been used for classifying the progression of flowering in apples (Dias et al., 2018; Wang et al., 2021). These studies showed that it is possible to evaluate stages of a plant life event (for e.g., fruiting) from images with ML methods. However, these approaches have not been attempted in more species rich and complex systems like Alpine wildflower meadows, where issues related to occlusion, complex backgrounds and a high floral richness may complicate these approaches (Osherov & Lindenbaum, 2017).

An evolving class of machine learning algorithms called deep neural networks (dNNs) have been particularly useful for detecting and segmenting multiple objects in an image. dNN methods can perform object detection (for e.g., a flower) and instance

segmentation (e.g., detect all the instances of a flower). Applications of such algorithms are wide and important, ranging from tree crown detection to identifying cancerous cells (Abdolali et al., 2020; Hao et al., 2021). Our use of dNNs for mapping flowers is also motivated by their ability to extract subtle features and learning from them efficiently (Dias et al., 2018). This means flowers can be individually tagged and segmented in a meadow image with dedicated dNNs.

Broadly, dNN approaches can be divided into one-stage and two-stage techniques. A one-stage algorithm called YOLO (Redmon et al., 2016) is a well-known object instance detection method, but has issues with objects with multiple sizes (pictures where objects are taken at difference distances), and background noise. RetinaNet is a comparable one-stage algorithm that overcomes these limitations (Iglovikov & Shvets, 2018). However, neither of these methods are able to use some features for classification, so a two-stage algorithm like Mask R-CNN (He et al., 2017), where feature-extraction is built-in with segmentation and pixel-level classification is known to perform more accurately (Hao et al., 2021; Jia et al., 2020; Machefer et al., 2020). All three of these methods i.e., YOLO, RetinaNet, and Mask R-CNN apply bounding box detection (i.e., localize the object), but Mask R-CNN, in addition, gives pixel level mask of the class. In addition, Mask R-CNN supports pluggable feature extraction network backbone like U-Net (Ronneberger et al., 2015) that could cover wide range of domains.

In this paper, we explore these three state-of-the-art dNN methods (YOLO, RetinaNet, and Mask R-CNN) for the detection and localization of Alpine wildflowers in complex settings – i.e., montane meadows. We define identification of a species by its flowering phenophase only i.e., the stage where the species flower(s) are visible.

Specifically, we focus on two objectives; i) Evaluating the three dNN based techniques in their ability to detect flowering species in alpine meadows to derive diversity and abundance and ii) using the data to explore an ecological hypothesis on the relationship between elevation and floral richness to demonstrate the utility of this approach. Our expectation is that diversity declines with increasing elevation but in a non-linear way, and that ML approaches applied to pictures can capture this relationship.

2. Materials and Methods

2.1 Study Area

We conducted our studies in subalpine regions (upward of 1400 m) at Mount Rainier National Park (MORA), which have an impressive wildflower display that is one of the main summertime visitor attractions. Meadows are snow covered most of the year, even late into July, with peak-flowering that lasts between 2 and 3 weeks between late July and early September – depending on snowmelt dates (Theobald et al., 2017). We collected data along an existing trail called Reflections Lakes Trail that has been a site for focused meadow phenology observations (Hille Ris Lambers et al., 2021; Manzanedo et al., 2022). The trail is on the south side of MORA and covers an elevational gradient of 1400 m to 1950 m (Fig. 1).

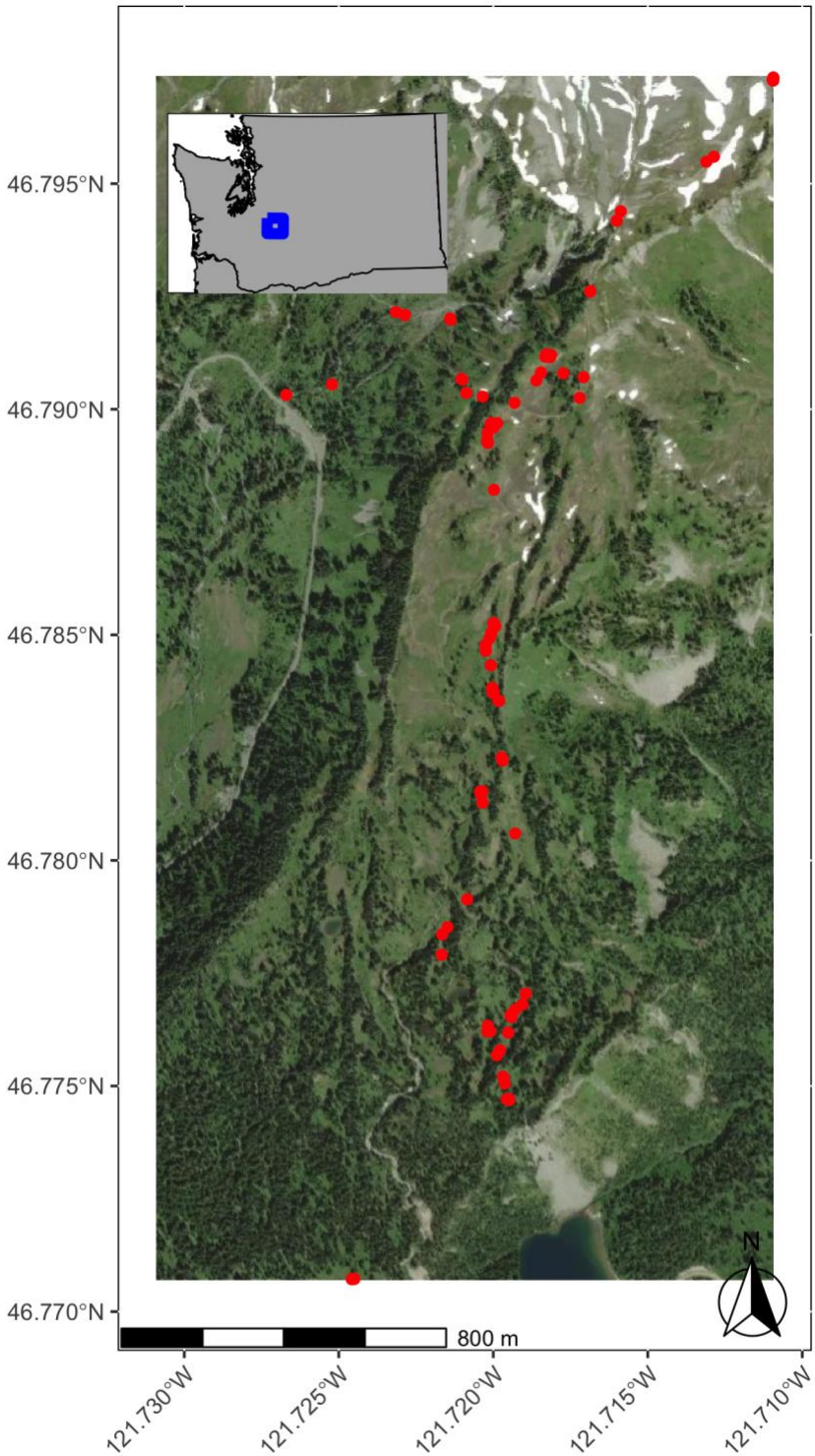

Figure 1: Study area at Mt Rainier National Park, red dots indicate the sites along the Reflections Lakes trail at which the pictures were taken for the study. The inset shows the location (in blue) of the study area in the context of Washington State, USA.

2.2 Data

Volunteers participating in this study collected camera images using an iPhone camera (version 11 Pro) during the flowering season of 2020 and 2021. Sixteen of the 42 species that commonly occur at the study site were targeted in this study (see Table 1). Photos were taken from the trail overlooking the meadows. The curated dataset contained 1545 high resolution photos: 768 x 1024-pixel (landscape) and 1024 x 768-pixel (portrait). The portrait and landscape images were then tiled for easier annotation after converting them to a common dimension of 1024 pixel x 1024 pixel. Padding was done so that it was easier to tile the images in equal sizes. For e.g., tiling into 256 x 256 of a 1024 x 1024 format image results in 8 images. In total, we used 1221 images for training and 324 images for validation and testing.

For our training dataset, we annotated each individual image, identifying the number and identity of flowers in each image. We used the LabelMe software to perform the annotation (Russell et al., 2008), which was then outputted in a JSON (JavaScript Object Notation) file format. These annotations included multiple labels (flowers) with their annotation mask (see Fig. 2 for sample annotations). For application of the Mask R-CNN and RetinaNet dNN algorithm, the annotation outputs were in JSON format, which was converted to a COCO format by the training framework. Because the YOLO algorithms require a specific format (the YOLO format), we converted the LabelMe annotations to this format prior to analysis.

Table 1: The training dataset is comprised a total of 1221 images having 4349 instances of flowers annotated. The validation dataset had a total of 166 images having 597 instances of flowers annotated, and the test dataset comprised of a total of 158 images having 407 instances of flowers annotated. All the images were 256 by 256 pixels and collectively represented 16 wildflower species.

Common Name	Scientific Name	Training Instances	Validation Instances	Test Instances
Western Anemone	*Anemone occidentalis*	508	75	24
Bracted Lousewort	*Pedicularis bracteosa*	119	20	21
Mountain Daisy	*Erigenon peregrinus*	265	39	27
Subalpine Lupine	*Lupinus arcticus*	902	108	31
Glacier Lily	*Erythronium grandiflorum*	103	23	21
Cascade Aster	*Aster ledophyllus*	177	55	20
American Bistort	*Polygonum bistortoides*	322	69	26
Grays Lovage	*Ligusticum grayi*	123	23	28
North Microseris	*Microseris alpestris*	213	20	28
Scarlet Paintbrush	*Castilleja miniata*	364	21	20
Sharptooth Angelica	*Angelica arguta*	96	22	26
Avalanche Lily	*Erythronium montanum*	129	21	29
Magenta Paintbrush	*Castilleja parviflora*	638	34	33
Sitka Valerian	*Valeriana sitchensis*	95	19	27
Tall Bluebell	*Mertensia paniculata*	145	26	26
Broadleaf Arnica	*Arnica latifolia*	150	22	20

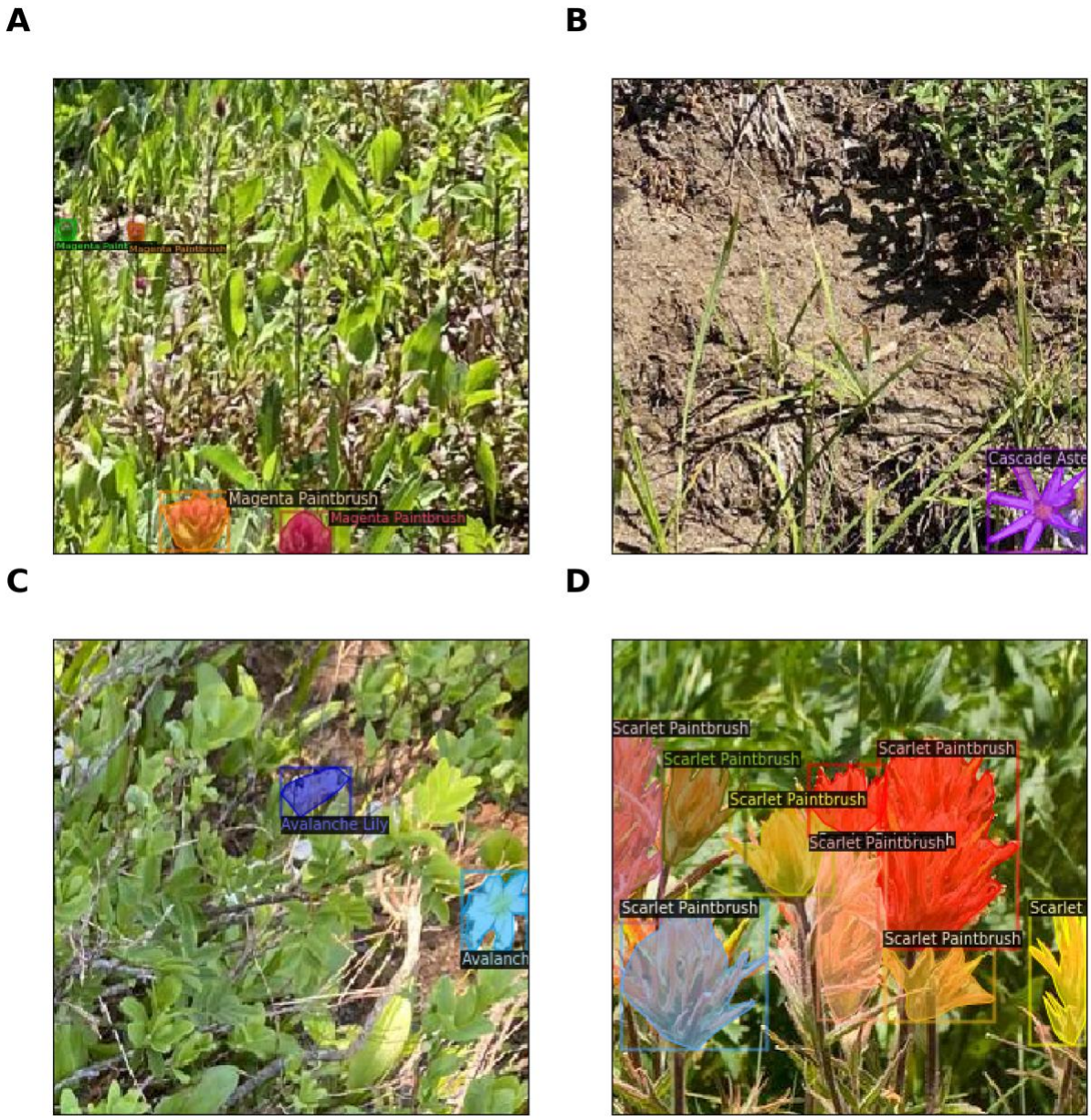

Figure 2: Example annotated images from the training dataset. (A) Magenta Paintbrush (*Castilleja parviflora*) flowers (B) A flowering Cascade Aster (*Aster ledophyllus*) (C) Avalanche lilies (*Erythronium montanum*); particularly found earlier in the season (D) Cluster of Scarlet Paintbrush (*Castilleja miniata*) in full bloom.

2.3 Machine Learning Methods

We explored how three dNN algorithms performed in detection and segmentation: YOLO, RetinaNet and Mask R-CNN. These three methods are inherently able to extract features and learn from them efficiently (Dias et al., 2018). YOLO and RetinaNet support bounding box detection only, whereas Mask R-CNN gives the mask of the detected object in addition to bounding-box. We briefly describe the three methods in Appendix A. We used the Detectron2 framework (an implementation of the PyTorch deep learning library) from Facebook Artificial Intelligence Research (FAIR) to train deep neural network models for flower detection for RetinaNet and Mask R-CNN. The Detectron2 has an out-of-the-box implementation of many of the latest CNN algorithms that perform detection and segmentation (Wu et al., 2019). Detectron2 allows writing reproducible code with a standardized way of dealing with input data and annotations. Detectron2 also provides boiler plate code for dataset handling, augmentations, training, visualization, and performance metrics. The development, training and inference of the models were performed on Azure Cloud on a server having the configuration Standard NC12_Promo (12 vCPUs, 112 GiB memory with 2 NVIDIA Tesla K80 GPUs). Hyperparameter fine-tuning of all three models was achieved with training for 1500 iterations on Google Colab's K80 GPU.

2.4 Hyperparameter tuning

We performed hyperparameter tuning using the validation data composed of 500 instances (compared with 4300 instances used in training). Anchors are predefined with aspect ratio and scale to establish the location and size of the bounding box for an object. We used different anchor sizes (Kalantar et al., 2020) for the three algorithms. We kept

the learning rate at the default value of 0.00025 with a batch size of 128. We also kept the aspect ratio of 1:1 and scale to double with a total of 5 increments.

2.5 Evaluation Metrics

We used detection evaluation metrics as defined by the COCO dataset (Lin et al., 2014). Intersection over Union (IoU) is a metric that evaluates how the ground truth and predicted detections overlap. IoU of 1 means an ideal detection whereby there is an exact overlap whereas IoU of zero means that there is no overlap. Average Precision (AP) indicates how a detection method performed at a particular IoU. Here, we report AP at 0.5, 0.75 and 1. AP is calculated by taking average of AP of ten IoU thresholds (t= [0.5,0.55,0.60,0.65,0.70,0.75,0.80,.0.85,90,.95] and when averaged across all categories the metric provides us mean average precision (mAP). True positive (TP) would mean IoU > = Threshold, and false positive (FP) is IoU < Threshold. We further inspect the Precision (TP/TP+FP) and Recall (TP/TP+FN) to evaluate frequency of false detections or missed ones; note that higher mAP indicates better detection performance. Mask R-CNN identifies the anchor boxes based on the IoU, which is a critical step in the first part of network (RPN).

3. RESULTS

3.1 Hyperparameter tuning results

We found that maintaining anchor box variations that are multiple of 16 i.e., [16,32,64,128,256] yielded better accuracy (Table 2). The results were consistent with YOLO and RetinaNet.

Table 2: Results of anchor box variation with Mask R-CNN.

Anchor Box Size	AP	AP50	AP75	AP	AP50	AP75
	Bounding Box			Segmentation		
[4, 8, 16, 32, 64]	11.708	23.180	10.338	12.230	22.296	12.217
[8, 16, 32, 64, 128]	13.515	24.992	12.023	13.340	23.783	13.358
[16, 32, 64, 128, 256]	18.128	31.767	17.148	17.871	30.838	20.211
[32, 64, 128, 256,512]	17.485	31.555	16.395	17.031	30.935	16.596

3.2 Performance of flower detection methods

We tested the three dNNs algorithms using over 316 images with an average number of 40 labels per flower category. We used two augmentations in training: Resize Shortest Edge and Random Flip. Each of the augmentation methods were trained for 10000 epochs. The time needed for training differed between the three algorithms, ranging from 3 hours for YOLO to 12 hours in Mask R-CNN.

Table 3 shows the mAPs and different IoU thresholds for all the methods. In addition, Mask R-CNN provides a classification metric by identified object size as well. In our case, for small, medium, and large flowers, the mAP was 29.27, 42.76 and 48.80, respectively. Bounding box detection applies to all the methods, but segmentation (drawing of masks) only applies to Mask R-CNN, so, segmentation scores are only reported for Mask R-CNN.

Table 3: Evaluation results for the BBox and Segmentation across the three algorithms. Mean Average precision (mAP) for the three methods. Mask R-CNN has better overall performance.

Method	mAP BBox	mAP50 BBox	mAP75 BBox	mAP Seg	mAP50 Seg	mAP75 Seg	Training time (hours)	Iterations (Epochs)
Mask R-CNN	45.80	67.24	52.10	31.32	59.05	30.78	12	10000
RetinaNet	23.59	51.28	18.63	N/A	N/A	N/A	8	10000
YOLO	32.66	60.68	31.91	N/A	N/A	N/A	3	10000

Table 4: Per category BBox evaluation (using mAP) results across all three methods. Generally, Mask R-CNN performs better, but YOLO and RetinaNet is better for some of the flowers.

Flower	Mask R-CNN AP50	RetinaNet AP50	YOLO AP50
Western Anemone	58.45	35.22	27.90
American Bistort	42.79	23.55	56.80
Avalanche Lily	40.30	18.74	52.2
Bracted Lousewort	58.05	18.28	4.42
Gray's Lovage	36.02	20.07	43.90
Magenta Paintbrush	42.01	29.98	27.80
Mountain Daisy	51.42	23.31	67.70
North Microseris	68.22	39.10	77.80
Sitka Valerian	45.43	21.31	10.40
Subalpine Lupine	38.36	24.67	39.20
Scarlet Paintbrush	59.91	33.00	74.60
Tall Bluebell	46.04	14.45	83.00
Glacier Lily	29.93	11.56	14.70
Sharptooth Angelica	24.34	08.11	48.30
Broadleaf Arnica	61.09	21.80	41.50
Cascade Aster	26.83	34.34	07.62

All three methods were able to isolate the flowers within the visual complexity of a meadow. Table 4 gives the breakdown of mAP by species for all the three methods. On average, Mask R-CNN performs better for all species, but we note differences in identifying individual species across the methods. For example, Scarlet Paintbrush, Tall Bluebell and North Microseris are detected more accurately by YOLO than by Mask R-

CNN or RetinaNet. Regardless of the species, they are detected with higher accuracy if they are towards the foreground of the image and if the image is in focus - see for example Bracted Lousewort being isolated by Mask R-CNN while two species in the horizon are missed (Fig. 3A, B). Similarly, occluded flowers are being missed for example some of the Mountain Daisy flowers that are behind the stalks of other species (Fig. 3C, D).

Figure 3: Predictions from the Mask R-CNN method showing the fluency of the model; the percent next to the predicted class represents model confidence. (A and B) A meadow in peak flowering with predictions (B) corresponding original tile. (C and D) Another meadow in peak flowering with predictions (D) corresponding original tile.

3.3 Richness and abundance of flowering species

We found that floral species richness and abundance per photo varies along the elevational gradient. Specifically, we see lower floral richness at lower and higher elevations, and increased richness along mid elevations i.e., 1700-1800 m (Fig. 4A). We also see increased density of flowers at the mid-elevation compared to lower and higher elevations (Fig. 4B). Floral abundance in pictures was also found to vary over time, even over very short periods (Fig. 5).

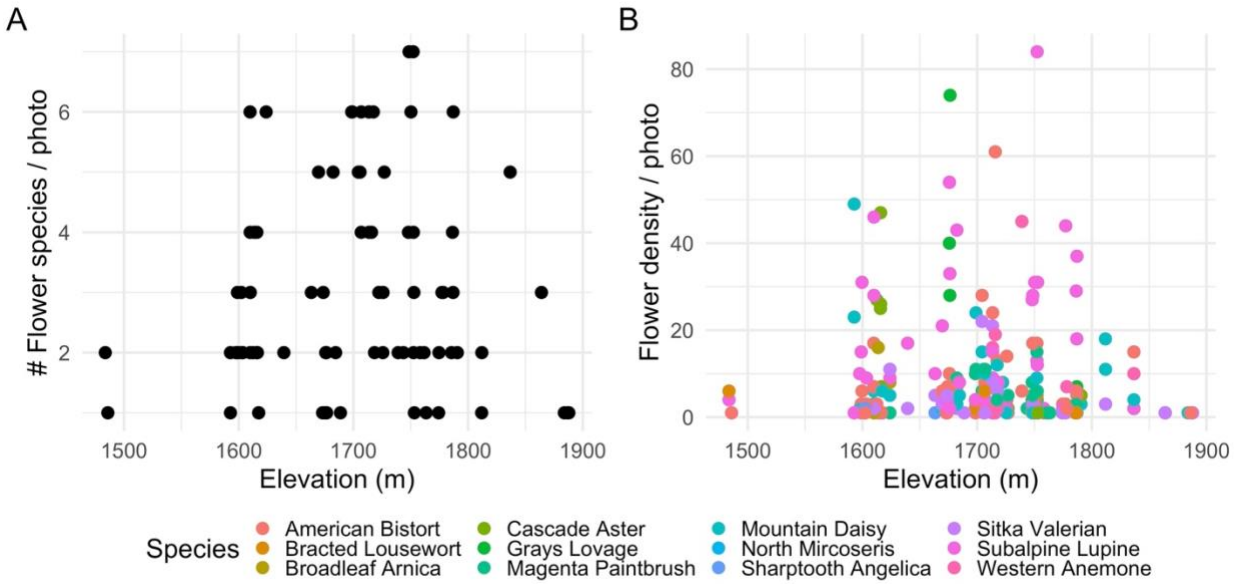

Figure 4: Detected species from all the collections using images collected in August 2020; predictions are from YOLO method. (A) Number of unique flower species detected per photo, (B) number of occurrences of each flower species per picture.

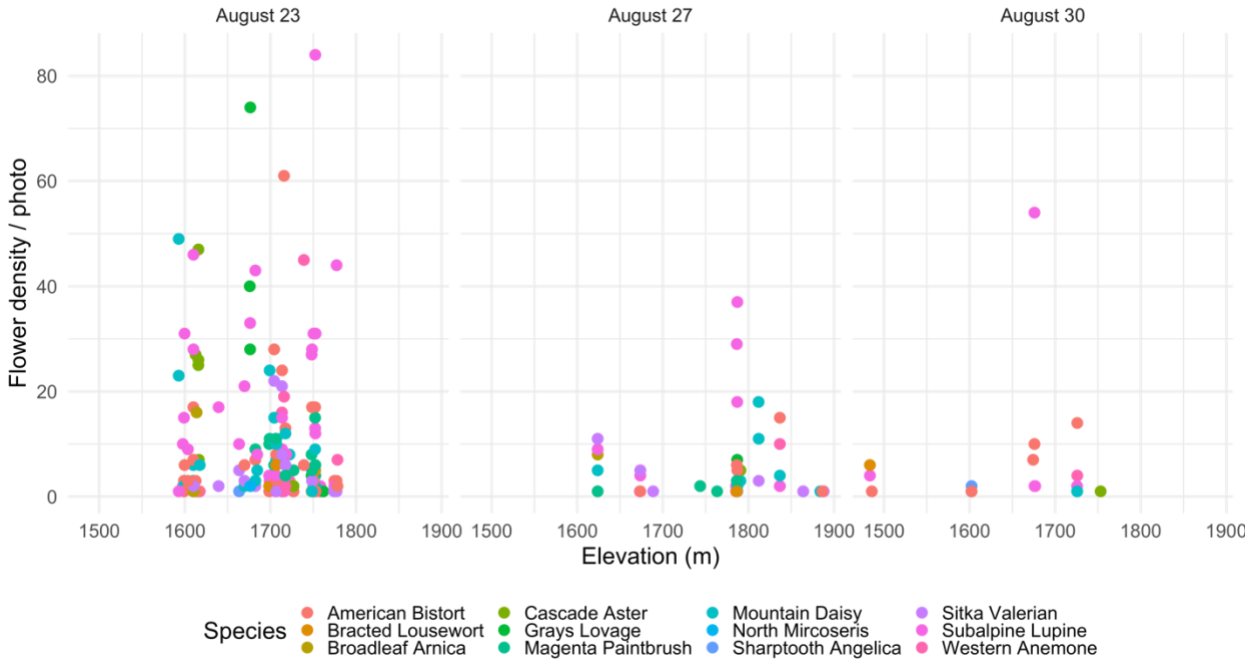

Figure 5: Floral density of species by picture for all the collection dates in August 2020.

4. Discussion

We demonstrate that deep learning techniques can detect, identify, and count wildflowers in photographs, and thereby provide detailed information on flowering occurrences in complex mountain meadow systems. Furthermore, we show that these approaches verify known ecological patterns – that species flowering varies temporally and by elevation at our study site (Kudo & Suzuki, 1999; Prevéy, 2020). Our results show, that with timestamped, geo-coded photographs, deep learning techniques can identify and count flowers, potentially facilitating detailed analyses on flowering richness as well as floral abundance, both key ecological metrics relevant to Alpine wildflower fitness and pollinator performance.

4.1 Differences in performance and methodologies for identifying flowers in camera images

In our application, the two-stage detector (Mask-R-CNN) was more accurate but slower in its predictions than the one stage detectors (YOLO, RetinaNet). This is consistent with other studies using this approach to count and identify individual flowers of a single species (Hao et al., 2021; Machefer et al., 2020; Yu et al., 2019) . Single stage detectors perform classification and regression together on the predicted anchor boxes. The trade-off is that adding an additional stage incurs computation time (but see (Suh et al., 2021)). The YOLO algorithm which is a single stage detector is able to accurately draw boxes around the flowers as well as classify them correctly more speedily than Mask R-CNN (similar finding in (Prasetyo et al., 2020; Sumit et al., 2020)). However, many flowers are missed in the labelling of the test images, but this is expected since flowers are also missed in the training images.

The imagery obtained for our study came in two dimensions (1024 x 768 and 768 x 1024), but we found that slicing large format images into 256 x 256-pixel image had the lowest classification error. The 256x256 images appear to be of adequate size for object detection for flowers of similar size in the dataset. We found that larger format image samples were computationally demanding. When interpreting the metrics, it is important to note that larger images have greater boxes and objectness errors because sub-images are taken from the same image, and if the sub-image is larger, it will have more boxes in them. And, these errors are summed for each candidate box, the box and objectness error will tend to be larger for the larger images.

4.2 Flower characteristics, species abundance and implications for detection

Several factors led to variation in our ability to classify and detect flowers. Most wildflower meadows (and thus pictures) include large variation in the abundance of species, like Subalpine Lupine, which tends to be more abundant than other flowers. This results in Subalpine Lupine being detected more so than other flowers like Mountain Daisy which appears more sparsely, a finding that reflects real differences in floral abundance. However, the algorithm also makes mistakes in species identity, and it is likely that the similar characteristics of some flowers are responsible. For example, some meadow wildflowers have an elongated floral structure (e.g., Bracted Lousewort and Subalpine Lupine), while others are more circular in nature (e.g., Mountain Daisy and Cascade Aster). Misclassification tended to occur when structures and color were similar (e.g., Sharptooth Angelica and Gray's Lovage). Unlike in other studies, in which data enhancement helped prevent overfitting and improved accuracy (Tian et al., 2020), we did not see improvement in accuracy with image augmentations. We also see the shortcoming where occluded flowers were not being isolated (Fig. 3A, C).

Despite these challenges, we were encouraged by the accuracy we achieved in this study as these pictures are inherently complex and therefore challenging for classifiers. Some challenges include inconsistent light levels (e.g., because of slope and aspect) and heterogenous backgrounds (e.g., rocks, lots of plants, etc.). Additionally, labelling errors, namely flowers that are missed while annotating could contribute to decreased accuracy. For example, the YOLO method penalizes incorrectly drawn boxes - if a flower is not

labelled in the training set, YOLO would penalize the model for drawing a box around the flower despite it being correct.

There also is likely to be sampling bias in this study. Undoubtedly, the chances of picking a location and photographing it is positively correlated with the probability of a flower existing in that place. That means that our pictures are disproportionally likely to contain flowers, potentially predisposing our algorithm to bias toward flowers. One other limitation is that our study does not capture the length of species flowering and does not quantify the flowers by location (e.g., elevation) but this could be done if a planned study is performed, for example if images are captured from intentionally placed PhenoCams along an elevational gradient.

4.3 Applicability to ecological research

We believe that combining image analysis with automated floral detection can provide important information on metrics of ecological interest, which can either complement or in some cases even replace more traditional ecological sampling. For example, our analyses show that floral richness and abundance are linked to elevation in a non-linear way (Fig. 4A, B), similar to patterns shown by other studies. Floral richness is driven both by plant diversity (which is influenced by many biotic and abiotic factors), as well as by the probability that species are flowering (Fabbro & Körner, 2004; Sargent & Ackerly, 2008; Theobald et al., 2017) – an important indicator of plant fitness resources for pollinators. Thus, this approach could be used to provide information on diversity patterns across gradients, phenological patterns of flowering relative to climate, and floral resources for pollinators.

For abundant species with recognizable flowers, these approaches may also allow for the detection of distributional shifts, if conducted annually. For example, climate change might alter the distribution of specific wildflowers found in montane environments; possibly as the result of elevational shifts (Gottfried et al., 2012; Steinbauer et al., 2018). Similarly, a rapid invasion of a non-native flowering species can be detected using this approach. The combination of the floral detection approaches introduced here with drone imagery could allow for assessment of such shifts over large spatial areas, or in remote areas.

However, there are some caveats to using flowers in pictures to quantify richness and / or abundance. For one, floral richness is not total species richness, as many perennial plants do not flower every year or in every location. A second important caveat in our measures of floral abundance is that fields of view vary from picture to picture, which means the total area available to flowers (and thus flowering abundance) will vary even if underlying patterns detected by more traditional ecological approaches (e.g., m^2 quadrats) do not.

In total, however, we believe the promise of these approaches for generating large volumes of data with less manpower (as described in (Wilson et al., 2017)) outweigh these issues. Moreover, these challenges can be overcome with large volumes of pictures / data or by employing fixed cameras (e.g., webcams, PhenoCams) with common fields of view. For example, if pictures are taken automatically via PhenoCams or TrailCams, these fixed cameras allow for pictures to be taken in the same place repeatedly, which saves time and gives an advantage over taking them oneself as one gets to control when and where the pictures are to be taken. Then, differences in floral richness would not be due to

differences in field of view (the way picture was taken). Regardless, we feel that floral richness derived from photos is still of interest as it gives quick proxy of site-specific flowering patterns.

We also believe our approach can also be used to address questions about phenology that otherwise would not be possible with traditional ecological sampling. As photos are engrained with date/time and location information, we could also have linked these measures to time to provide information on phenology (as in Breckheimer et al 2019). In this case, crowd sourced pictures (e.g., Flickr, iNaturalist, Instagram) increased the data volume (# of observations) and allowed for quantification of phenology in previous years (i.e., going back in time). This and similar approaches, however, require specific statistical approaches. For example, crowd sourced pictures (e.g., from Flickr) are not taken according to a specific experimental design, which means using these pictures could result in an unbalanced representation – e.g., spatial or temporal gaps in distributions (e.g., Mt. Rainier meadow pictures predominantly may be from around visitor centers, weather permitting times and might have weekend effects). However, one can deal with skewness introduced by source images by statistically controlling for any spatiotemporal bias in pictures taking (Breckheimer et al., 2020).

Finally, we believe that the floral detection combined with ML approaches could allow for quick assessment of ecological patterns, which could be important in a changing world. For example, it might be valuable to know about the distribution of a rare species threatened by climate change and / or the co-occurrence of wildflowers that compete from pollinators whose phenology shift at different rates or due to climate driven changes in species composition (Taheri et al., 2021). Documenting species presence-absence using

any of our methods as applied to existing (crowd-sourced) pictures could address questions such as these, and provide a preliminary assessment of patterns before designing new (and costly) experiments (Elliott & Davies, 2019).

4.4 Future directions

Although our flower detection algorithm performed well, there are likely improvements that could be made to detect a greater number of wildflowers and better distinguish between similar looking flowers. For example, we have not looked at the florescence signal but hypothesize that shape and color are being learnt during feature extraction, and as future directions, incorporation of additional information (e.g., thermal, or infrared bands) might help in the presented algorithms.

Embedding the trained models in community science apps (Mobile Applications) could be one of the end uses of these algorithms. In other domains, apps have increased community involvement, e.g., the bird identification app, Merlin (Nugent, 2018) and the plant identification functionality of iNaturalist. Use in apps both provides the public with a way to identify flowers and a way to gather data.

Combining photo data with drone and remotely sensed products could potentially offer opportunities to measure things in remote areas and on larger spatial scales. Improvement of algorithms that can use additional bands (produced in hyperspectral or multispectral imagery) could be promising and might detect more kinds of flowers and distinguish between flowers that are more similar.

5. Conclusions

We explored three deep learning techniques to detect and count flowering plants in alpine meadows. The two-stage detector we used (Mask R-CNN) performed better than the single-stage detectors (YOLO and RetinaNet), with the first stage cropping flowers and filtering out background; and the second stage classifying and detecting the flowers. However, all techniques gave us detailed information on flowering occurrences in meadows, allowing us to calculate floral richness as well as flower abundance. These approaches were also able to capture known ecological patterns; namely that flowering varies temporally (i.e., phenology) and by elevation. Our trained models could be applied in areas where our focal species (from Mt. Rainier National Park) are also dominant, including subalpine sites in other high mountain sites in the Pacific Northwest (e.g., Washington, Oregon, British Columbia). In the future, including a larger catalog of species for training could allow for coverage from other areas, for example Rocky Mountain meadows or Swiss Alpine meadows. More generally, these approaches could aid in climate change studies, because they can be used in a non-invasive, low-investment way to rapidly get information on spatiotemporal flowering patterns.

Acknowledgements

We want to acknowledge support of the University of Washington eScience Institute and Hille Ris Lambers lab in developing the ideas and supporting discussions. Authors want to acknowledge assistance from John H., Sapti S., Tommy L., and Richard L. We also acknowledge support from Microsoft AI for Earth and Microsoft Azure collegial

support. This study was carried out on the ancestral lands of the people of the Nisqually, Puyallup, Squaxin Island, Muckleshoot, Yakama, and Cowlitz Nations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' contributions

A.J. and J.H.R.L. conceived the ideas; A.J., J.H.R.L., N.C., A.T. designed the methodology; A.J. and MeadoWatch volunteers collected the data; A.J. analyzed the data; A.J., E.J.T. and J.H.R.L. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Data Availability Statement

All code will be made available on public GitHub repositories and will be archived in Zenodo.

References

Abdolali, F., Kapur, J., Jaremko, J. L., Noga, M., Hareendranathan, A. R., & Punithakumar, K. (2020). Automated thyroid nodule detection from ultrasound imaging using deep convolutional neural networks. *Computers in Biology and Medicine*, *122*, 103871. https://doi.org/10.1016/j.compbiomed.2020.103871

Anthelme, F., & Dangles, O. (2012). Plant–plant interactions in tropical alpine environments. *Perspectives in Plant Ecology, Evolution and Systematics*, *14*(5), 363–372. https://doi.org/10.1016/j.ppees.2012.05.002

Breckheimer, I. K., Theobald, E. J., Cristea, N. C., Wilson, A. K., Lundquist, J. D., Rochefort, R. M., & HilleRisLambers, J. (2020). Crowd-sourced data reveal social–ecological mismatches in phenology driven by climate. *Frontiers in Ecology and the Environment*, *18*(2), 76–82. https://doi.org/10.1002/fee.2142

Cardinale, B. J., Wright, J. P., Cadotte, M. W., Carroll, I. T., Hector, A., Srivastava, D. S., Loreau, M., & Weis, J. J. (2007). Impacts of plant diversity on biomass production increase through time because of species complementarity. *Proceedings of the National Academy of Sciences*, *104*(46), 18123–18128. https://doi.org/10.1073/pnas.0709069104

Chen, Y., Lee, W. S., Gan, H., Peres, N., Fraisse, C., Zhang, Y., & He, Y. (2019). Strawberry Yield Prediction Based on a Deep Neural Network Using High-Resolution Aerial Orthoimages. *Remote Sensing*, *11*(13), 1584. https://doi.org/10.3390/rs11131584

Dias, P. A., Tabb, A., & Medeiros, H. (2018). Apple flower detection using deep convolutional networks. *Computers in Industry*, *99*, 17–28. https://doi.org/10.1016/j.compind.2018.03.010

Dreyer, L. L., Esler, K. J., & Zietsman, J. (2006). Flowering phenology of South African Oxalis—Possible indicator of climate change? *South African Journal of Botany*, *72*(1), 150–156. https://doi.org/10.1016/j.sajb.2005.06.009

Elliott, T. L., & Davies, T. J. (2019). A comparison of phylogenetic and species beta diversity measures describing vegetation assemblages along an elevation gradient. *Journal of Vegetation Science*, *30*(1), 98–107. https://doi.org/10.1111/jvs.12700

Fabbro, T., & Körner, C. (2004). Altitudinal differences in flower traits and reproductive allocation. *Flora - Morphology, Distribution, Functional Ecology of Plants*, *199*(1), 70–81. https://doi.org/10.1078/0367-2530-00128

Gallagher, R. V., Hughes, L., & Leishman, M. R. (2009). Phenological trends among Australian alpine species: Using herbarium records to identify climate-change indicators. *Australian Journal of Botany*, *57*(1), 1. https://doi.org/10.1071/BT08051

Ganjurjav, H., Gao, Q., Gornish, E. S., Schwartz, M. W., Liang, Y., Cao, X., Zhang, W., Zhang, Y., Li, W., Wan, Y., Li, Y., Danjiu, L., Guo, H., & Lin, E. (2016). Differential response of alpine steppe and alpine meadow to climate warming in the central Qinghai–Tibetan Plateau. *Agricultural and Forest Meteorology*, *223*, 233–240. https://doi.org/10.1016/j.agrformet.2016.03.017

Gottfried, M., Pauli, H., Futschik, A., Akhalkatsi, M., Barančok, P., Benito Alonso, J. L., Coldea, G., Dick, J., Erschbamer, B., Fernández Calzado, M. R., Kazakis, G., Krajči, J., Larsson, P., Mallaun, M., Michelsen, O., Moiseev, D., Moiseev, P., Molau, U., Merzouki, A., … Grabherr, G. (2012). Continent-wide response of mountain vegetation to climate change. *Nature Climate Change*, *2*(2), 111–115. https://doi.org/10.1038/nclimate1329

Hao, Z., Lin, L., Post, C. J., Mikhailova, E. A., Li, M., Chen, Y., Yu, K., & Liu, J. (2021). Automated tree-crown and height detection in a young forest plantation using mask region-based convolutional neural network (Mask R-CNN). *ISPRS Journal of Photogrammetry and Remote Sensing*, *178*, 112–123. https://doi.org/10.1016/j.isprsjprs.2021.06.003

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask r-cnn. *Proceedings of the IEEE International Conference on Computer Vision*, 2961–2969.

Hille Ris Lambers, J., Cannistra, A. F., John, A., Lia, E., Manzanedo, R. D., Sethi, M., Sevigny, J., Theobald, E. J., & Waugh, J. K. (2021). Climate change impacts on natural icons: Do phenological shifts threaten the relationship between peak wildflowers and visitor satisfaction? *Climate Change Ecology*, *2*, 100008. https://doi.org/10.1016/j.ecochg.2021.100008

Iglovikov, V., & Shvets, A. (2018). TernausNet: U-Net with VGG11 Encoder Pre-Trained on ImageNet for Image Segmentation. *ArXiv:1801.05746 [Cs]*. http://arxiv.org/abs/1801.05746

Inouye, D. W. (2008). EFFECTS OF CLIMATE CHANGE ON PHENOLOGY, FROST DAMAGE, AND FLORAL ABUNDANCE OF MONTANE WILDFLOWERS. *Ecology*, *89*(2), 353–362. https://doi.org/10.1890/06-2128.1

Inouye, D. W., Saavedra, F., & Lee-Yang, W. (2003). Environmental influences on the phenology and abundance of flowering by Androsace septentrionalis (Primulaceae). *American Journal of Botany*. https://doi.org/10.3732/ajb.90.6.905

Jia, W., Tian, Y., Luo, R., Zhang, Z., Lian, J., & Zheng, Y. (2020). Detection and segmentation of overlapped fruits based on optimized mask R-CNN application in apple harvesting robot. *Computers and Electronics in Agriculture*, *172*, 105380. https://doi.org/10.1016/j.compag.2020.105380

Jiang, Y., Li, C., Xu, R., Sun, S., Robertson, J. S., & Paterson, A. H. (2020). DeepFlower: A deep learning-based approach to characterize flowering patterns of cotton plants in the field. *Plant Methods*, *16*(1), 156. https://doi.org/10.1186/s13007-020-00698-y

Kalantar, A., Edan, Y., Gur, A., & Klapp, I. (2020). A deep learning system for single and overall weight estimation of melons using unmanned aerial vehicle images. *Computers*

and Electronics in Agriculture, *178*, 105748. https://doi.org/10.1016/j.compag.2020.105748

Klein, G., Rebetez, M., Rixen, C., & Vitasse, Y. (2018). Unchanged risk of frost exposure for subalpine and alpine plants after snowmelt in Switzerland despite climate warming. *International Journal of Biometeorology*, *62*(9), 1755–1762. https://doi.org/10.1007/s00484-018-1578-3

Kudo, G., & Suzuki, S. (1999). Flowering phenology of alpine plant communities along gradient of snowmelt timing. *Polar Bioscience*, *12*, 100–113.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., & Zitnick, C. L. (2014). Microsoft coco: Common objects in context. *European Conference on Computer Vision*, 740–755.

Machefer, M., Lemarchand, F., Bonnefond, V., Hitchins, A., & Sidiropoulos, P. (2020). Mask R-CNN Refitting Strategy for Plant Counting and Sizing in UAV Imagery. *Remote Sensing*, *12*(18), 3015. https://doi.org/10.3390/rs12183015

Manzanedo, R. D., John, A., Sethi, M. L., Theobald, E. J., Brosi, B., Jenkins, J., Kloss-Schmidt, A., Lia, E., Schiffer, A., Sevigny, J., Wilson, A., Yogev, Y., & Hille Ris Lambers, J. (2022). MeadoWatch: A long-term community-science database of wildflower phenology in Mount Rainier National Park. *Scientific Data*, *9*(1), 151. https://doi.org/10.1038/s41597-022-01206-8

Miller-Rushing, A. J., Inouye, D. W., & Primack, R. B. (2008). How well do first flowering dates measure plant responses to climate change? The effects of population size and sampling frequency. *Journal of Ecology*, *96*(6), 1289–1296. https://doi.org/10.1111/j.1365-2745.2008.01436.x

Moyroud, E., & Glover, B. J. (2017). The Evolution of Diverse Floral Morphologies. *Current Biology*, *27*(17), R941–R951. https://doi.org/10.1016/j.cub.2017.06.053

Nugent, J. (2018). Citizen Science: Birds, Binoculars, and Biodiversity. *Science Scope*, *041*(05). https://doi.org/10.2505/4/ss18_041_05_16

Ogilvie, J. E., Griffin, S. R., Gezon, Z. J., Inouye, B. D., Underwood, N., Inouye, D. W., & Irwin, R. E. (2017). Interannual bumble bee abundance is driven by indirect climate effects on floral resource phenology. *Ecology Letters*, *20*(12), 1507–1515. https://doi.org/10.1111/ele.12854

Osherov, E., & Lindenbaum, M. (2017). Increasing CNN Robustness to Occlusions by Reducing Filter Support. *2017 IEEE International Conference on Computer Vision (ICCV)*, 550–561. https://doi.org/10.1109/ICCV.2017.67

Prasetyo, E., Suciati, N., & Fatichah, C. (2020). A Comparison of YOLO and Mask R-CNN for Segmenting Head and Tail of Fish. *2020 4th International Conference on Informatics and Computational Sciences (ICICoS)*, 1–6. https://doi.org/10.1109/ICICoS51170.2020.9299024

Prevéy, J. S. (2020). Climate Change: Flowering Time May Be Shifting in Surprising Ways. *Current Biology*, *30*(3), R112–R114. https://doi.org/10.1016/j.cub.2019.12.009

Rawal, D. S., Kasel, S., Keatley, M. R., & Nitschke, C. R. (2015). Herbarium records identify sensitivity of flowering phenology of eucalypts to climate: Implications for species response to climate change: Herbarium Records Identify Phenological Shift. *Austral Ecology*, *40*(2), 117–125. https://doi.org/10.1111/aec.12183

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. *ArXiv:1506.02640 [Cs]*. http://arxiv.org/abs/1506.02640

Redmon, J., & Farhadi, A. (2017). YOLO9000: Better, Faster, Stronger. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 6517–6525. https://doi.org/10.1109/CVPR.2017.690

Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. *ArXiv:1804.02767 [Cs]*. http://arxiv.org/abs/1804.02767

Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *39*(6), 1137–1149. https://doi.org/10.1109/TPAMI.2016.2577031

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 234–241.

Roslin, T., Antão, L., Hällfors, M., Meyke, E., Lo, C., Tikhonov, G., Delgado, M. del M., Gurarie, E., Abadonova, M., Abduraimov, O., Adrianova, O., Akimova, T., Akkiev, M., Ananin, A., Andreeva, E., Andriychuk, N., Antipin, M., Arzamascev, K., Babina, S., … Ovaskainen, O. (2021). Phenological shifts of abiotic events, producers and consumers across a continent. *Nature Climate Change*, *11*(3), 241–248. https://doi.org/10.1038/s41558-020-00967-7

Russell, B. C., Torralba, A., Murphy, K. P., & Freeman, W. T. (2008). LabelMe: A Database and Web-Based Tool for Image Annotation. *International Journal of Computer Vision*, *77*(1–3), 157–173. https://doi.org/10.1007/s11263-007-0090-8

Santos Pereira, L. F., Barbon, S., Valous, N. A., & Barbin, D. F. (2018). Predicting the ripening of papaya fruit with digital imaging and random forests. *Computers and Electronics in Agriculture*, *145*, 76–82. https://doi.org/10.1016/j.compag.2017.12.029

Sargent, R. D., & Ackerly, D. D. (2008). Plant–pollinator interactions and the assembly of plant communities. *Trends in Ecology & Evolution*, *23*(3), 123–130. https://doi.org/10.1016/j.tree.2007.11.003

Steinbauer, M. J., Grytnes, J.-A., Jurasinski, G., Kulonen, A., Lenoir, J., Pauli, H., Rixen, C., Winkler, M., Bardy-Durchhalter, M., Barni, E., Bjorkman, A. D., Breiner, F. T., Burg, S., Czortek, P., Dawes, M. A., Delimat, A., Dullinger, S., Erschbamer, B., Felde, V. A., … Wipf, S. (2018). Accelerated increase in plant species richness on mountain summits is linked to warming. *Nature*, *556*(7700), 231–234. https://doi.org/10.1038/s41586-018-0005-6

Suh, S., Park, Y., Ko, K., Yang, S., Ahn, J., Shin, J.-K., & Kim, S. (2021). Weighted Mask R-CNN for Improving Adjacent Boundary Segmentation. *Journal of Sensors*, *2021*, 1–8. https://doi.org/10.1155/2021/8872947

Sumit, S. S., Watada, J., Roy, A., & Rambli, D. (2020). In object detection deep learning methods, YOLO shows supremum to Mask R-CNN. *Journal of Physics: Conference Series*, *1529*(4), 042086. https://doi.org/10.1088/1742-6596/1529/4/042086

Taheri, S., Naimi, B., Rahbek, C., & Araújo, M. B. (2021). Improvements in reports of species redistribution under climate change are required. *Science Advances*, *7*(15), eabe1110. https://doi.org/10.1126/sciadv.abe1110

Theobald, E. J., Breckheimer, I., & HilleRisLambers, J. (2017). Climate drives phenological reassembly of a mountain wildflower meadow community. *Ecology*, *98*(11), 2799–2812. https://doi.org/10.1002/ecy.1996

Tian, Y., Yang, G., Wang, Z., Li, E., & Liang, Z. (2020). Instance segmentation of apple flowers using the improved mask R–CNN model. *Biosystems Engineering*, *193*, 264–278. https://doi.org/10.1016/j.biosystemseng.2020.03.008

Tu, S., Xue, Y., Zheng, C., Qi, Y., Wan, H., & Mao, L. (2018). Detection of passion fruits and maturity classification using Red-Green-Blue Depth images. *Biosystems Engineering*, *175*, 156–167. https://doi.org/10.1016/j.biosystemseng.2018.09.004

Vorkauf, M., Kahmen, A., Körner, C., & Hiltbrunner, E. (2021). Flowering phenology in alpine grassland strongly responds to shifts in snowmelt but weakly to summer drought. *Alpine Botany*, *131*(1), 73–88. https://doi.org/10.1007/s00035-021-00252-z

Wan, P., Toudeshki, A., Tan, H., & Ehsani, R. (2018). A methodology for fresh tomato maturity detection using computer vision. *Computers and Electronics in Agriculture*, *146*, 43–50. https://doi.org/10.1016/j.compag.2018.01.011

Wang, X. (Annie), Tang, J., & Whitty, M. (2021). DeepPhenology: Estimation of apple flower phenology distributions based on deep learning. *Computers and Electronics in Agriculture*, *185*, 106123. https://doi.org/10.1016/j.compag.2021.106123

Wilson, A., Bacher, K., Breckheimer, I., Lundquist, J., Rochefort, R., Theobald, E., Whiteaker, L., & HilleRisLambers, J. (2017). Monitoring wildflower phenology using traditional science, citizen science, and crowd sourcing. *Park Science*, *33*(1), 17–26.

Wu, Y., Kirillov, A., Massa, F., Lo, W.-Y., & Girshick, R. (2019). *Detectron2*.

Yu, Y., Zhang, K., Yang, L., & Zhang, D. (2019). Fruit detection for strawberry harvesting robot in non-structural environment based on Mask-RCNN. *Computers and Electronics in Agriculture*, *163*, 104846. https://doi.org/10.1016/j.compag.2019.06.001

6. Appendix A

Mask R-CNN

We used Mask R-CNN (Mask Region based CNN), a deep learning algorithm that generates bounding boxes and segmentation for each instance of an object (here a flower) in an image (Fig. A.1). It is classified as two-pass network; where the first part is dedicated to feature learning, while the second part is for detection and segmentation. In the end, the network identifies individual objects in an image and localizes each of them with a bounding box (Machefer et al., 2020) along with predicting pixel level segmentation masks. Instance segmentation in Mask R-CNN comprises of object detection and semantic segmentation. Mask R-CNN is an improvement upon Faster R-CNN (Ren et al., 2017) which used region proposal and classification networks to detect region of interest (RoI) and bounding boxes. Mask R-CNN supports various backbones as feature pyramid network (FPN) in order to produce feature map of the input image. Region proposal network (RPN) is then applied atop feature maps that returns object proposals with corresponding objectness scores. Objectness tells how good the model did to predict an object regardless of class. A RoIAlign layer is then applied to filter the proposals; the predecessor (Faster R-CNN (Ren et al., 2017)) used RoI pooling which made it slower. The key feature is the use RoI Align instead of RoiPool (quantization free layer). The proposals are then passed to a fully connected layer that returns class and bounding boxes for the objects. Simultaneously, the mask branch that is a fully convolutional network (FCN) works on each RoI, and outputs a segmented mask at a pixel level. Mask R-CNN uses class loss, box loss and mask loss for scoring the model. In our study Mask R-CNN was configured with ResNext 101 backbone.

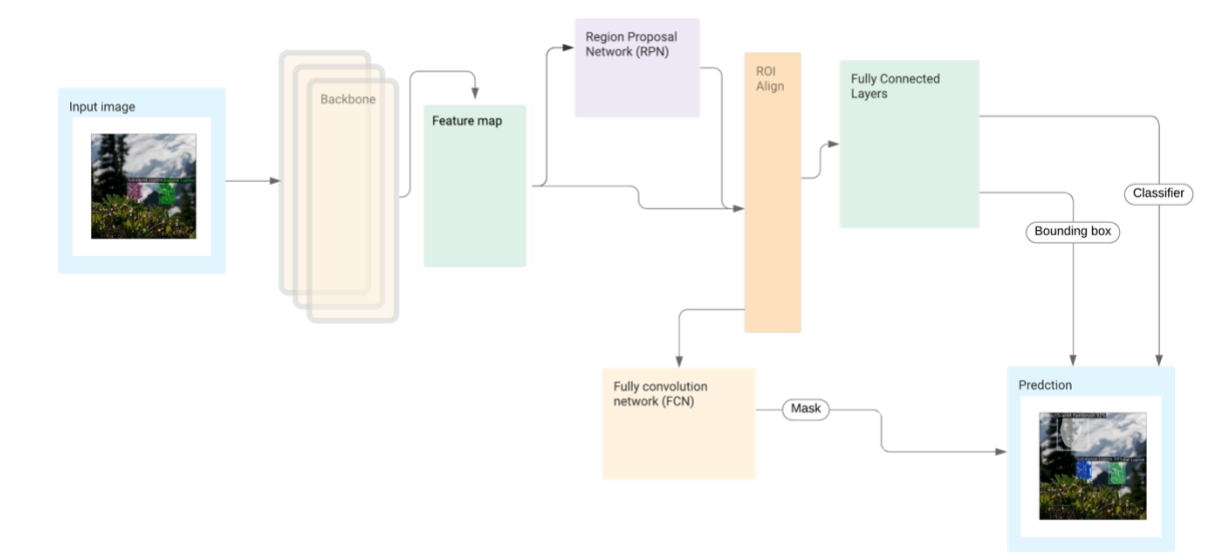

Figure A.1: High level architecture of the Mask R-CNN algorithm. See the Appendix B for more details.

YOLO

YOLO stands for "You Only Look Once" that uses regression to achieve object detection and localization (Redmon et al., 2016; Redmon & Farhadi, 2018). YOLO is a one stage method that works by regressing the bounding boxes and class probabilities and is known for its accuracy and high speed (Fig. A.2). YOLO has constantly evolved by releasing significant iterations with changes to its network structure resulting in better speed, consistent classification accuracy and recognizing smaller targets (Redmon et al., 2016; Redmon & Farhadi, 2017, 2018). The YOLO method divides each input into regions or grids (S by S where S =8 for e.g.). For each grid it predicts B bounding boxes with confidence scores along with class conditional probabilities C. Confidence score translates to accuracy of the predicted object(s) in a grid. YOLO employs non-maximum suppression (NMS) similarly to Mask R-CNN if there are multiple candidate bounding

boxes for the same target object. The loss function has three parts: objectness, box and classification. Objectness like in Mask R-CNN is a measure of how well the model did to predict an object irrespective of the class, Box tells how close the predicted box aligns with the actual box regardless of class and Classification loss tells how well each grid is classified with respect to its class probabilities. The YOLO algorithm penalizes model's inability to draw the bounding box correctly and where it missed estimating it completely. YOLO v3 was the last publicly available version by the original authors, and the recent release (unofficially known as Yolo v5) is now maintained by Ultralytics (GitHub handle - https://github.com/ ultralytics/yolov3)

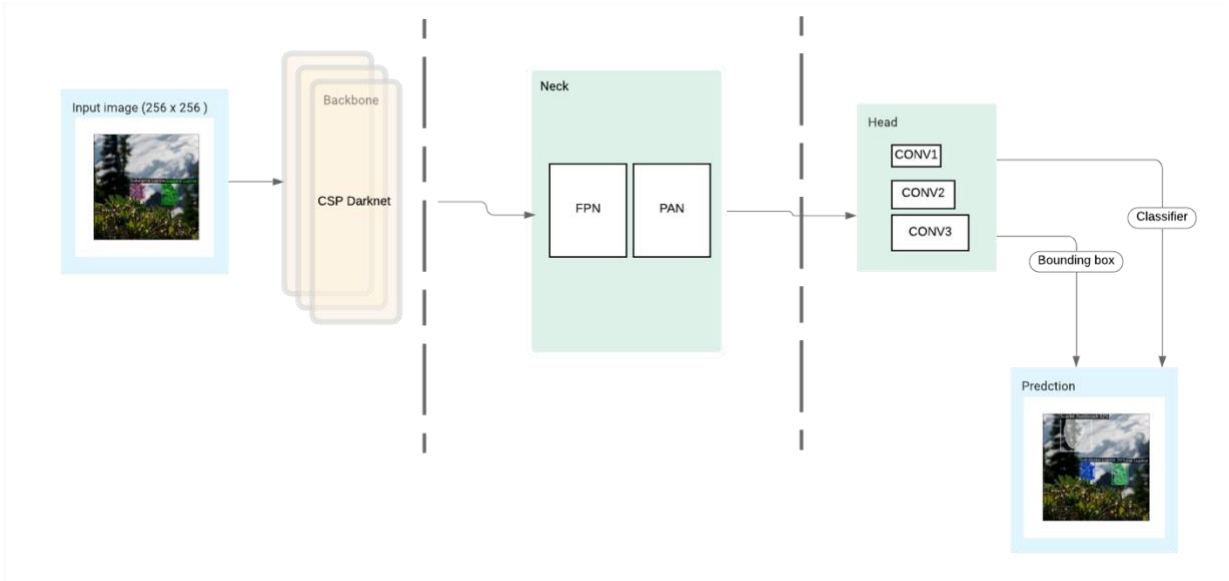

Figure A.2: High level architecture of the YOLO algorithm. See the Appendix A for more details.

Retina-Net

RetinaNet is a two-part learner where the convolution layer learns from the architecture of the images. The architecture uses a feature pyramid network (FPN) backbone on the top of ResNet architecture to generate a rich, multi-scale convolutional feature pyramid (Fig. A.3). Two subnetworks are attached to it next – classification subnet and regression subnet. The first subnetwork is for classifying anchor boxes, while the second subnetwork is for regressing anchor boxes to the ground-truth boxes. The complex head and body of the network involves convolutions which reduces the image to a deep low-resolution image. The network is tuned by using the regression loss and the classification loss. Both metrics look at overall objectness and classification ability of the model. Regression loss is calculated by using smooth L1 whereas classification is evaluated by Focal loss.

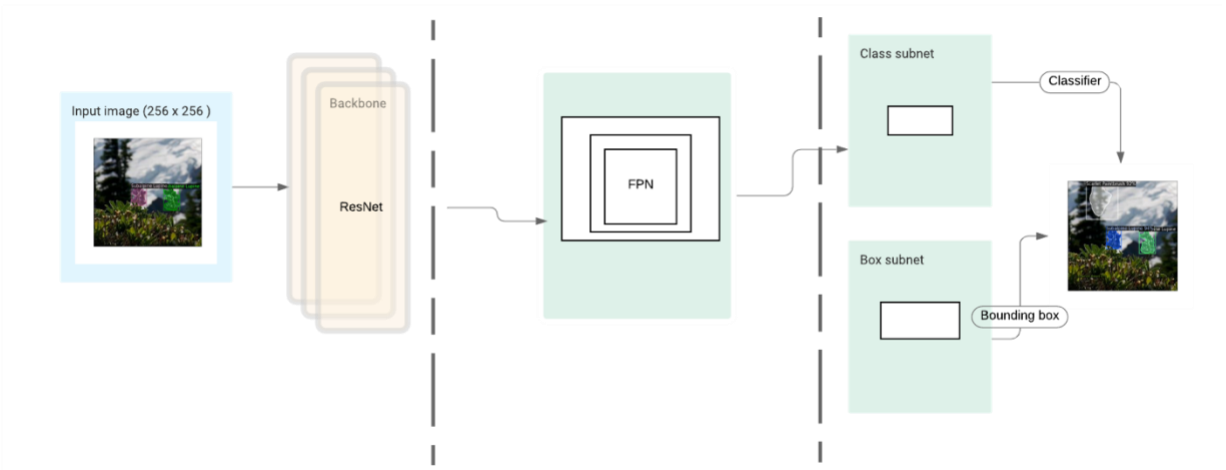

Figure A.3: High level architecture of the RetinaNet algorithm.