Wheat Head Detection using Convolutional Neural Networks for Yield Monitoring

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Contents

Introduction

- Continued development of global wheat is crucial for long-term food security.
- Wheat head numbers per unit ground area, among all attributes, is an important yield component that is still manually examined in breeding trials.
- Wheat head count is also the main component of estimating crop yield potential.

Yield Estimation can be useful in the following ways:

- Determine fertilizer recommendations
- Estimate nutrient removal
- Making replanting decisions
- Crop Insurance purposes
- Developing pest management recommendations
- Harvest and inventory planning
- Sale and Marketing decisions

Hence, an automated wheat head detection method is required to assist the wheat head detection task that can help estimate the yield of the crop.

Justification

- The number of wheat heads per unit area is an important component of estimating the crop yield potential.
- Not only just yield, it also helps in determining pertinent wheat traits such as head population density and head characteristics like health, size, maturity stage, presence of awns, etc.
- After 12-22 weeks of sowing, i.e. when the wheat is headed, it is possible to make a good estimate of the crop's yield using the count method.

Based on seed weight

$$Yield\ (ton/ha) = \frac{Heads\ (per\ m^2) \times N_{grains\ per\ head} \times W_{seed\ (est.)}(mg)}{100{,}000}$$

(Approximate wheat seed weighs 30-45mg)

Based on row spacing

$$Yield\ (bushels/acre) = \frac{Heads\ (per\ ft.) \times N_{kernels\ per\ head}}{Row\ Space\ (inches)} \times 0.48$$

(1 wheat bushel = 36.74 ton)

Accuracy of yield estimates depends upon an adequate number of counts being taken so as to get a healthy representative average of the paddock.

Hence to aid working with a large sample, computerized methods for detection are necessary to reduce man hours involved.

Objectives

1. To identify the important attributes of the Wheat Head Detection from the GWHD Dataset

2. To develop a Faster-RCNN and EfficientDet model for the detection of Wheat heads and yield estimation.

3. To compare the performance of developed models for yield estimation in terms of accuracy and computational time.

Review of Literature

Authors	Year	Major Findings
David et al.	2020	The Global Wheat Head Detection (GWHD) dataset is a big, diversified, and well-labeled dataset of wheat pictures that was created through a joint international collaborative effort. It includes 4700 high-resolution RGB photos and 190000 labelled wheat heads from various countries throughout the world at various stages of growth and genotypes.
Lyon et al.	2007	Devised several methods to calculate the wheat yield potential. They use several crop attributes like row spacing, average number of heads per foot, average number of kernels per head, etc. They also describe in detail the steps to follow and the precautions to take while conducting the experiment.

Review of Literature

Authors	Year	Major Findings
Girshick et al.	2015	Faster R-CNN model proposed, presenting RPNs for efficient and accurate region proposal generation. Their approach shares convolutional features with the downstream detection network, hence making the region proposal step nearly cost-free. Their method enables a unified, deep-learning-based object detection system to run at near real-time frame rates. The learned RPN also improves region proposal quality and thus the overall object detection accuracy.
Minxing et al.	2020	Proposed a weighted bi-directional feature pyramid network (BiFPN), which allows easy and fast multiscale feature fusion. They also developed a compound scaling method that uniformly scales the resolution, depth, and width for all backbone, feature network, and box/class prediction networks at the same time. Based on these optimizations and better backbones, they finally made a new family of object detectors, called EfficientDet, which consistently achieve much better efficiency than prior art across a wide spectrum of resource constraints.

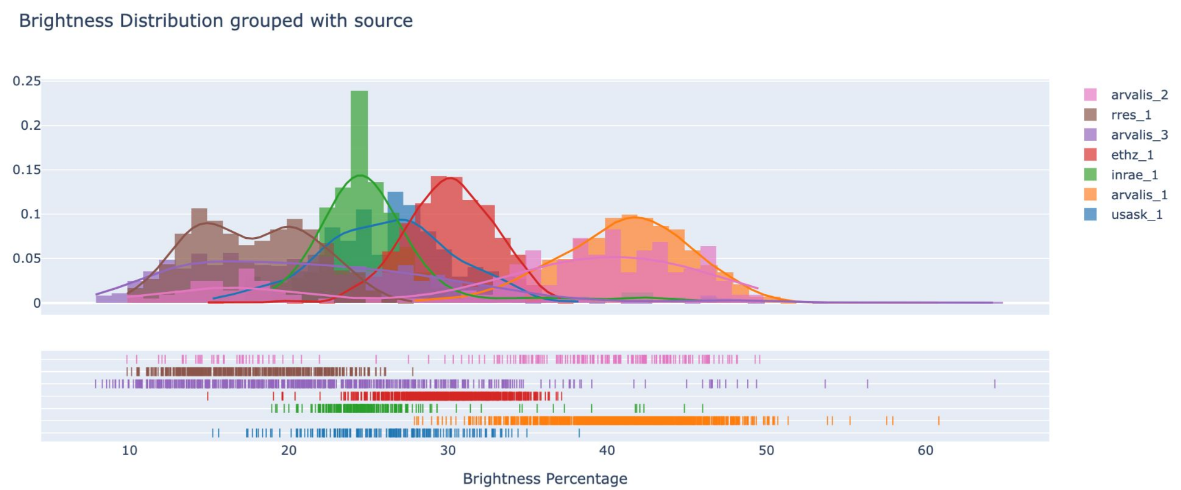
Materials and Methods

Dataset

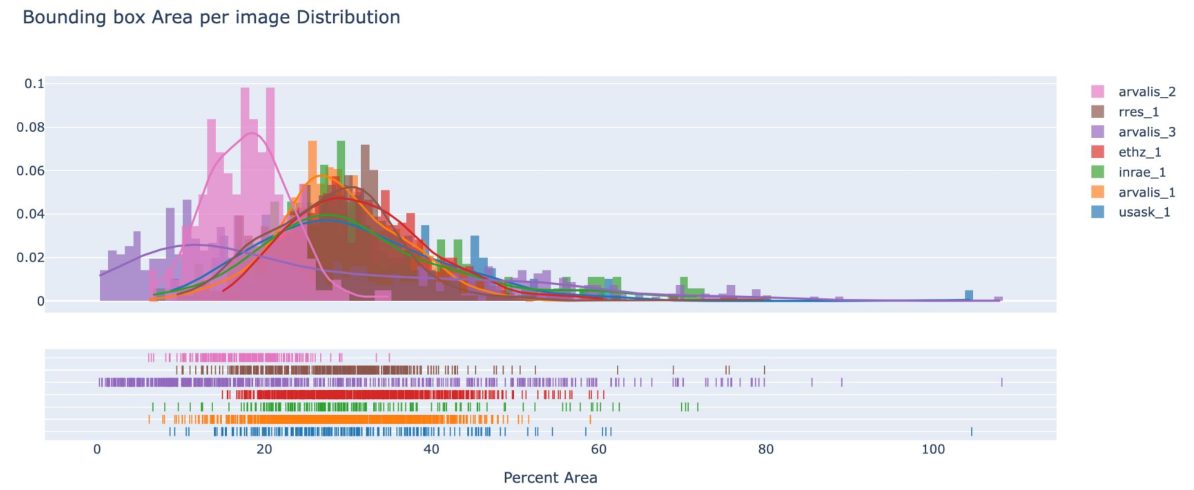
The standard for wheat head detection is the GWHD (Global Wheat Head Detection) dataset. From 2016 to 2019, data was collected from nine research organisations in various places, totaling 507 genotypes from Europe, North America, Australia, and Asia. RGB photos from a number of field-based phenotyping systems with cameras are included in the GWHD collection.

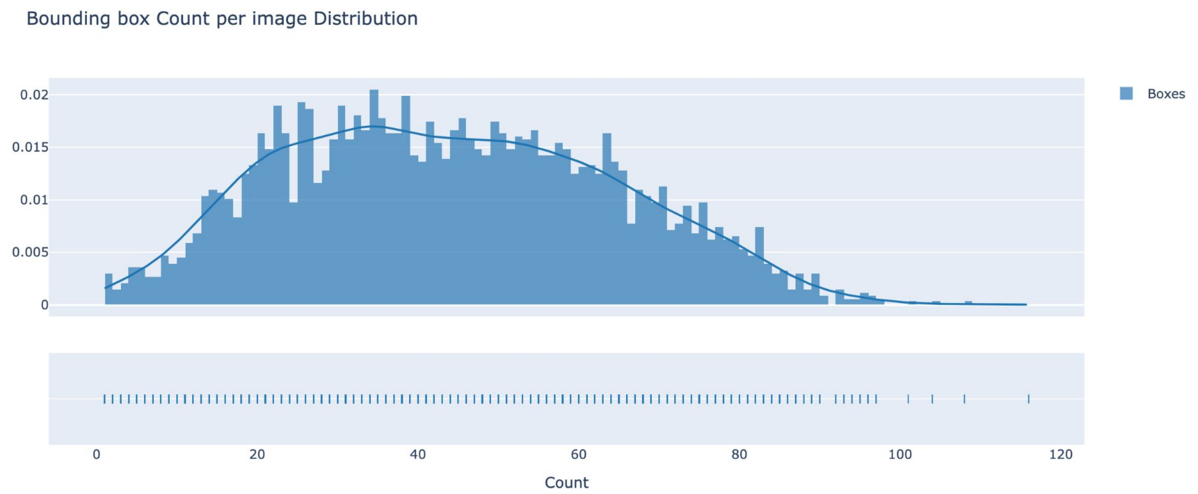
(a) (b) (c)

Exploratory Data Analysis



Exploratory Data Analysis

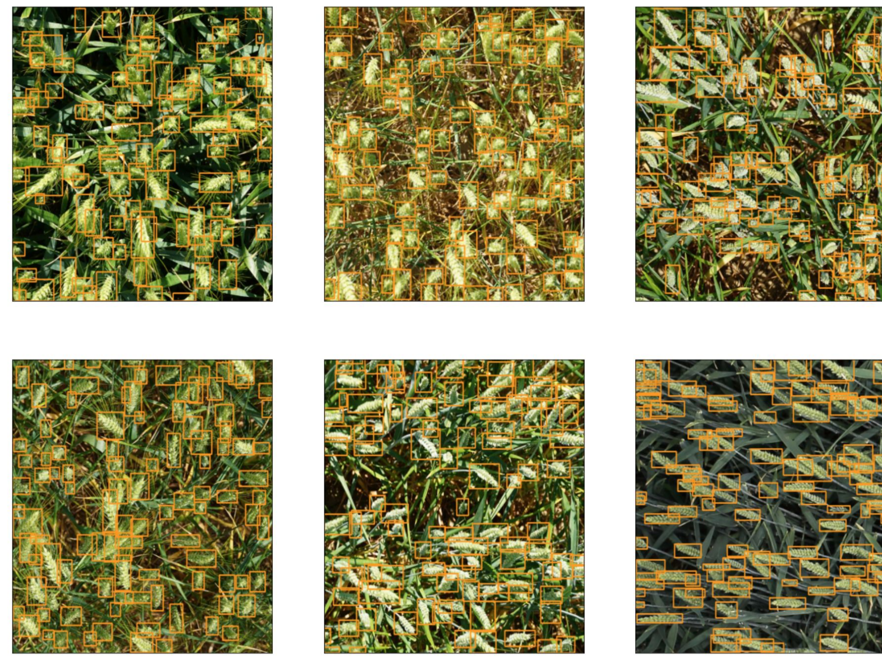




Exploratory Data Analysis

Images with low density bounding boxes

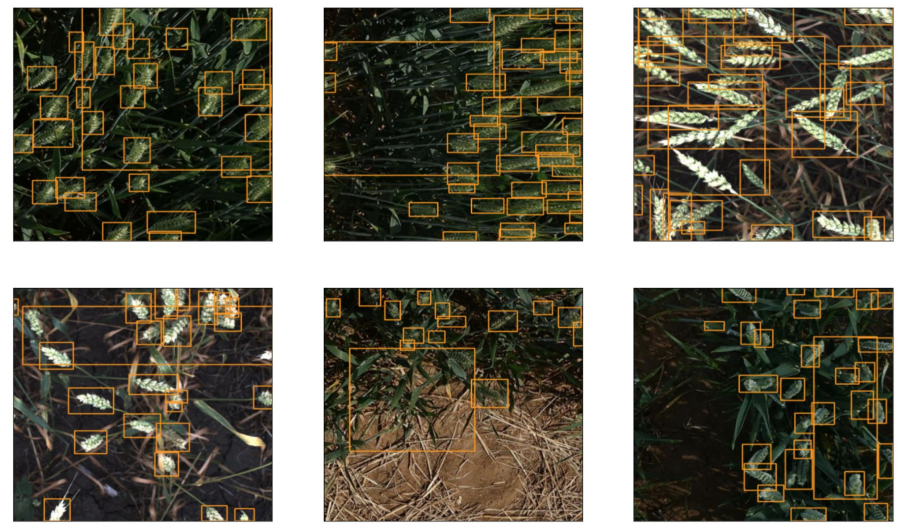
Images with high density bounding boxes



Exploratory Data Analysis

Images with Low Area Bounding boxes

Images with High Area Bounding boxes



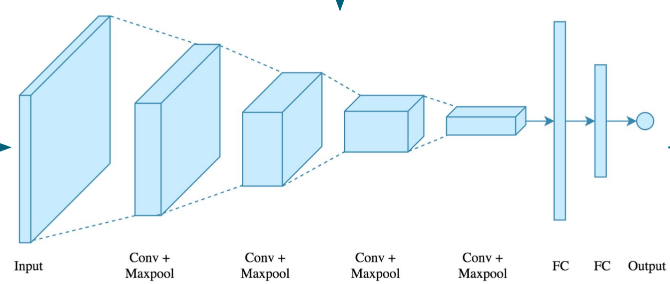
Exploratory Data Analysis

Object Detection: A brief flow overview

Train dataset
(with images and targets)

Train model with data

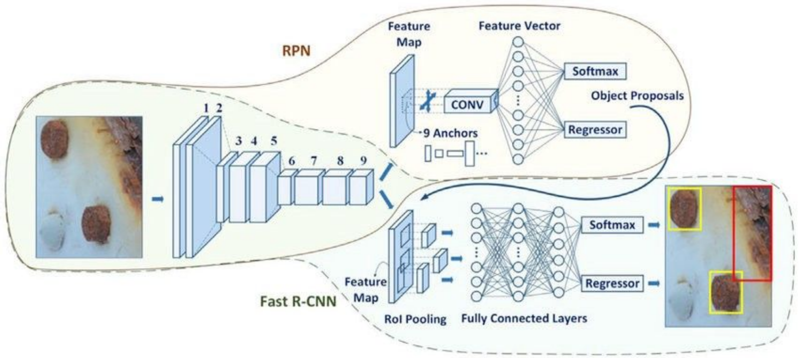
Test image

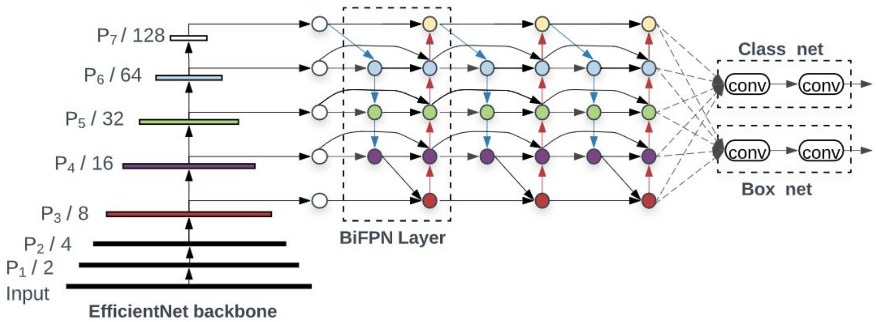


Model

Bounding box predicted

Methodology



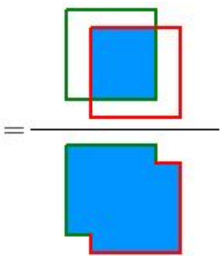


For the Faster-RCNN model, the training is carried out with a batch size of 4 with the Stochastic Gradient Descent optimizer. The learning rate is initially set to 0.0001. The complete network is trained for 2 epochs (650*2 = 1300 iterations). The training in total took about 35 minutes.

For the EfficientDet model, the training is carried out with a batch size of 2 with the Stochastic Gradient Descent optimizer. The learning rate is initially set to 0.0002, and then a plateau based scheduler is used to decrease the learning rate as the training progresses.

Results and Discussions

$$IOU = \frac{\text{area of overlap}}{\text{area of union}} =$$



For the Faster RCNN Model:

For the EfficientDet model

	Confidence Score	Intersection over Union (IOU)
Faster RCNN	0.8169	0.7223
EfficientDet	0.76219	0.7066

As per our study’s results, the Faster RCNN has better overall metrics, hence is our model of choice.

References

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[2] Sandesh Bhagat, Manesh Kokare , Vineet Haswani, Praful Hambarde, Ravi Kamble, et al. *WheatNet-Lite: A Novel lightweight Network for Wheat Head Detection*

[3] Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun, et al. *Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks*

[4] Drew J. Lyon, Robert N. Klein, et al. *Estimating Winter Wheat Grain Yields.* University of Nebraska–Lincoln

[5] Mingxing Tan Ruoming Pang Quoc V. Le Google Research, Brain Team, *EfficientDet: Scalable and Efficient Object Detection*

[6] Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi, *You Only Look Once: Unified, Real-Time Object Detection*

[7] Zhong-Qiu Zhao, Member, IEEE, Peng Zheng, Shou-tao Xu, and Xindong Wu; *Object Detection with Deep Learning: A Review*

[8] Non Maximum Suppression, https://paperswithcode.com/method/non-maximum-suppression

Thank You