Global Wheat Head Detection

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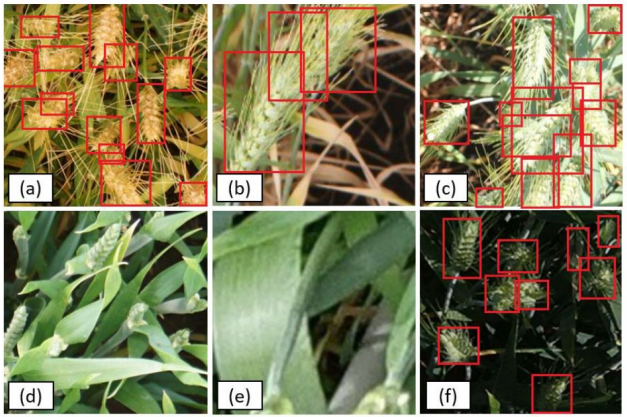
Problem statement

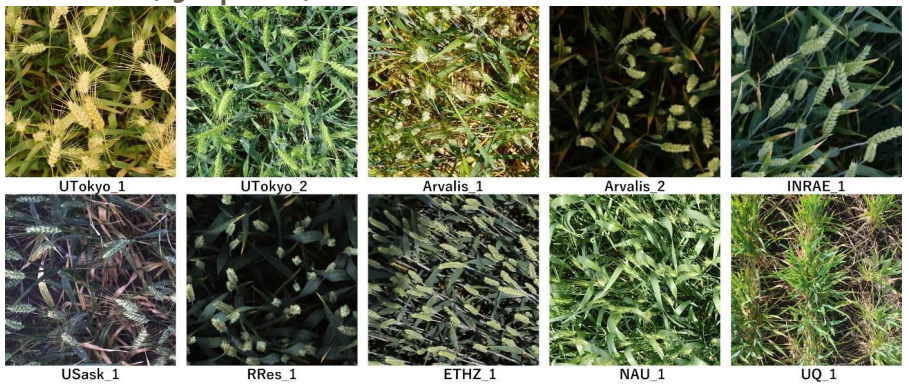
- Object detection: to detect wheat head from images taken in the field
- Developing a model with high accuracy of wheat heads counting and high precision of wheat heads detection in the field to help breeders and growers to predict production



Source: Global Wheat Head Detection (GWHD) dataset

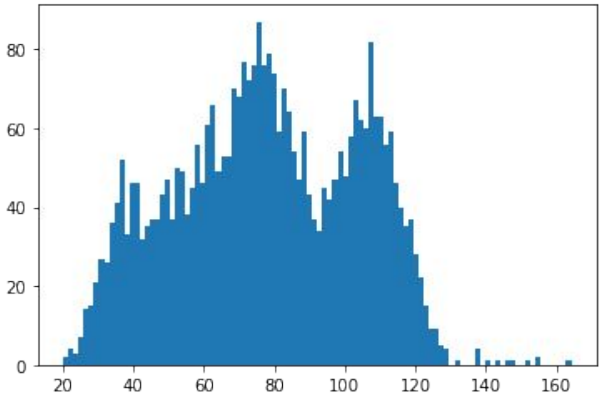
Dataset

- Contains 4,700 high-resolution RGB images and well labelled wheat heads collected from 7 countries around the world at different growth stages with a wide range of genotypes.
- Common format of 1024 * 1024 with resolution of 0.1-0.3 mm per pixel
- Training on 73% of images from Europe and North America
- Testing on 27% of images from Australia, Japan, and China

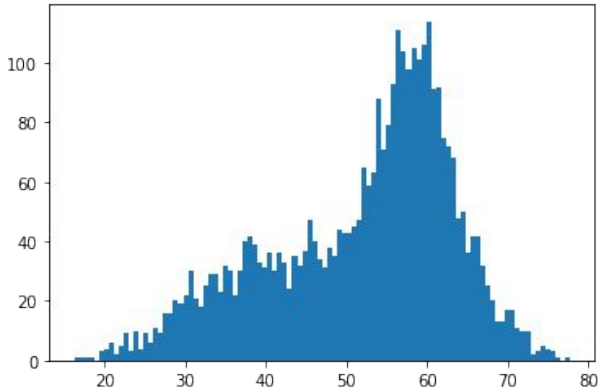


Exploratory Data Analysis

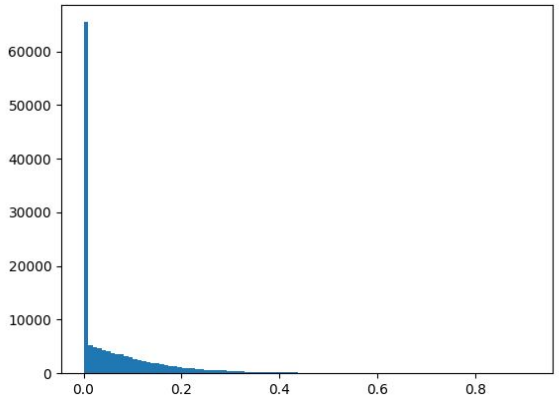
- The distribution of brightness and contrast are relatively broad
- There are a total of 138831 labelled bounding boxes, of which over 50% have overlap with at least one bounding box



Distribution of Brightness



Distribution of Contrast



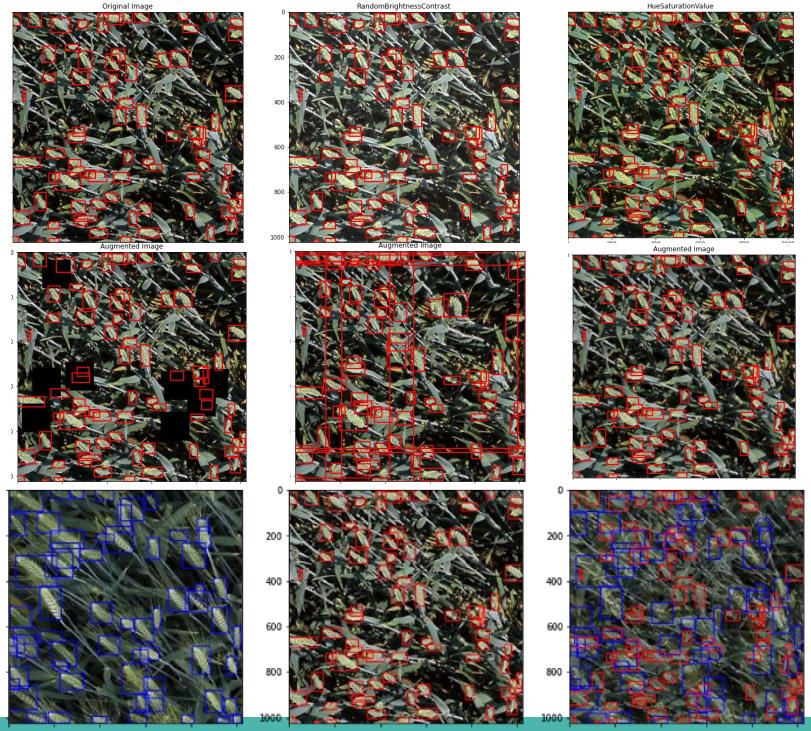
Distribution of IoU

Workflow

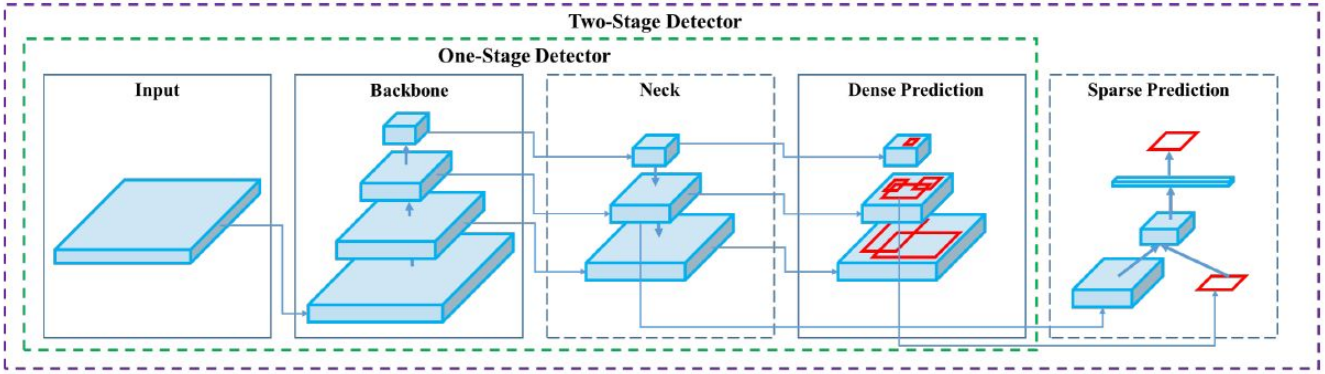
- Step 1: Images were splitted into 5 folders, of which 4 folders were used for training models and 1 folder was used for model evaluation;
- Step 2: Heavy image augmentation was performed while loading images to model training;
- Step 3: YOLO, EfficientDet and Faster R-CNN were implemented using Pytorch and trained on NVIDIA Tesla P100;
- Step 4: Models were evaluated on the mean average precision (mAP), as well as root mean squared error (RMSE) and the relative RMSE (rRMSE).

Image Augmentation

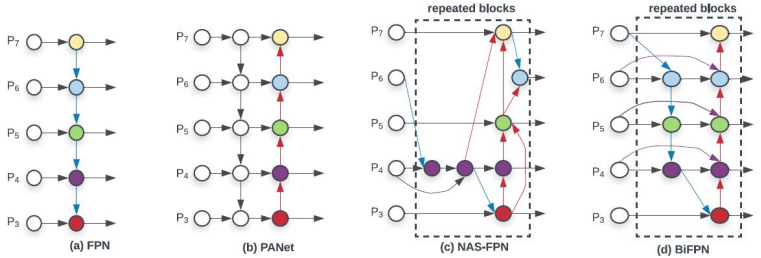
- HorizontalFlip, VerticalFlip and RandomRotate90
- RandomBrightnessContrast
- HueSaturationValue
- CoarseDropout
- PiecewiseAffine
- Blur
- MixUp



One-stage Object Detection: YOLO and EfficientDet



Model	Backbone	Neck	Parameters
YOLO	CSPDarknet53	PANet	27.6M
EfficientDet-D5	EfficientNet-B5	BiFPN	34M

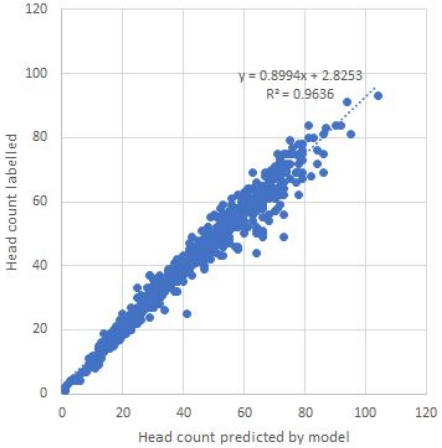


Training YOLO

- The open-source repository created by Ultralytics was cloned from (https://github.com/ultralytics/yolov5)
- YOLOv5 training pipeline employs some other augmentations, such as CutMix, Mosaic, etc.
- YOLOv5x was trained on images sizes of 1024*1024, batch size of 2, for 100 epochs.
- Learning rate was set as 0.01, with momentum of 0.937, and weight_decay of 0.0005.

Evaluation of YOLO

- On the validation dataset, the model got $AP_{50...75}$ of 0.75, mAP@0.5 of 0.86, MSE of 4.33, and rMSE of 10.3%.
- On the test dataset, the model got $AP_{50...75}$ of 0.70.
- The head count estimated with model YOLO was in relatively good agreement with the head count labelled with R^2 of 0.96

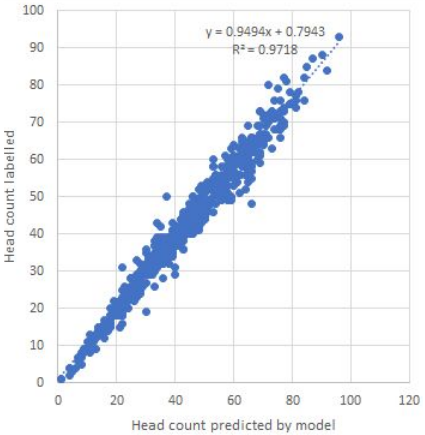


Training EfficientDet

- EfficientDet-D5 was trained on images sizes of both 512*512 and 1024*1024.
- Random search for hyperparameter tuning
  - lr: loguniform (0.001, 0.00001), **0.0002**
  - lr_optimizer: Adam, **AdamW**, SGD
  - lr_scheduler: OneCycleLR, **ReduceLROnPlateau**, CosineAnnelingLR

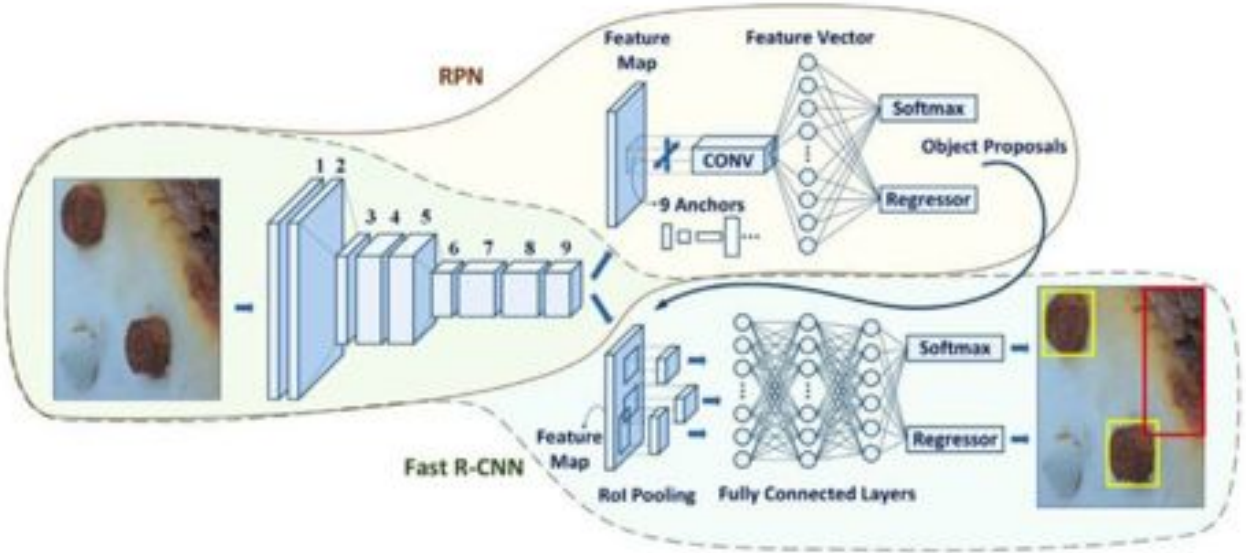
Evaluation of EfficientDet

Model	APval	mAP@0.5	RMSE	rRMSE	APtest	R2
YOLO	0.75	0.86	4.33	10.3%	0.70	0.96
EfficientDet	0.72	0.81	3.44	10.6%	0.63	0.97



Faster R-CNN Architecture

- Obtain from image:
  - list of bounding boxes
  - label assigned to each bounding box
  - probability for each label and bounding box



Faster R-CNN Process

- Input images are passed through a pre-trained CNN up until an intermediate layer (Transfer Learning)
  - End with a convolutional feature map
- Feature Extractor - A Region Proposal Network (RPN) uses the features that the CNN computed to find up to a predefined number of regions (bounding boxes), which may contain objects
- Region of Interest (RoI) Pooling - Extract previous features which would correspond to the relevant objects into a new tensor
- R-CNN module
  - Classifies the content in the bounding box (or discard it, using “background” as a label)
  - Adjust the bounding box coordinates (so it better fits the object)

Faster R-CNN Hyperparameter Tuning

- DataLoader
  - Batch size
- Optimizer
  - SDG
    - Learning Rate
    - Momentum
    - Weight Decay
    - Nesterov
  - Adam
    - Learning Rate
    - Weight Decay

Faster R-CNN Results (SGD)

```
optimizer = torch.optim.SGD(params, lr=0.0001, momentum=0.95, weight_decay=0.0005,
nesterov=True)
num_epochs = 10
```

Epoch: 5 Training Loss: 0.631314
Validation IOU: 0.6625
Epoch: 6 Training Loss: 0.628712
Validation precision increased(0.661849 --> **0.662546**). Saving model ...
Iteration #300 loss: 0.6001112461090088
Validation IOU: 0.6612
Epoch: 7 Training Loss: 0.624271
Iteration #360 loss: 0.5466078519821167
Validation IOU: 0.6604
Epoch: 8 Training Loss: 0.619354
Validation IOU: 0.6576
Epoch: 9 Training Loss: 0.619932
END--------------------------

Faster R-CNN Results (SGD)

```
optimizer = torch.optim.Adam(params, lr=0.0001, betas=(0.9, 0.999), eps=1e-08,
weight_decay=0.0005, amsgrad=False)
num_epochs = 10
```

Epoch: 5 Training Loss: 0.656384
Validation IOU: 0.7188
Epoch: 6 Training Loss: 0.647585
Validation precision increased(0.635841 --> 0.718781). Saving model ...
Iteration #300 loss: 0.6084125638008118
Validation IOU: 0.7061
Epoch: 7 Training Loss: 0.641469
Iteration #360 loss: 0.6902428269386292
Validation IOU: 0.6905
Epoch: 8 Training Loss: 0.635929
Validation IOU: 0.6913
Epoch: 9 Training Loss: 0.632648

Faster R-CNN SGD vs Adam

10 Epochs

Optimizer	Learning Rate	Momentum	Weight Decay	Betas	Epsilon	Precision
SGD	.001	.005	.0005			.672453
SGD	.0001	.95	.0005			.672577
SGD	.0001	.0005	.0005			.672613
Adam	.0001		.0005	(0.9, 0.999)	1e-08	.718781
Adam	.001		.0005	(0.9, 0.999)	1e-08	.327536

Faster R-CNN SGD vs Adam

50 Epochs

Optimizer	Learning Rate	Momentum	Weight Decay	Betas	Epsilon	Precision
SGD	.0001	.005	.0005			.748047
Adam	.0001		.0005	(0.9, 0.999)	1e-08	.761707

Faster R-CNN Observations

- Adam Optimizer performing better than SGD over a smaller number of Epochs
- Over 50 epochs, Adam still performed better but SGD was comparable
- CoarseDropout increased overall precision after 5 epochs (most runs)
  - Without it, precision hovers around .66-.68
- Resize at 512x512 didn’t perform as well as 1024x1024

Conclusion

In this study three types of CNN architectures were investigated:

(i) YOLO, (ii) EfficientDet, and (iii) Faster R-CNN.

YOLO got the best performance with AP of 0.75, mAP@0.5 of 0.86, and rMSE of 10%.