Developing a DETR Model for Global Wheat Detection

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Abstract

This report details our work on the Global Wheat Detection challenge [1] from Kaggle, focusing on detecting wheat heads from outdoor imagery under diverse conditions. We present two distinct deep learning models: a Vanilla UNet [2], implementing a standard encoder-decoder architecture for semantic segmentation, and a custom Detection Transformer (DETR) [3], which combines a ResNet-50 backbone with Transformer encoder-decoder architecture for precise object detection. The UNet model utilizes binary cross-entropy (BCE) loss optimized at a pixel-level precision metric, whereas the DETR model employs the Hungarian loss with Mean Average Precision (mAP) as its evaluation metric. Our findings indicate that DETR demonstrates superior detection accuracy and generalization capability compared to the vanilla UNet approach, underscoring the effectiveness of Transformer-based methods for object detection tasks. Our full implementation can be viewed on Github here.

Figure 1: Data Samples (With Bounding Boxes)

1 Introduction

1.1 Global Wheat Detection Challenge

The Global Wheat Detection challenge [1] is an image processing task designed to detect wheat heads in outdoor agricultural environments. This task presents significant complexity due to variability in lighting conditions, wheat genotypes, camera viewpoints, and occlusion by overlapping wheat heads. Developing accurate and generalized models for this application is vital for agricultural management, yield prediction, and automated harvesting processes.

1.2 Dataset

The dataset, provided by the Kaggle competition, comprises thousands of high-resolution images (1024×1024) capturing wheat fields from diverse geographic regions and environmental conditions. Each image is annotated with bounding boxes marking individual wheat heads. The dataset showcases considerable variability, including differences in illumination, wheat density, and wheat head sizes. Exploratory data analysis reveals uneven distributions and potential class imbalance, making the detection task particularly challenging. Visualization of sample data highlights the complexity and diversity within the

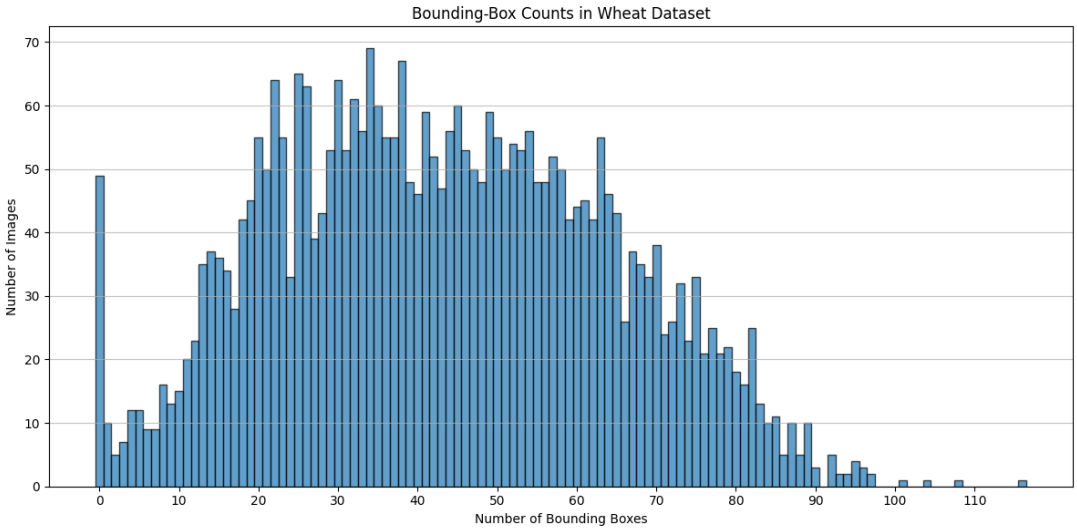


Figure 2: Number Of Bounding Boxes (Objects) In The Images

dataset, providing insights into necessary preprocessing and augmentation strategies to enhance model performance. The complexity of finding wheat-heads demonstrated in Figure 1. The data distribution can be seen in Figure 2.

1.3 Evaluation Metrics

For the evaluation of our models, we employed specific metrics aligned with each model's architecture and task objectives. For the Vanilla UNet model, we adopted pixel-wise Binary Cross-Entropy (BCE) loss alongside avarage precision, which measures the accuracy of pixel-level segmentation predictions. In contrast, for our DETR model, we utilized the Hungarian loss, integrating classification loss, bounding box regression loss (L1), and Generalized Intersection-over-Union (GIoU), coupled with Mean Average Precision (mAP) to evaluate the effectiveness of object detection comprehensively. These metrics provide a robust assessment of each model's ability to accurately identify and localize wheat heads in diverse conditions.

2 Vanilla UNet

2.1 Architecture

The Vanilla UNet architecture, as seen in Figure 3, is a convolutional neural network designed for semantic segmentation tasks, specifically for segmenting wheat heads from images. The architecture follows an encoder-decoder structure, widely recognized for its efficiency in capturing both contextual information and precise localization.

Encoder Path The encoder comprises multiple stages, each featuring a DoubleConv block consisting of two consecutive convolutional layers with a kernel size of 3x3, each followed by a ReLU activation. At each stage, the number of feature channels is progressively increased, starting from 64 and doubling at each subsequent level, resulting in 64, 128, 256, and 512 feature channels. Between these stages, max pooling layers with a

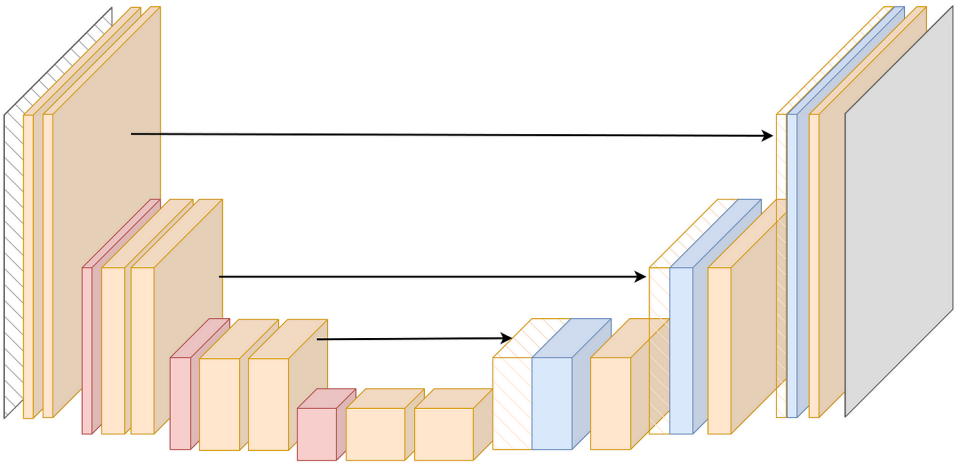


Figure 3: UNet Architecture Diagram

kernel size of 2x2 are employed to reduce the spatial dimensions of feature maps by half, thereby capturing hierarchical features and reducing computational complexity.

Bottleneck At the lowest level of the encoder, the bottleneck layer integrates two convolutional layers doubling the channel dimension to 1024. This layer captures deep semantic features and is essential for aggregating context-rich information.

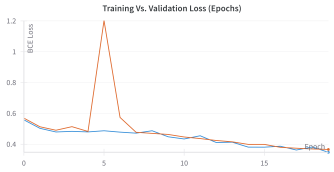
Decoder Path The decoder mirrors the encoder structure but includes transpose convolution layers to progressively upsample feature maps back to the original input dimensions. Each decoding stage consists of a transpose convolutional layer with kernel size 2x2 and stride 2, followed by a DoubleConv block. The skip connections from corresponding encoder stages concatenate feature maps from the encoder path to those in the decoder, effectively preserving spatial details and enabling precise segmentation.

Final Layer The architecture concludes with a 1x1 convolutional layer that maps the feature channels down to a single channel, representing the probability map of wheat head presence. The output is passed through a sigmoid activation scaled by a factor of 0.1, producing pixel-wise predictions indicating segmentation masks.

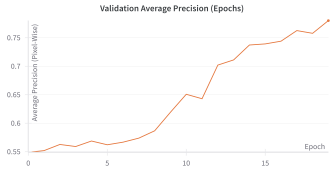
Loss and Metrics We optimize the UNet using binary cross-entropy (BCE) loss, suitable for binary pixel-wise segmentation tasks. Model performance is evaluated using pixel-level precision and Average Precision (AP), computed using the torchmetrics library.

2.2 Data Preprocessing

Data preprocessing for the Vanilla UNet involved creating segmentation masks from the provided dataset by pairing images with their corresponding binary masks. Images and masks were resized uniformly to a resolution of 256x256 pixels to maintain computational efficiency and consistency across training and validation datasets. Further preprocessing



(a) Loss Over Epochs



(b) Average Precision Over Epochs

Figure 4: Training metrics of the UNet model over epochs.

Figure 5: Original Image Vs. Created Mask Vs. Predicted Mask (UNet)

steps included normalization of pixel values to a range of [0,1], and conversion of image data from Height-Width-Channel (HWC) format to Channel-Height-Width (CHW) format to align with PyTorch input standards.

While this preprocessing approach significantly simplified the segmentation task and enhanced training stability, it was tailored specifically for binary mask generation. This method, although effective for segmentation, is not directly suitable for the original Global Wheat Detection challenge, which requires bounding box predictions rather than binary pixel-wise masks. Consequently, this approach, despite providing valuable insights into UNet's segmentation capability, does not fully align with the bounding-box-based evaluation criteria of the challenge, potentially limiting its applicability and comparability with object detection methods like DETR.

2.3 Hyperparameters

Implementation Details The UNet model is implemented using PyTorch Lightning, facilitating structured and reproducible experimentation. The Adam optimizer with a learning rate of $1e^{-}3$ is utilized, and training progress is monitored through detailed logging mechanisms via Weights & Biases (WandB). The batch size was 32 and weight decay of $1e-4$ was used. Validation visualizations include side-by-side comparisons of original images, ground-truth masks, and predicted masks, enabling intuitive evaluation of segmentation performance. At this point, we ran for 20 epochs only, to get basic results, due to the absence of a cuda GPU.

2.4 Results

After training for 20 epochs, the Vanilla UNet model achieved a training loss of approximately 0.36 and a validation loss of 0.34, as seen in Figure 4a, indicating stable convergence behavior. The validation pixel-wise precision metric reached 78%, as seen in Figure 4b, demonstrating robust segmentation accuracy, but compared to the original target output based on the challenge - it does not suffice.
As seen in Figure 5, UNet is capable of good semantic segmentation of objects, with no object seperation, and its output does not match the bounding boxes expected output.

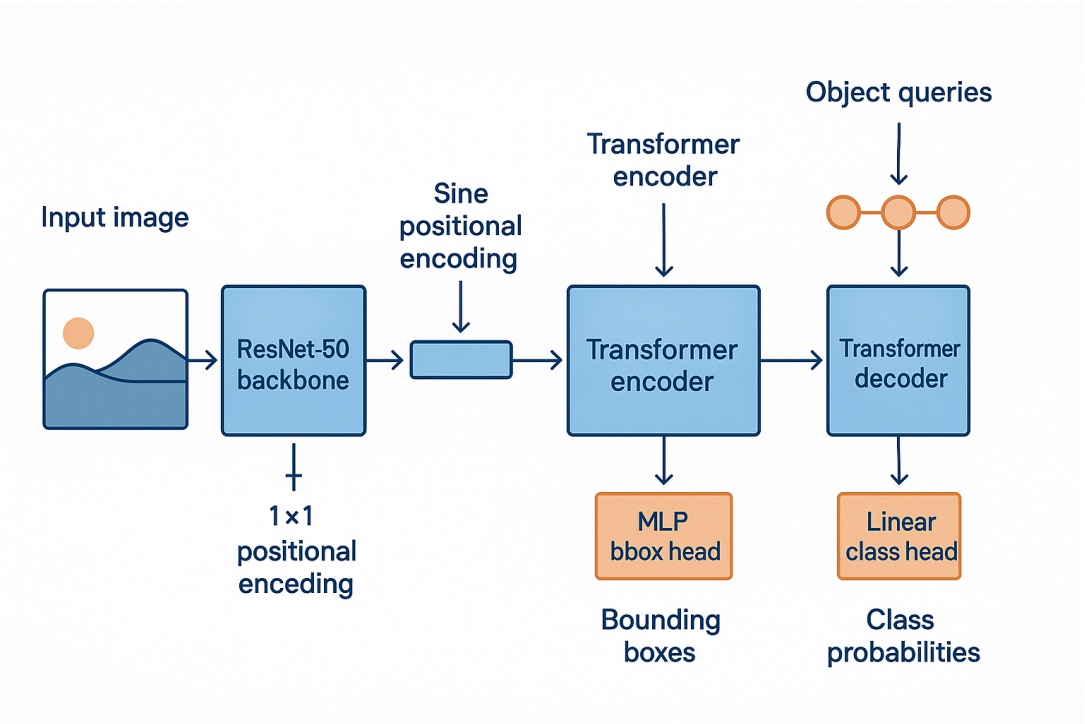


Figure 6: Detection Transformer (DETR) Pipeline

3 Detection Transformer (DETR)

DETR is an object detector. A CNN backbone converts an image into a feature map, sine positional encodings are added, and a Transformer encoder–decoder processes the sequence. A fixed set of learned *object queries* flows through the decoder, each producing a class probability and a normalised box (c_x, c_y, w, h). A Hungarian assignment matches these predictions to ground-truth objects during training.

3.1 Architecture

Backbone A ResNet-50 pre-trained on ImageNet is truncated before the global-pooling stage, producing a feature map $\mathbf{F} \in \mathbb{R}^{B\times 2048\times H'\times W'}$. A 1×1 convolution projects $\mathbf{F}$ to the Transformer dimension d=256, yielding $\mathbf{X} \in \mathbb{R}^{B\times 256\times H'\times W'}$.

Positional Encoding A sine embedding $\mathbf{P} \in \mathbb{R}^{B\times 256\times H'\times W'}$ (normalized by $\sqrt{d}$) is added to $\mathbf{X}$ to inject spatial information. After flattening the spatial axes, the source sequence becomes $\mathbf{S} \in \mathbb{R}^{L\times B\times 256}$ with $L = H'W'$.

Transformer Encoder–Decoder A stock `nn.Transformer` configured with six encoder and six decoder layers ($n_{\text{heads}} = 8$) processes the sequence. The decoder is driven by N_q=100 learned *object-query* embeddings $\mathbf{Q} \in \mathbb{R}^{N_q\times 256}$. With an all-zero initial target, cross-attention yields $\mathbf{H} \in \mathbb{R}^{N_q\times B\times 256}$, where each row competes to represent exactly one object or "no-object".

Prediction Heads For every query vector $\mathbf{h}_k$ the network predicts

$$\hat{\mathbf{p}}_k = \text{Linear}_{256\to C+1}(\mathbf{h}_k), \qquad \hat{\mathbf{b}}_k = \sigma\big(\text{MLP}_{256\to 256\to 256\to 4}(\mathbf{h}_k)\big),$$

where $\hat{\mathbf{p}}_k$ are class logits over C foreground classes plus an *EOS* label, and $\hat{\mathbf{b}}_k = (c_x, c_y, w, h) \in [0,1]^4$ are normalized bounding boxes.

Loss Function Ground-truth objects are matched to predictions via the Hungarian algorithm. The total loss is a weighted sum of

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \lambda_1 \mathcal{L}_1 + \lambda_{\text{GIoU}}(1 - \text{GIoU}), \quad (\lambda_1, \lambda_{\text{GIoU}}, \lambda_{\text{EOS}}) = (5,\ 2,\ 0.1),$$

where $\mathcal{L}_{\text{CE}}$ is a class-weighted cross-entropy that down-weights the *no-object* class by λ_{EOS}.

Evaluation Metrics Model performance is monitored with mean Average Precision (mAP) in "cxcywh" format, computed on-the-fly using the `torchmetrics` library. The implementation is wrapped in a `pl.LightningModule`, enabling reproducible training, automatic logging.

3.2 Dataset

Every input image is duplicated once for each augmentation in a user-supplied dictionary. With N raw images and K augmentations the effective dataset size is $N \times K + 1$.

Augmentations The nine Albumentations pipelines used are

- **HFlip** (Horizontal flip)
- **VFlip** (Vertical flip)
- **Crop** (Random 768×768 crop, then resize to 256×256)
- **Blur** (Gaussian blur)
- **Gaussian Noise**
- **HFlip + Noise**
- **Crop + Blur**
- **HFlip + VFlip**
- **VFlip + Crop + Noise**

Loading + augmenting. For each *image* we

1. Read the JPEG.
2. Retrieve pixel-space bounding boxes from the CSV.
3. run the chosen pipeline, which applies the listed transforms, while keeping boxes aligned, then resizes the frame to 256×256. A 1024×1024 variant was tested but converged much slower.

Target dictionary. Each label yields {`boxes, labels=0, image_id="<id>|<aug>", orig_size=(256,256)`}. Encoding the augmentation name inside `image_id` simplifies visual debugging.

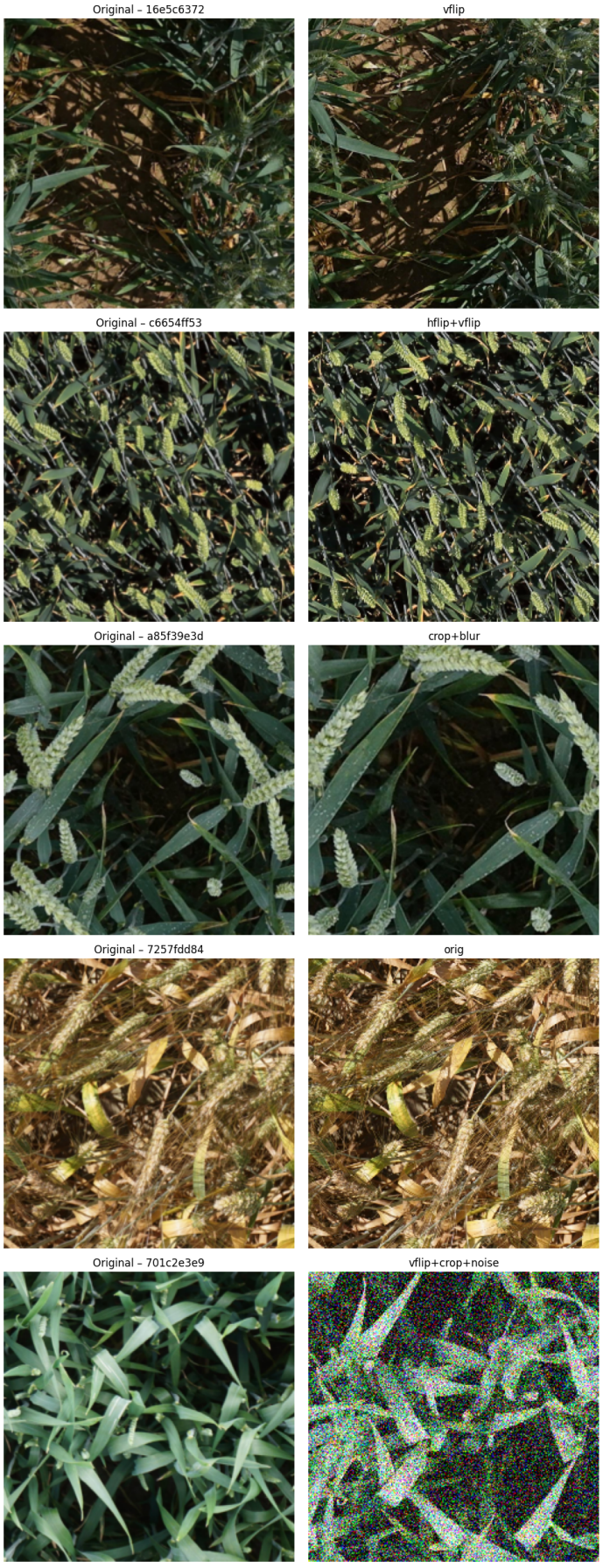


Figure 7: Examples of the nine augmentations applied during training.

Batching. A custom `collate_fn` stacks the image tensors and leaves the target dicts as a list, exactly as required by the DETR set-loss.

3.3 Hyperparameters

The DETR model is also implemented in `PyTorch Lightning`, ensuring structured, fully-reproducible experiments and seamless logging. Optimisation is performed with **AdamW**, using a learning rate of $1e-4$ and a weight decay of $1e-4$. A linear warm-up schedule is applied during the first five epochs to stabilise training. We train with a batch size of 32 and 256 and track performance via Weights & Biases, recording training loss as well as mean Average Precision (mAP) on both train and validation sets.

Key architectural hyper-parameters are kept at the DETR defaults: 100 learned object queries, hidden dimension 256, eight attention heads, and a 6-layer encoder–decoder Transformer. During validation, the model logs side-by-side composites of the original image, ground-truth boxes (blue) and predicted boxes (red and filtered by a confidence threshold of 0.5), providing an intuitive qualitative check. We run **500 epochs** (and stopped mid-run, because of lack in time and resources).

3.4 Results

This section reports the behaviour of the DETR model during *training*.

Table 1: Best *validation* mAP and lowest *validation* loss for each run (values eyeballed from the curves — replace with exact logs).

Run	**Best mAP**		**Lowest Loss**	
	Value	Epoch	Value	Epoch
Aug. + no-resize, BS = 32	22.42%	97	37.81	97
Aug., BS = 256	**39.60%**	155	252.11	150
Aug., BS = 32	28.92%	148	35.67	66
No-aug., BS = 32	8.64%	253	48.88	253

Key Takeaways.

- **Aug. + BS 256 wins:** fastest loss drop and highest mAP ($\approx 40\%$).
- **Aug. + no-resize (1024) shows promise:** mAP climbs sharply, but training was cut short; worth a longer run.
- **Aug. + BS 32 is solid:** smooth convergence, mAP stabilizes around 0.30.
- **No-aug baseline lags:** lowest mAP, highlighting the importance of augmentation.

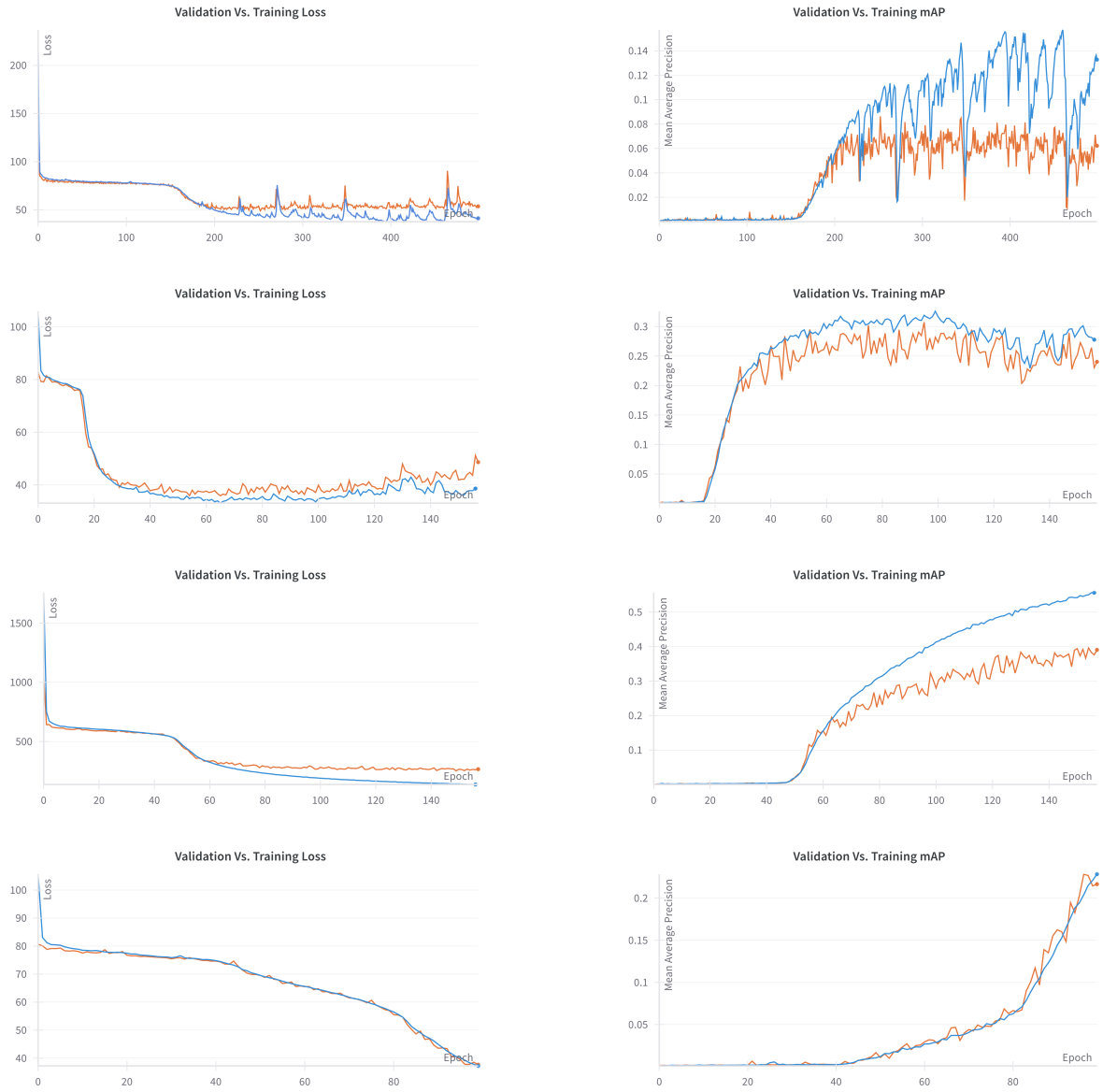
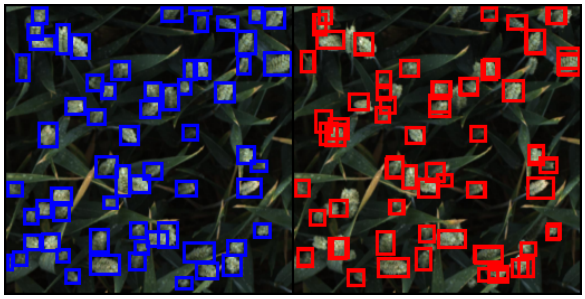
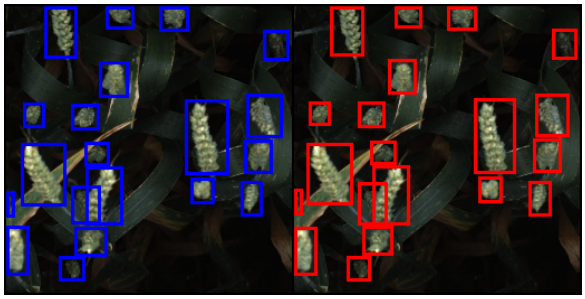


Figure 8: Loss (left) and mAP (right) curves for four training configurations: (1) no augmentations, BS = 32; (2) augmentations, BS = 32; (3) augmentations, BS = 256; (4) augmentations without resizing (native 1024×1024), BS = 32.

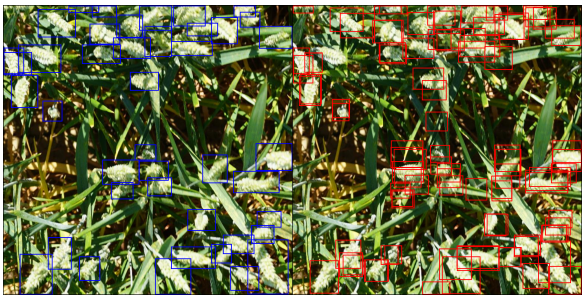


No augmentations, BS = 32

Augmentations, BS = 32



Augmentations, BS = 256

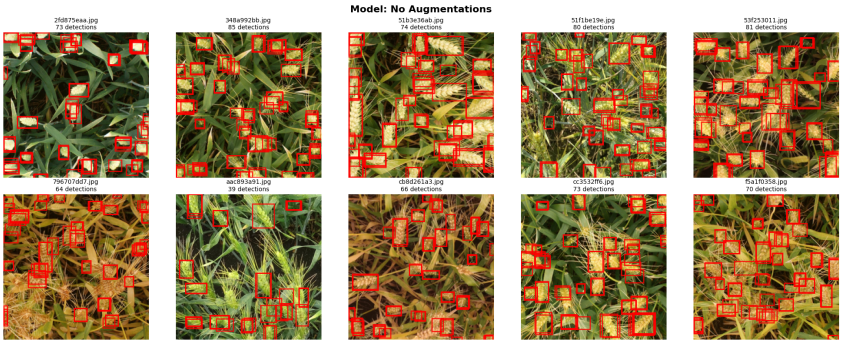


Augmentations + no resize (1024×1024), BS = 32

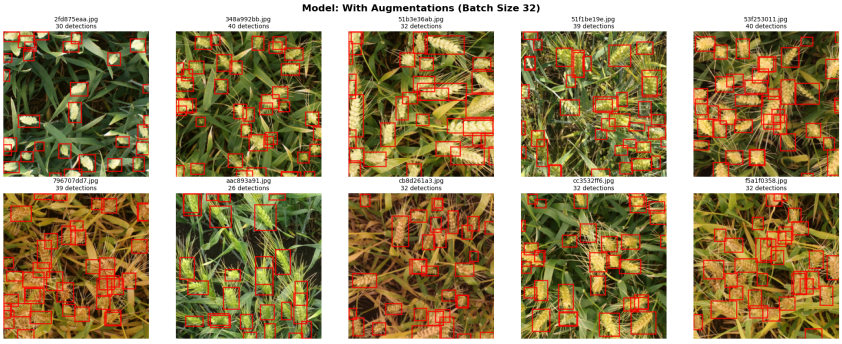
Figure 9: Representative validation detections for the four runs in Fig. 8.
Blue - GT, and Red - Predictions

Test Evaluation

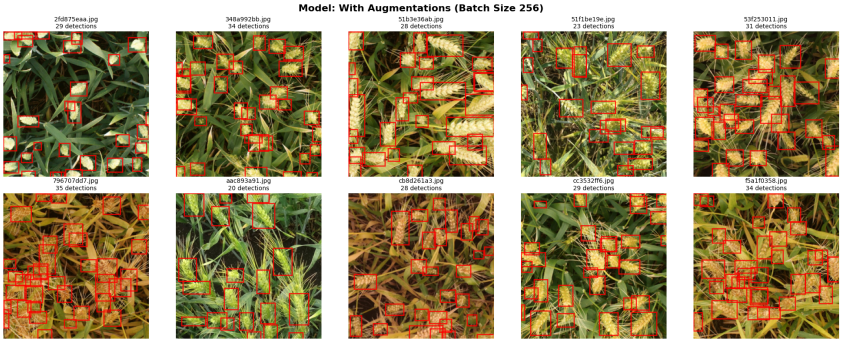
1. **Dataset.** Ten unlabelled wheat-field images held back for blind inference.
2. **Protocol.** Run the best checkpoint on the images and visualise the predicted boxes (no quantitative score available).
3. **Deliverables.** Prediction(bbox) on test images



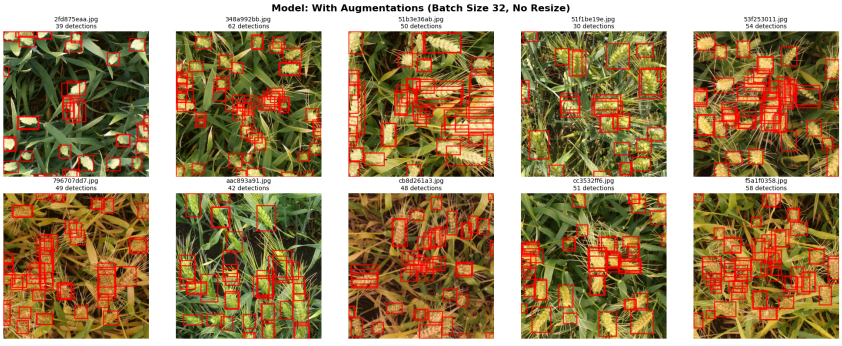
No augmentations, BS = 32



Augmentations, BS = 32



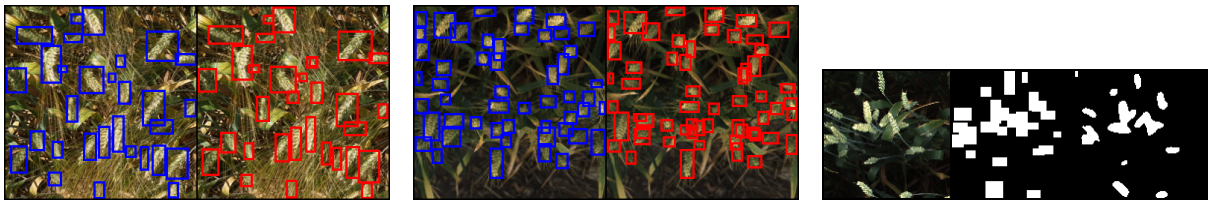
Augmentations, BS = 256



Augmentations + no resize (1024×1024), BS = 32

Figure 10: Representative test-set inference results for each training configuration.

4 Results



(a) Successful result by DETR (b) Poor Result by DETR (c) Poor Result by UNet

Figure 11: Qualitative comparison: DETR succeeds in localizing distinct wheat heads (a), but may miss or misplace boxes in some cases (b). U-Net often merges close instances and lacks instance separation (c).

4.1 Qualitative Analysis

We present four distinct qualitative scenarios to evaluate the relative performances of the Vanilla UNet (Model 1) and Detection Transformer (DETR, Model 2):

Scenario 1: Both Models Performed Well In our evaluation, this scenario was not encountered, as the Vanilla UNet consistently struggled with providing precise bounding-box predictions due to its inherent design as a segmentation model rather than an object detector.

Scenario 2: Both Models Performed Poorly Figure 11 illustrates two instances where both models demonstrated significant shortcomings in accurately detecting wheat heads. The errors primarily arose due to challenging lighting conditions, occlusions, and dense wheat head distributions, highlighting the inherent difficulties in the dataset.

Scenario 3: Model 1 Performed Well and Model 2 Did Not This scenario did not occur in our experiments. Model 2 (DETR) consistently outperformed Model 1 (UNet).

Scenario 4: Model 2 Performed Well and Model 1 Did Not Figure 11 demonstrating DETR successfully detecting wheat heads with accurate bounding boxes while Vanilla UNet failed to produce meaningful segmentation masks.

4.2 Quantitative Comparison

Quantitatively, the DETR model notably outperformed the Vanilla UNet in terms of Mean Average Precision (mAP) metrics, achieving a top mAP of approximately 40%. In contrast, the UNet achieved a pixel-wise precision of only 78%, indicating good segmentation performance but inadequate for bounding box detection evaluation.

4.3 Discussion

The Detection Transformer (DETR) significantly outperformed the Vanilla UNet due to its intrinsic design tailored for precise object detection tasks with bounding boxes. DETR's Transformer-based architecture, combined with the Hungarian assignment algorithm, allowed for effective handling of overlapping and densely populated wheat head scenarios. Conversely, the Vanilla UNet, designed primarily for semantic segmentation, inherently lacks the ability to distinguish between individual object instances, severely limiting its effectiveness in bounding-box-based object detection tasks. This difference clearly demonstrates that DETR's capability aligns more appropriately with the objectives of the Global Wheat Detection challenge, thereby validating our choice to utilize Transformer-based models for this application.

5 Ablation Study

Motivation. Early experiments without data augmentation reached only $\sim 8\%$ mAP after **500** epochs, and the loss curve showed strong oscillations, suggesting over-fitting to the limited training set. We therefore introduced a lightweight augmentation suite (*HFlip, VFlip, Crop, Blur, Gauss Noise* and their composites; see Figure 7) to enlarge data diversity without altering the wheat-head semantics.

Experimental setup. Two DETR variants were trained under identical settings:

- **Baseline** — only-resized images, no augmentation.
- **Augmented** — nine-way augmentation as described above.

All other hyper-parameters (optimizer, learning rate, batch size, etc.) were kept fixed to isolate the effect of augmentation.

Table 2: Validation metrics (best checkpoint).

Model	mAP ↑	Val. Loss ↓
No Augmentations	8.64%	48.88
Augmented Best (BS=256)	39.60%	252.11

Quantitative results. Table 2 confirms the large gap in detection quality. As the no-augmentations model oscillated throughout its 500 epochs, and finally achieved only 8.6% Mean Average Precision, the augmented model achieved $\approx 40\%$ in the same metric, and produced much better detections.

Qualitative comparison. The difference in preformance is well demonstrated in Fig.10, the augmented model produces tighter and more numerous bounding boxes at the correct locations, whereas the baseline often misses small heads or predicts spurious boxes.

Summary of insights. Data augmentation more than doubled the achievable mAP and reduced training time by a factor of six. The experiment demonstrates that poor initial performance was due mainly to limited data variability rather than model capacity, and highlights the crucial role of simple, label-preserving augmentations in driving detection accuracy.

6 Conclusions & Summary

In this report, we explored the Global Wheat Detection challenge by employing two distinct deep learning models: a Vanilla UNet tailored for semantic segmentation and a custom Detection Transformer (DETR) optimized for precise bounding box detection.

The Vanilla UNet demonstrated solid convergence and robust segmentation accuracy, achieving a training loss of 0.36 and a validation loss of 0.34 after 20 epochs. The pixel-wise precision of 78% confirmed its capability for semantic segmentation tasks; however,

the model output (binary masks) did not directly align with the challenge's requirement for bounding box predictions. This limitation emphasizes that UNet, despite its strengths in pixel-level segmentation, is not suitable as a standalone solution for object detection tasks evaluated via bounding box metrics.

Conversely, our custom DETR model leveraged a ResNet-50 backbone combined with Transformer encoder-decoder architecture, employing Hungarian loss and mAP for evaluation. Extensive experimentation with hyperparameters and augmentations revealed critical insights: augmentations drastically improved model performance, doubling mean Average Precision (mAP) and ensuring smoother convergence. Specifically, the DETR model trained with augmentations and a batch size of 256 achieved the highest mAP of approximately 0.39. Additionally, augmentations accelerated training convergence and significantly stabilized the training dynamics, underlining their necessity in object detection tasks.

The ablation study further solidified these findings, clearly demonstrating the transformative effect of data augmentation on detection performance. Models trained without augmentations severely underperformed, highlighting the vital importance of strategic data preprocessing and augmentation in overcoming challenges related to dataset complexity, variability, and limited computational resources.

In summary, our comparative analysis underscores the superiority of DETR-based architectures in handling object detection tasks requiring bounding boxes, especially in complex agricultural scenarios such as global wheat head detection. The DETR approach provides a more accurate, robust, and efficient solution compared to purely segmentation-oriented models like Vanilla UNet, particularly when coupled with thoughtfully designed augmentations.

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