Wheat Head Detection from Close-range Digital Imagery using Deep Learning

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INTRODUCTION

- Wheat is one of the most crucial cereal crops for global food security, serving as a staple for billions. As the world population increases, the demand for wheat production continues to rise.
- Wheat production faces threats from climate change and population growth, necessitating efficient crop management practices.
- The wheat spike (head) count per unit ground area is a key factor in estimating grain yield. Manual counting methods are time-consuming, labor-intensive, and error-prone.
- Deep learning-based object detection algorithms using high-resolution imagery, offer a promising solution to automate head detection and counting, with high accuracy and scalability.

OBJECTIVES

- To evaluate deep learning-based object detection methods to accurately detect and count wheat spikes from high-resolution digital imagery.
- To investigate the YOLOv8 (You Only Look Once) algorithm performance to detect and count wheat spikes from close-range digital imagery at different orientations for enhanced grain yield estimation and agriculture management.

RESULTS AND ANALYSIS

Table 1: Evaluation Metrics for the test sample

METRIC	VALUE
Epoch	36
Precision (B)	0.92
Recall (B)	0.86
mAP@50 (B)	0.92
mAP@50-95 (B)	0.51
Validation Box Loss	1.56
Validation Classification Loss	0.63

* B refers to metrics specific to the bounding box performance

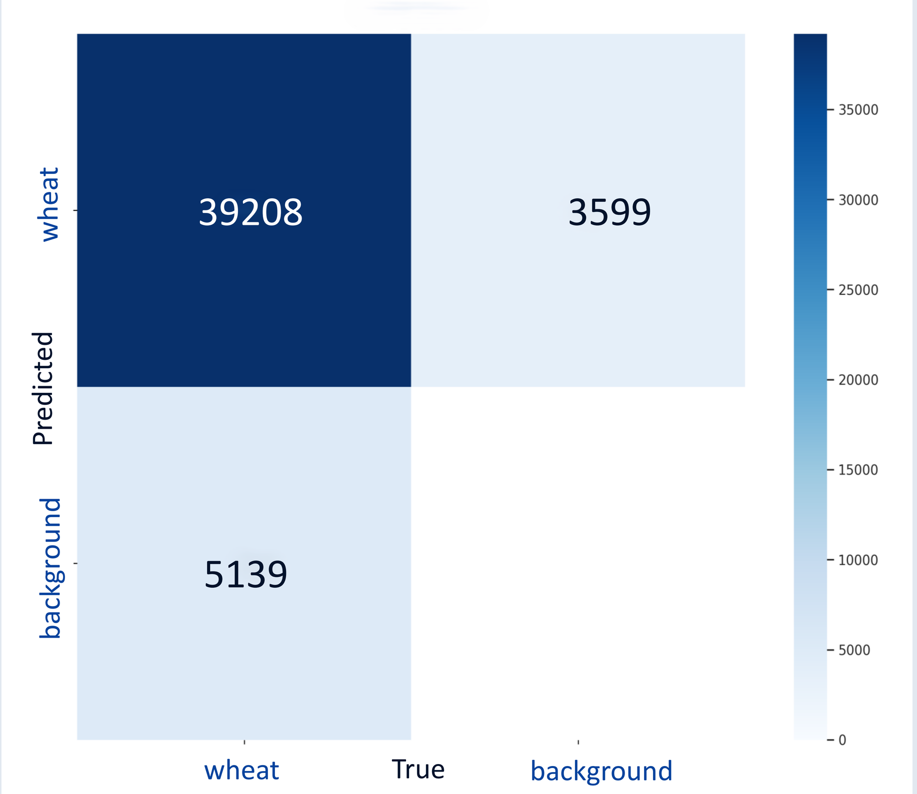

Figure 3: Confusion matrix for the test sample

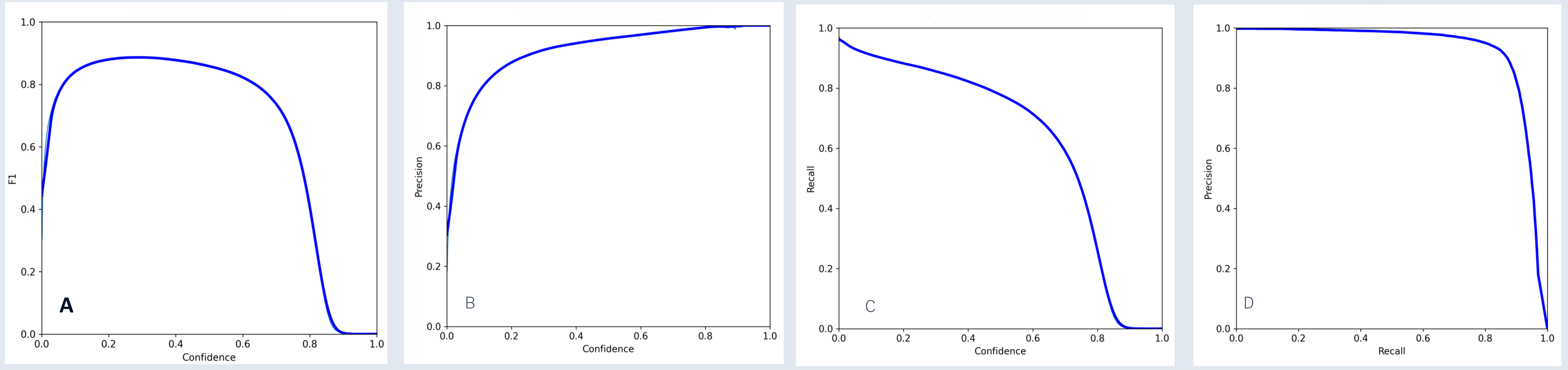

Figure 4: (a) F1 Score vs. Confidence, (b) Precision vs. Confidence, (c) Recall vs. Confidence, (d) Precision-Recall Curves

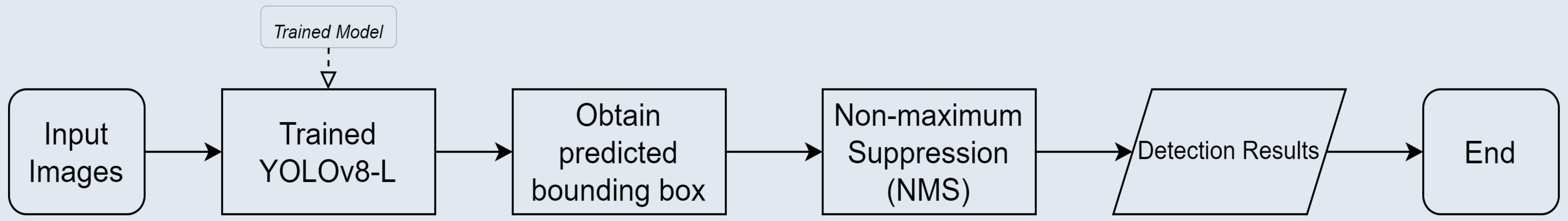

Figure 5: Inferencing process of the YOLOv8 model

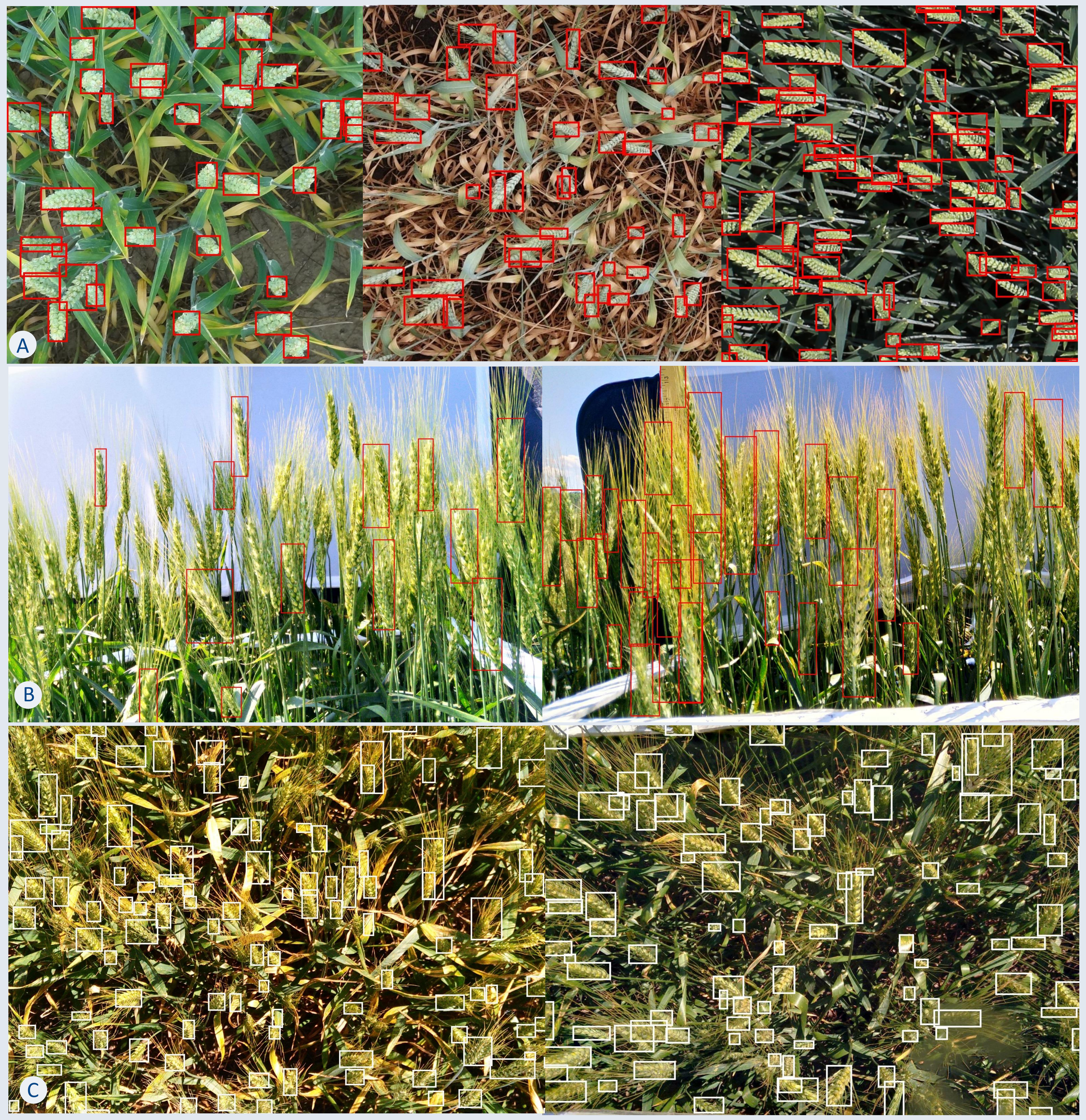

Figure 6: Predicted bounding box on (a) GWHD 2021 data, (b) SDSU smartphone images taken from side view, (c) SDSU smartphone images taken from top view

MATERIALS AND METHODS

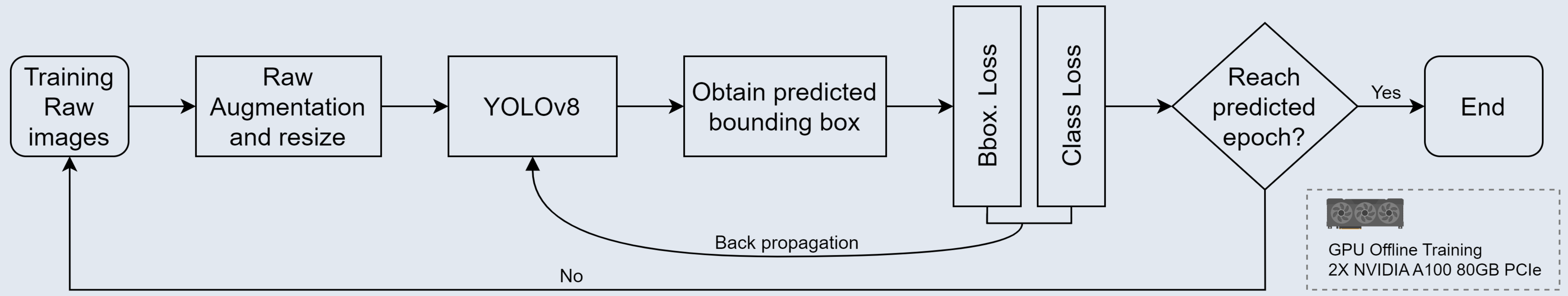

Figure 1: Schematic workflow of the YOLOv8 model training process

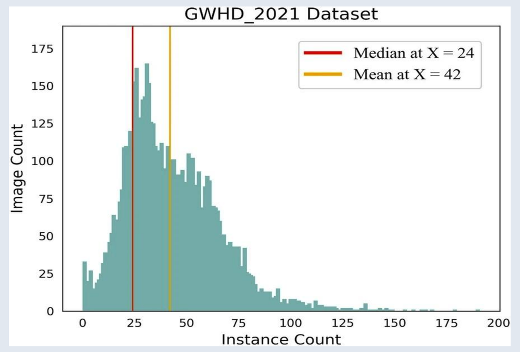

Figure 2: Bounding box distribution in GWHD 2021 dataset

Dataset used

- Global Wheat Head Data (GWHD) - 2021
- SDSU Smartphone Images

Object detection approach

- You Only Look Once (YOLOv8L)

CONCLUSION

- YOLOv8 offers an effective, scalable solution for wheat head detection, reducing labor and improving accuracy in grain yield estimation.

Future works

- Model Generalization: Improve model generalizability across images obtained at diverse orientations by integrating multi-modal imagery.
- Improve detection in noisier, lower-resolution imagery captured by unmanned aerial systems (UAS), enabling more scalable and efficient solutions for large-scale applications.

REFERENCES

- Ye, J., Yu, Z., Wang, Y. et al. WheatLFANet: in-field detection and counting of wheat heads with high-real-time global regression network. Plant Methods 19, 103 (2023). https://doi.org/10.1186/s13007-023-01079-x
- David, E., et al. (2021). "Global Wheat Head Detection 2021: An Improved Dataset for Benchmarking Wheat Head Detection Methods." Plant Phenomics 2021: 9846158.

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