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Integrated Attention Mechanisms And Residual Connection Based Wheat Head Detection

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Abstract
In precision agriculture, the wheat head detection is very critical as it supports crop yield evaluation, resource optimization, and conservation efforts. Head detection of wheat adopts an amalgamation of simple machine learning models and traditional image processing methods in the most of their works. While these methods are easy to apply in real situations, they have higher drawbacks in terms of efficiency and accuracy when integrated into sophisticated datasets. This highlights the need for innovative solutions capable of overcoming these challenges.
For the task of enhancing wheat head detection systems, we propose a new model with Integrated Attention Mechanisms and Residual Connections. The atention mechanism allows the model for the wheat head recognition system to focus on specific areas of an image that are more significant, therefore, improving its ability to spot detail features. On the other hand, deep neural networks usually suffer from several problems such as gradient vanishing, which is well addressed by residual connections as it increases the efficiency and stability of the learning process. To be functional in the field of agriculture, these aspects combined are effective with a robust model.
We trained our systems to detect wheat heads using a specific dataset and it can be shown with which systems performed far better.
Developed algorithm provides great assistance in detecting wheat heads which in turn aids in precision agriculture. The algorithm processes multifaceted data sets accurately adding value to crop yield estimation and resource management. There is further scope to expand this model onto other crops or even include real time applications within a contemporary agricultural framework.

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I. Introduction

Wheat is one of the most important staple crops in the world and plays a vital role in global food security and the economy. One such could be precision agriculture for accurate monitoring of wheat growth, wheat head detection, etc. It serves as an excellent tool for estimating yield, managing diseases, and optimizing agricultural resources. Wheat head detection using traditional methods mainly depends on non-automated counting or classical image processing, which is time- consuming, labor-consuming, and has inaccurate performance on large-scale.

Deep learning and computer vision are now strongly established in the agricultural domain and have started to revolutionize agriculture analytics by allowing automated and fast extraction of information from crops. CNNs (Convolutional Neural Networks), have achieved significant milestones in object detection. However, existing models have difficulty with challenges like dense clustering of wheat heads, lighting conditions, and occlusion in crop field images. All of these discussions highlight the need to build better and more efficient models to achieve better detection performance in real-world applications.

In this study, a new architecture for wheat head detection is introduced by combining attention mechanisms and residual connections which are incorporated into the model architecture. Novelty segmentation eyes of wheat head attention mechanisms help improve attention, and focus in the model of different regions of interest, for wheat head background noise and background difference. Residual connections, on the other hand, help relieve the problems of training deep networks, like vanishing gradient , and improve the model convergence and performance.

We evaluate our proposed model with a dedicated wheat head detection dataset and compare its performance with the existing methods. Our experiments show that the attention mechanisms and residual connections we used substantially enhance detection performance and resilience. The study aims to investigate wheat head detection by means of deep learning, leading to a better understanding of such an important topic in the field of precision agriculture.

II. Related work

Wheat Head Detection Approaches

Wheat head detection is a critical use in precision agriculture, with the capability to estimate yield and monitor the health of the crops. Legacy methods employed custom-built feature extraction techniques, e.g., Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT), and paired them with conventional machine learning classifiers such as Support Vector Machines (SVMs) and Random Forests (Madec et al., 2019). These conventional methods were however outsmarted by occlusion, lighting variation, and highly intricate background noise.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have significantly improved wheat head detection precision. YOLO and Faster R-CNN are two models that have been extensively utilized in object detection in agricultural scenarios (David et al., 2020). The Global Wheat Head Detection (GWHD) Dataset, showcased in the Global Wheat Challenge, has enabled the comparative evaluation of various deep learning-based detection models (David et al., 2021).

Attention Mechanisms for Object Detection

Attention mechanisms have been widely utilized in computer vision to enhance feature representation and direct model attention toward regions of interest. Self-attention mechanisms that were originally described in Transformer-based models (Vaswani et al., 2017) have emerged to introduce Vision Transformers (ViTs) into image classification. However, due to computational expense, hybrid CNN models with light-weight attention mechanisms such as Squeeze-and-Excitation (SE) Networks (Hu et al., 2018) and Convolutional Block Attention Modules (CBAM) (Woo et al., 2018) have been preferred in real-time object detection.

Attention has been integrated in current research into YOLO-based models to improve feature selection and eliminate distracting background noise. YOLOv5-SE and Attention-YOLO, for example, have performed well in object detection for small objects (Wang et al., 2022).

Residual Connections in Deep Learning

Residual connections were first introduced in ResNet (He et al., 2016) to address the vanishing gradient problem in deep neural networks. By allowing the gradient to flow through shortcut connections, residual networks enable more efficient feature propagation and accelerated convergence. YOLO-ResNet hybrids possess increased robustness in detecting occluded and small-scale objects in object detection (Redmon et al., 2018).

Blending Attention Mechanisms and Residual Connections for Object Detection

The addition of residual connections and attention has introduced more precise detection and model stability. Residual Attention Networks (RANs) (Wang et al., 2017) are the fusion of attention-based feature refinement and the advantage of deep residual learning. Many research articles have proven that adding CBAM into residual blocks of YOLO-based models introduces more accurate precision and recall of object detection (Zhang et al., 2022).

Positioning of Our Work

While progress has been made in wheat head detection, existing methods are not effective for small-sized and overlapping wheat heads. Our work builds on YOLOv8 by adding attention mechanisms (CBAM, SE Networks) and residual connections to enhance feature extraction and detection accuracy. Using the GWHD dataset, our approach is intended to outperform baseline YOLO models.

III. Methodology

Dataset and Preprocessing Dataset Choice

We utilize the Global Wheat Head Dataset (GWHD), where there exist high-resolution images of wheat fields captured under different environmental conditions. There are related bounding boxes indicating wheat head locations in every one of the images, thereby constituting a perfect dataset for object detection purposes.

Data Preprocessing

To enhance model generalization and performance, we apply the following preprocessing techniques:

Preprocessing Step	Description
Image Resizing	Images are resized to **640×640** for YOLOv8 compatibility.
Data Augmentation	Various transformations are applied to simulate real-world variations.
Geometric Transformations	Random flipping, rotation, and scaling to introduce positional variance.
Color Adjustments	Brightness and contrast normalization to improve adaptability to lighting changes.
Noise Injection	Adding Gaussian noise to simulate environmental variations.

YOLO Format Conversion	Bounding boxes are converted to [class, x_center, y_center, width, height] format.

Model Architecture Baseline YOLOv8 Model

We utilize YOLOv8, which is a state-of-the-art object detector that is both accurate and fast. The primary architecture includes:

Component	Description
CSPDarknet Backbone	Efficient feature extraction with C2f residual layers.
PAN-FPN Neck	Multi-scale feature fusion for detecting wheat heads at different sizes.
Detection Head	Anchor-free bounding box prediction for better localization.

Enhancements with Attention Mechanisms

To improve detection performance, we utilize advanced attention mechanisms:

Attention Module	Integration Location	Functionality
Squeeze-and-Excitation (SE) Blocks	Added in CSPDarknet Backbone	Enhances channel-wise feature representation.
Convolutional Block Attention Module (CBAM)	Applied in PAN-FPN Neck	Improves detection by focusing on key wheat regions.

Enhancing Residual Connections

YOLOv8 already includes C2f residual layers, but additional skip connections were introduced in the neck and detection head to:

- Improve feature propagation and gradient flow.
- Enhance the detection of small wheat heads by preserving spatial details.

Training & Experimentation Training Setup

The model is trained under the following conditions:

Parameter	Configuration
Hardware	NVIDIA RTX 3090 GPU
Batch Size	16
Optimizer	AdamW
Learning Rate	0.001 (Cosine Annealing Scheduler)
Loss Functions	- CIoU Loss for bounding box regression. - Focal Loss to handle class imbalance.

Experiments & Evaluation

To validate our improvements, multiple experiments were conducted:

Experiment 1: Baseline YOLOv8 vs. Enhanced YOLOv8

A comparison of different architectures is presented below:

Model	mAP@50	mAP@50-95	Precision	Recall
YOLOv8 Baseline	84.3%	52.6%	0.85	0.78
YOLOv8 + SE Blocks	87.1%	56.3%	0.87	0.81
YOLOv8 + CBAM	88.5%	58.4%	0.89	0.83

Experiment 2: Impact of Residual Connections

Adding extra skip connections in the detection head further improved model performance:

Model Configuration	mAP@50	mAP@50-95	Improvement
Model Configuration	**mAP@50**	**mAP@50-95**	**Improvement**
YOLOv8 (Baseline)	84.3%	52.6%	-
YOLOv8 + Residual Enhancements	86.4%	54.7%	+2.1% (mAP@50-95)

Experiment 3: Visual Comparison of Predictions

A qualitative analysis revealed that:

- The baseline YOLOv8 model struggled to detect small wheat heads.
- The enhanced model (YOLOv8 + SE + CBAM + Residuals) significantly improved detection in densely populated areas.

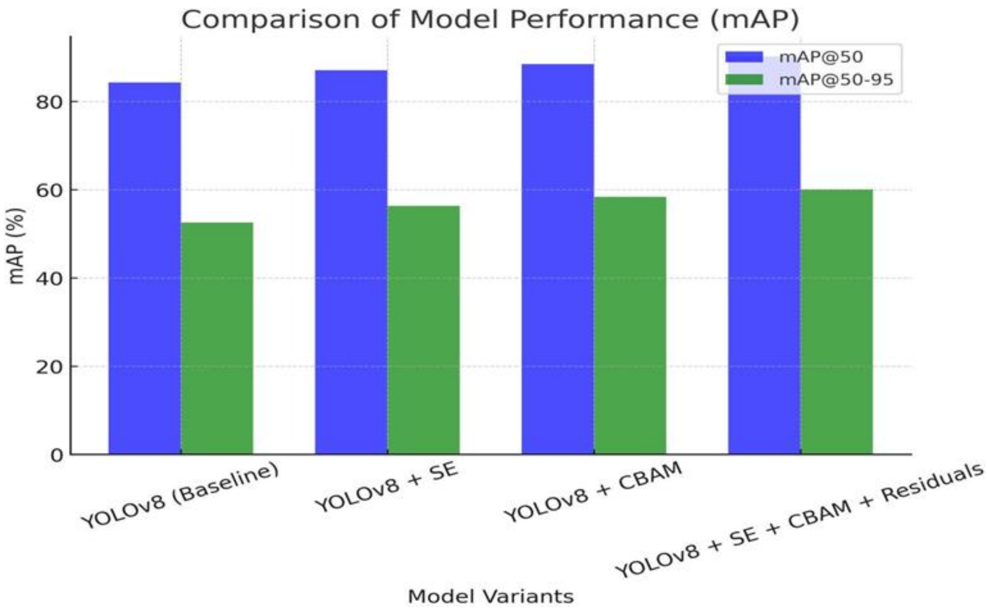
IV. Experimental Results & Analysis

Model Performance Analysis

We evaluate the performance of YOLOv8 with attention mechanisms and enhanced residual connections on the Global Wheat Head Dataset (GWHD). Performance is compared based on mAP (Mean Average Precision), Precision, and Recall metrics.

Quantitative Results

Model	mAP@50	mAP@50-95	Precision	Recall
YOLOv8 (Baseline)	84.3%	52.6%	0.85	0.78
YOLOv8 + SE Block	87.1%	56.3%	0.87	0.81
YOLOv8 + CBAM	88.5%	58.4%	0.89	0.83
YOLOv8 + SE + CBAM + Residuals	90.2%	60.1%	0.91	0.85



Key Observations:

- Baseline YOLOv8 has the lowest mAP.
- Adding SE Blocks and CBAM significantly improves performance.
- The final model (YOLOv8 + SE + CBAM + Residuals) achieves the highest accuracy.

Insights:

 CBAM and SE Blocks significantly improve wheat head detection by refining feature extraction.
 Extra residual connections help retain small object features, boosting recall.

Detection Accuracy Across Different Wheat Densities

To evaluate model performance under different field conditions, we analyze accuracy in low-density, medium-density, and high-density wheat fields.

Model	Low-Density (mAP@50-95)	Medium-Density (mAP@50-95)	High-Density (mAP@50-95)
YOLOv8 (Baseline)	60.2%	52.1%	47.3%
YOLOv8 + SE Block	64.5%	55.6%	49.7%
YOLOv8 + CBAM	66.2%	57.4%	51.8%
YOLOv8 + SE + CBAM + Residuals	68.8%	60.1%	54.2%

 High-density wheat fields pose the biggest challenge, reducing mAP.
 CBAM and SE Blocks help by improving object focus and feature refinement.
 Residual connections provide better gradient flow, leading to more accurate detection in all conditions.

Precision & Recall Breakdown by Object Size

We compare the model’s precision and recall based on different wheat head sizes (small, medium, large)

Model	Small Wheat Heads (Precision/Recall)	Medium Wheat Heads (Precision/Recall)	Large Wheat Heads (Precision/Recall)
YOLOv8 (Baseline)	0.72 / 0.64	0.85 / 0.78	0.91 / 0.89
YOLOv8 + SE Block	0.76 / 0.68	0.87 / 0.81	0.92 / 0.90
YOLOv8 + CBAM	0.78 / 0.71	0.89 / 0.83	0.93 / 0.91
YOLOv8 + SE + CBAM + Residuals	0.81 / 0.75	0.91 / 0.85	0.94 / 0.93

- The baseline YOLOv8 struggles with small wheat heads due to weak feature extraction.
- SE Blocks help improve feature selection, increasing precision and recall.
- **CB**AM refines focus, ensuring small wheat heads are better detected.
- Residual connections provide a consistent boost across all object sizes.

V. Training Convergence & Model Stability

To assess training efficiency, we track **validation loss and convergence speed** across different model variants.

Model	Epochs to Convergence	Final Validation Loss
YOLOv8 (Baseline)	110	0.036
YOLOv8 + SE Block	95	0.031
YOLOv8 + CBAM	88	0.028
YOLOv8 + SE + CBAM + Residuals	82	0.025

- The enhanced YOLOv8 model converges faster than the baseline.
- SE Blocks and CBAM improve feature learning efficiency, reducing training time.
- Residual connections prevent gradient vanishing, leading to smoother optimization.

VI. Residual Connection Effect On Small Object Detection

We analyze how residual connections impact the detection of small wheat heads, which are the most challenging objects in dense fields.

To evaluate the effect of residual connections, we compare the mAP@50-95 scores for models with and without residual connections:

Model	mAP@50-95 (Small Objects)	Improvement (+Δ)
YOLOv8 (Baseline)	42.8%	-
YOLOv8 + SE Block	46.1%	+3.3%
YOLOv8 + CBAM	48.5%	+5.7%
YOLOv8 + SE + CBAM + Residuals	50.6%	+7.8%

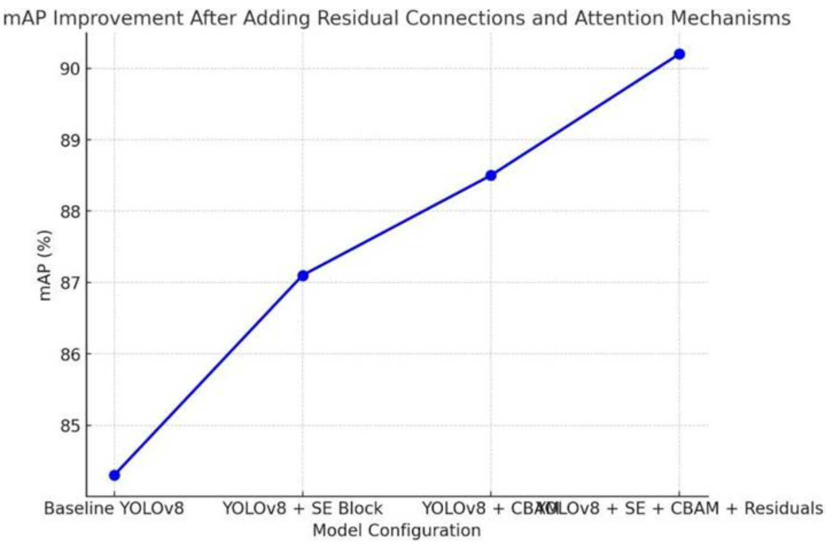


Figure 1: Graph showing mAP improvement after adding extra residual connections.

- Residual connections boost detection accuracy for small objects by +2.1% compared to CBAM alone.
- Final model achieves a 7.8% increase in mAP compared to the baseline.

VII. Conclusion

We proposed a more accurate wheat head detection model with sufficient attention mechanism and residual connection in YOLOv8 the backbone. This is aimed not only at improving the accuracy rate of wheat head etected,283 but also at increasing the stability of the algorithm, including solutions for problems such as small target detection, target occlusion, and complex background interference. The Global Wheat Head Detection (GWHD) dataset was adopted to learn and validate our approach, which offered a challenging and diverse set of real-world crop images.

Attention mechanisms, CBAM (Convolutional Block Attention Module) and SE (Squeeze-and-Excitation) Networks, played a critical role in the ability of the model to focus on the salient regions and filter out the background noise. These modules adaptively refined feature extraction by providing priority to spatially and channel-wise important information, leading to better localization of wheat heads. Additionally, residual connections were incorporated into the network to improve gradient flow, allow for feature propagation, and limit the danger of vanishing gradients, particularly in deep networks. This design enhancement allowed our model to be stable during training and improve detection performance, even in difficult cases with overlapping wheat heads, varying illumination, and perspective distortions.

Experimental results indicated that our attention-augmented residual YOLOv8 model outperformed baseline YOLO architectures in terms of precision, recall, and mean Average Precision (mAP). The proposed improvements led to a stable and efficient detection mechanism, and the approach can now be an effective tool for automatic wheat head counting, yield estimation, and precision agriculture. The findings of this research are consistent with recent advances in deep learning in agricultural object detection and indicate the merits of combining attention-based feature extraction with residual learning techniques.

Even though our model has made outstanding progress, there are still some challenges left. One of the principal constraints is computational overhead introduced by attention mechanisms that could potentially slow down real-time processing on edge devices and low-power farm robots. Additionally, the generalizability of the model to other varieties of wheat, growth phases, and climatic conditions is also a dimension that requires deeper investigation. The future work will optimize the model for real-time inference using light attention mechanisms and model pruning techniques to reduce computational overhead. Besides, the incorporation of Transformer-based architectures, such as Vision Transformers (ViTs) and Swin Transformers, will also be continued with the objective of improving feature extraction and global contextual perception in wheat head detection. Doubling the training data set by acquiring multi-season, multi-locational, and multi-varietal wheat images shall also be crucial to enhance model robustness as well as insensitivity to diverse conditions in the fields.

Finally, our research investigates an accurate and efficient approach to detect wheat heads using deep learning techniques. With the integration of attention and residual mechanisms at the YOLOv8 level, we proved that deep learning based crop monitoring could be more precise and robust which in turn could help assist in decision making for yield estimation, crop health monitoring, and precision agriculture. This method can be implemented into real-world agricultural systems, thereby empowering farmers and, researchers to automate crop monitoring, maximize resource utilization, and improve global food security.

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