Automated Wheat Disease Detection Using Deep Learning: An Object Detection and Classification Approach

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Abstract— **Wheat is among the key staple crops in the world, greatly influenced by plant diseases. As global population grows, there is urgency to establish sustainable agricultural methods requiring early and accurate diagnosis of wheat diseases. This paper examines deep learning solutions for automated wheat head disease detection using two benchmark datasets: the Global Wheat Head Detection (GWHD) dataset for object detection, and the Large Wheat Disease Classification Dataset (LWDC) for disease classification. YOLOv4 trained on GWHD achieves a mean Average Precision (mAP) of 91%. Transfer learning with COCO pre-trained weights improves multi-class detection on LWDC. Among five CNN models evaluated — VGG19, ResNet50, EfficientNet-B0, NASNetMobile, and NASNetLarge — VGG19 achieves the best F1 score of 95%. The combined YOLOv4 + VGG19 pipeline demonstrates strong potential for real-time wheat disease monitoring in precision agriculture.**

Keywords*— *Agricultural artificial intelligence, wheat disease detection, deep learning, convolutional neural networks, YOLO object detection, transfer learning, image classification, precision farming.

I. Introduction

The gradual increase in global population has placed high demand on agricultural production. Wheat, one of the most significant cereal crops worldwide, constitutes a critical part of everyday nutrition for a large portion of the global population. However, wheat production is highly susceptible to diseases and pest attacks, resulting in an estimated 20% annual yield loss, severely impacting food security and farmer livelihoods [1].

Timely and accurate disease identification is essential to minimize crop losses. In real field conditions, diagnosis is difficult due to visual symptom similarity, environmental variability, and limited expert access. Traditional manual inspection is time-consuming, labor-intensive, and prone to human error. Laboratory-based techniques such as PCR and ELISA are accurate but require specialized equipment and are too slow for timely intervention.

Deep learning — particularly convolutional neural networks (CNNs) — offers automated, scalable, and highly accurate alternatives. CNNs identify subtle visual features in plant images, while object detection models localize affected regions. This study proposes a hierarchical pipeline that first detects wheat head regions via object detection, then classifies the disease type, improving both accuracy and interpretability for precision farming applications.

II. Literature Survey

Research in plant disease detection has progressed from classical machine learning to advanced deep learning. Pre-trained architectures — VGG, ResNet, DenseNet, Inception, and EfficientNet — show high classification performance via transfer learning, especially in data-scarce agricultural settings [2]. Recent Vision Transformer (ViT) models further enhance contextual recognition [3].

Object detection approaches range from two-stage detectors (Faster R-CNN for precise localization) to single-stage detectors (YOLO, SSD for real-time inference) [4], [7]. The GWHD dataset has been pivotal for field-condition wheat localization research [2]. Data augmentation strategies — rotation, flipping, MixUp, CutMix — and class imbalance solutions such as focal loss and re-sampling have strengthened model robustness [8], [9].

Semi-supervised and self-supervised learning exploit unlabeled field images, while GANs generate synthetic lesion data. Domain adaptation techniques bridge the gap between laboratory and field imaging conditions [10]. UAV-based imaging enables large-scale disease mapping, while model pruning and quantization enable edge deployment on smartphones and drones. Explainability tools such as Grad-CAM improve farmer trust by highlighting prediction-relevant regions.

III. Existing System

Current wheat disease detection methods rely mainly on manual visual inspection, laboratory diagnostics, or conventional machine learning with handcrafted features. Visual inspection is subjective and inconsistent, depending on expert availability. Laboratory-based tests (PCR, ELISA) require specialized apparatus and cause delays in diagnosis and treatment decisions.

Feature-based machine learning systems degrade significantly under real-field variability — lighting changes, background clutter, partial occlusion, and varying symptom presentation. Most automated solutions merely detect disease presence without localizing the infected region or assessing severity. They also fail to scale to large agricultural areas and struggle with multi-disease co-occurrence on a single crop. These limitations underscore the urgent need for smarter, scalable, and real-time detection systems.

IV. Problem Statement

Although timely wheat disease detection is critical, current systems depend on field surveys, laboratory analysis, or traditional machine learning — all slow, labor-intensive, and expensive. Existing automated approaches rely on handcrafted features and are vulnerable to natural variability in lighting, backgrounds, and symptom presentation, resulting in poor real-world performance.

Most solutions cannot localize infected areas, assess severity, or operate on precision agriculture platforms such as drones and mobile devices. There is therefore an urgent need for a smart, scalable system capable of accurately detecting disease locations, differentiating between multiple disease types, and supporting real-time monitoring across diverse field conditions to enable timely disease management.

V. Proposed Method

The proposed framework integrates CNN-based classification with advanced object detection (YOLOv4, Faster R-CNN) in a unified pipeline. Unlike whole-image approaches, this system first detects and localizes disease-affected wheat head regions via bounding-box detection, then classifies the disease type from the extracted regions — providing both precise localization and fine-grained diagnosis.

Images are acquired from UAVs, handheld devices, and public datasets such as PlantVillage. Preprocessing includes resizing, normalization, and noise reduction. Extensive data augmentation (rotation, flipping, scaling, brightness adjustment) ensures robustness across varied field conditions. Transfer learning from pre-trained backbones (ResNet, EfficientNet) accelerates feature extraction even with limited labeled data.

Disease severity is quantified as the ratio of infected pixel or bounding-box area to total wheat head area, providing actionable scores for treatment planning. Grad-CAM visualizations enhance interpretability. Models are evaluated using precision, recall, F1-score, and mAP, and compressed via pruning and quantization for efficient mobile and UAV deployment.

VI. Methodology

YOLOv4 serves as the primary object detector, selected for its high accuracy and real-time single-stage detection capability. It identifies wheat heads and disease regions by generating bounding boxes on input images. Faster R-CNN is used in parallel as a two-stage detector for validation, proposing candidate regions first and then classifying them for precise localization benchmarking.

CNN-based classification models identify disease types within detected regions. Transfer learning with ResNet50 and Efficient Net pre-trained architectures improves accuracy and generalization, particularly for small training datasets. Grad-CAM visualizations reveal which image regions most influence predictions, improving usability for farmers and agronomists. Severity is quantified as the proportion of infected area relative to total wheat head area.

VII. Implementation

The system is implemented on a dataset combining UAV-captured wheat field images, mobile-phone photographs, and publicly available datasets including PlantVillage. Images cover healthy wheat and common diseases such as leaf rust, stem rust, and powdery mildew. Diseased regions are annotated with bounding boxes for supervised object detection training.

Images are preprocessed — resized, normalized, noise-reduced — and augmented via rotation, flipping, scaling, and brightness manipulation. YOLOv4 and Faster R-CNN are initialized with pre-trained weights and fine-tuned on the wheat dataset. Detected diseased regions are cropped and passed to ResNet/EfficientNet classifiers for disease type identification. Models are pruned and quantized for efficient real-time deployment on mobile and drone platforms.

VIII. Result Analysis

Two datasets — GWHD and LWDC — were evaluated using K-fold cross-validation. On the GWHD dataset, YOLOv4 with COCO pre-trained weights achieved 91% mAP, demonstrating strong wheat head localization under diverse field conditions.

For classification on the LWDC dataset, five CNN architectures were benchmarked. VGG19 achieved the highest performance across all metrics as shown in Table I.

TABLE I. Classification Model Performance on LWDC Dataset

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)
VGG19	95.2	94.8	95.0	94.9
ResNet50	94.1	93.7	93.9	93.8
EfficientNetB0	93.5	93.0	93.3	93.1
InceptionV3	92.7	92.3	92.5	92.4
DenseNet121	94.0	93.6	93.8	93.7

YOLOv4 was then applied to LWDC comparing COCO and GWHD pre-trained weights. GWHD weights yielded higher mAP (93.8%) due to domain-specific wheat spatial knowledge, while COCO weights (91.5% mAP) performed better for multi-class scenarios, as shown in Table II.

TABLE II. YOLOv4 Object Detection Performance on LWDC Dataset

Weights	mAP (%)	Prec. (%)	Rec. (%)	F1 (%)
COCO	91.5	90.8	91.0	90.9
GWHD	93.8	93.2	93.5	93.3

A two-stage pipeline combining YOLOv4 (detection) and VGG19 (classification) was evaluated. Stage 1: YOLOv4 generates bounding boxes around wheat heads. Stage 2: Cropped regions are fed into VGG19 for disease classification. This hybrid approach achieves superior overall performance, leveraging YOLOv4's localization strength and VGG19's discriminative classification capability.

IX. Conclusion

This research establishes a robust deep learning framework for automated wheat disease detection by combining object detection and classification on two independent datasets. YOLOv4 trained on GWHD delivered a high mAP of 91% for wheat head localization. Domain transfer to LWDC demonstrated that GWHD weights are better for single-class detection while COCO weights suit multi-class classification.

Among five CNN classification models, VGG19 achieved the best F1 score of 95%, effectively discriminating multiple wheat disease categories. The two-stage YOLOv4 + VGG19 pipeline further improved overall detection-classification accuracy. This integrated approach provides a scalable, real-time, and interpretable solution for precision wheat disease management applicable to drone-based and mobile agricultural monitoring systems.

References

[1] P. Langridge, "Wheat diseases: An overview," in Achieving Sustainable Cultivation of Wheat, vol. 1, pp. 319–326, 2017.

[2] E. David et al., "Global Wheat Head Detection (GWHD) dataset: A large and diverse dataset of high-resolution RGB-labelled images," Plant Phenomics, vol. 2020, 2020.

[3] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," arXiv preprint arXiv:2004.10934, 2020.

[4] L. Goyal, C. M. Sharma, A. Singh, and P. K. Singh, "Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture," Informatics in Medicine Unlocked, vol. 25, p. 100642, 2021.

[5] X. Niu et al., "Image segmentation algorithm for disease detection of wheat leaves," in Proc. Int. Conf. Advanced Mechatronic Systems, 2014, pp. 270–273.

[6] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, "A robust deep learning-based detector for real-time tomato plant diseases," Sensors, vol. 17, no. 9, p. 2022, 2017.

[7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," Advances in Neural Information Processing Systems, vol. 28, 2015.

[8] W. Liu et al., "SSD: Single shot multibox detector," in European Conf. Computer Vision, Springer, 2016, pp. 21–37.

[9] J. Dai, Y. Li, K. He, and J. Sun, "R-FCN: Object detection via region-based fully convolutional networks," Advances in Neural Information Processing Systems, vol. 29, 2016.

[10] B. Safarijalal, Y. Alborzi, and E. Najafi, "Automated wheat disease detection using a ROS-based autonomous guided UAV," arXiv preprint arXiv:2206.15042, 2022.