

Research Paper

AN OPTIMIZED WHEAT DISEASE DETECTION FRAMEWORK USING YOLOV10

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ABSTRACT— Wheat leaf diseases, including rust, powdery mildew, and leaf blight, significantly impact crop yield and quality, making early detection essential for effective disease management. This project presents an advanced wheat disease detection framework using YOLOv10, a cutting-edge object detection model that combines high accuracy, real-time processing, and efficient feature extraction. YOLOv10's enhanced architecture and anchor-free detection capabilities allow it to accurately identify multiple disease types from wheat leaf images, even under varying lighting conditions, leaf orientations, and field environments. By training on a diverse and augmented dataset, the model achieves strong generalization and robustness, enabling rapid and reliable disease detection

through mobile devices, drones, or field cameras. The system not only provides precise classification and localization of diseased regions but also supports timely intervention and precision agriculture, helping farmers make data-driven decisions to protect crops. With its scalability, speed, and adaptability, YOLOv10 represents a powerful tool for automated plant disease management and sustainable farming practices.

Index Terms – Wheat leaf disease detection, YOLOv10, deep learning, object detection, precision agriculture, plant disease classification, computer vision, agricultural image analysis, real-time detection, crop health monitoring, smart farming, disease localization.

I. INTRODUCTION

Wheat is one of the most widely cultivated cereal crops worldwide and plays a vital role in ensuring food security. However, its productivity is often threatened by a variety of leaf diseases, including rust, powdery mildew, and leaf blight, which can cause significant yield losses and reduce grain quality. Traditional disease detection methods, which rely on manual inspection by experts, are time-consuming, labor-intensive, and prone to errors, making them unsuitable for large-scale agricultural monitoring. Advances in artificial intelligence, particularly deep learning and computer vision, have opened new avenues for automated, accurate, and real-time disease detection.

This project proposes an optimized wheat disease detection framework using YOLOv10, a state-of-the-art object detection model that offers high accuracy, efficient feature extraction, and rapid processing. By leveraging a diverse and augmented dataset of wheat leaf images, YOLOv10 can detect and classify multiple disease types under diverse environmental conditions, enabling timely intervention and supporting precision agriculture. The framework aims to empower farmers with a reliable, scalable, and

technology-driven tool for early disease detection, ultimately enhancing crop management, minimizing losses, and promoting sustainable farming practices.

II. RELATED WORK

A. Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in VHR Optical Remote Sensing Image

This research, published in the IEEE Transactions on Geoscience and Remote Sensing, focuses on addressing the challenges of object detection in very high-resolution (VHR) optical remote sensing images. The authors propose a novel approach involving rotation-invariant convolutional neural networks to enhance the accuracy of object detection. By learning rotation invariance, the model becomes more robust to variations in object orientation within the high-resolution imagery, leading to improved detection performance. The study contributes valuable insights into adapting deep learning techniques for the specific challenges posed by VHR optical remote sensing data.

B. Object Detection in Optical Remote Sensing Images: A Survey and a New Benchmark

Published in the ISPRS Journal of Photogrammetry and Remote Sensing, this survey article provides a comprehensive overview of object detection techniques applied to optical remote sensing images. The authors present a new benchmark for evaluating object detection models in this domain, emphasizing the importance of benchmark datasets for advancing research. The survey covers existing methodologies, challenges, and benchmarks, offering a valuable resource for researchers and practitioners engaged in object detection within optical remote sensing imagery.

C. Microsoft COCO: Common Objects in Context

This seminal work introduces the Microsoft COCO dataset, a widely used benchmark for object detection and segmentation. Presented at the European Conference on Computer Vision, the authors highlight the significance of a dataset that goes beyond object recognition to include context. The COCO dataset has become a standard evaluation platform for object detection algorithms, fostering advancements in computer vision research. The paper outlines the dataset creation process, its content, and its potential impact on the development of object detection models.

D. YOLOv4: Optimal Speed and Accuracy of Object Detection

This preprint introduces YOLOv4, a significant advancement in the YOLO series, focusing on achieving optimal speed and accuracy for object detection. The authors address the trade-offs between speed and accuracy, aiming to provide a state-of-the-art solution for real-time object detection. The paper presents the architecture, training strategies, and experimental results of YOLOv4, contributing to the ongoing evolution of object detection models and pushing the boundaries of speed and accuracy.

III. PROPOSED METHODOLOGY

YOLOv10, the latest advancement in the "You Only Look Once" object detection series, represents a significant leap forward in real-time object detection by combining high accuracy, exceptional speed, and deployment efficiency in a single unified architecture. Introduced in 2024, YOLOv10 was designed to overcome the limitations of earlier models by unifying the training and inference processes, thereby simplifying deployment and improving overall consistency in performance. Unlike previous versions that often required separate post-processing or anchor-based mechanisms, YOLOv10

embraces an anchor-free detection approach and integrates a fully decoupled head for classification and localization tasks. It also incorporates an efficient backbone and improved feature aggregation modules that allow for better representation of objects at multiple scales, enhancing detection precision for small and large objects alike.

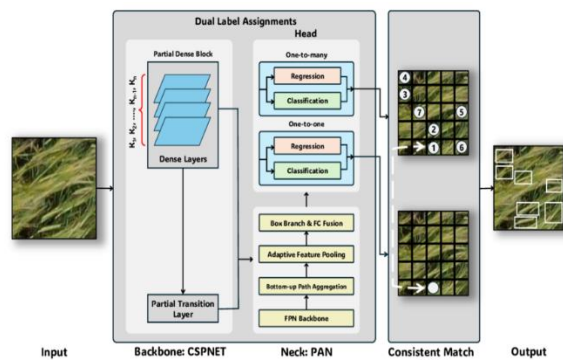


Fig. 1: System Overview

1. Data Augmentation

Data augmentation plays a vital role in improving the performance and generalization ability of the YOLOv10 model for wheat leaf disease detection. Since real-world datasets may contain limited samples of certain disease types or environmental variations, augmentation techniques are applied to artificially expand the dataset. These include transformations such as rotation, flipping, cropping, scaling, and brightness or contrast adjustments, which simulate diverse field conditions like different lighting, leaf angles, and

backgrounds. This helps the model become more robust to variations in environmental factors, camera perspectives, and image quality. By increasing the diversity of the dataset, data augmentation ensures that YOLOv10 can accurately detect and classify wheat leaf diseases under a wide range of real-world scenarios, thereby reducing the chances of overfitting and improving detection accuracy.

2. Data Preprocessing

Data preprocessing is an essential step to prepare the wheat leaf images for training the YOLOv10 model. This stage involves resizing images to a uniform dimension compatible with YOLOv10's input requirements, normalizing pixel values, and organizing image-label pairs for effective training. Each image is carefully annotated using bounding boxes to mark the diseased regions, enabling the model to learn the exact locations and types of infections such as rust, powdery mildew, or leaf blight. Preprocessing also includes noise removal and quality enhancement to ensure that the images are clear and consistent. By standardizing and cleaning the dataset, preprocessing ensures efficient training, faster convergence, and improved overall model accuracy.

3. Data Split

After preprocessing, the dataset is divided into three subsets — training, validation, and testing sets. The training set is used to teach the YOLOv10 model the distinguishing features of healthy and diseased wheat leaves. The validation set is used during model training to fine-tune parameters and monitor performance, ensuring that the model does not overfit the training data. The testing set, which contains unseen images, is used to evaluate the final performance of the model. A typical split ratio such as 70% training, 20% validation, and 10% testing ensures a balanced and fair evaluation of model accuracy and generalization capability.

4. Model Training

The model training phase is the core of the project, where YOLOv10 learns to detect and classify wheat leaf diseases from labeled images. YOLOv10's advanced architecture, featuring enhanced backbone and head designs, allows it to efficiently extract detailed features from wheat leaf images. The training process involves feeding batches of preprocessed and augmented images into the model, optimizing parameters using algorithms like AdamW or SGD. The loss function combines localization, objectness,

and classification losses to fine-tune the network's predictions.

5. Prediction

Once the model is successfully trained and validated, it is used for disease prediction on new and unseen wheat leaf images. During the prediction phase, YOLOv10 processes each image and outputs bounding boxes that indicate diseased regions, along with the predicted disease class and confidence score. Its real-time detection capability enables fast and accurate identification, even when multiple disease types are present in a single leaf. The output helps farmers and agricultural experts take immediate corrective actions, such as applying appropriate treatments or monitoring affected areas. The prediction results can also be visualized with bounding boxes and class labels overlaid on the input images, making the system highly interpretable and practical for field use.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed YOLOv10-based framework accurately detects and localizes multiple wheat leaf diseases in real time. The model demonstrates high detection accuracy and strong robustness under varying lighting

conditions, leaf orientations, and field environments. Data augmentation and optimized feature extraction improve the model's generalization performance while maintaining fast inference speed. Overall, the framework provides an efficient and reliable solution for precision agriculture and early wheat disease management.



Fig. 2: Registration

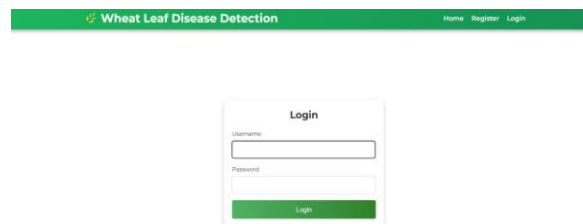


Fig. 3: Login

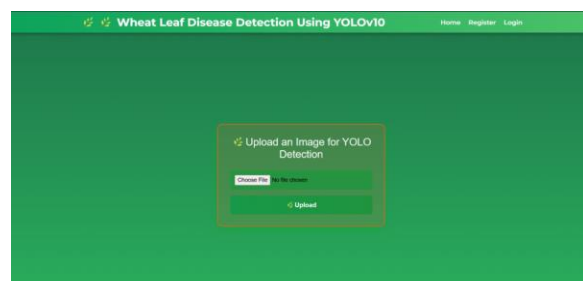


Fig. 4: Upload Image



Fig. 5: Result

V. CONCLUSION

In conclusion, this project successfully demonstrates the potential of deep learning technology, particularly the YOLOv10 model, in automating the detection and classification of wheat leaf diseases with high accuracy and efficiency. By leveraging real-time object detection and robust feature extraction, the proposed system effectively identifies major wheat diseases such as rust, powdery mildew, and leaf blight under diverse environmental conditions. Through systematic data collection, preprocessing, augmentation, and model training, the framework achieves reliable performance and strong generalization, reducing the need for manual inspection and expert intervention. The results highlight YOLOv10's capability to deliver fast, accurate, and scalable solutions for precision agriculture. This system not only aids farmers in early disease detection but also contributes to improved crop management, reduced yield

losses, and sustainable agricultural practices. Overall, the project establishes a strong foundation for future research and development in intelligent plant disease detection systems, paving the way for the integration of AI-driven tools in modern agriculture.

REFERENCES

- [1] Y. W. Yang and W. L. Lin, “Does the fiscal reform of counties directly managed by provinces promote grain production in counties—Evidence based on quasi-natural experiments,” *J. China Rural Economy*, vol. 2024, pp. 152–172, Jan. 2024, doi: 10.20077/j.cnki.11-1262/f.2024.06.008. [2] Y. Li, W. C. Liu, and Z. H. Zhao, “The occurrence and management of wheat insect pests and diseases in China in 2022 and reflections on pest control measures,” *J. China Plant Protection*, vol. 2023, pp. 52–54, Jan. 2023.
- [3] Y. B. Lan, T. W. Wang, S. D. Chen, and X. L. Deng, “Agricultural artificial intelligence technology: Wings of modern agricultural science and technology,” *J. South China Agricult. Univ.*, vol. 42, pp. 1–13, Sep. 2020.
- [4] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep neural networks based recognition of plant diseases by leaf image classification,” *Comput. Intell. Neurosci.*, vol. 2016, pp. 1–11, Jan. 2016.
- [5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017.
- [6] H. Zhang, C. Qing, W. Yingjie, W. Yaxin, Z. Chengming, and Y. Fuwei, “A method of wheat disease identification based on convolutional neural network,” *J. Shandong Agricult. Sci. China*, vol. 50, pp. 137–141, Jan. 2018.
- [7] S. Jia, H. Gao, and X. Hang, “Research progress on image recognition technology of crop pests and diseases based on deep learning,” *J. Trans. Chin. Soc. Agricult. Machinery*, vol. 50, pp. 313–317, Jan. 2019.
- [8] Bhagwat, V. B. (2025). Simplifying Payroll Balance Conversions in Payroll Systems Implementation through the Use of Generative AI.
- [9] Z. Xue, R. Xu, D. Bai, and H. Lin, “YOLO-tea: A tea disease detection

model improved by YOLOv5,” *Forests*, vol. 14, no. 2, p. 415, Feb. 2023.

- [10] Q. Huang, X. Wu, Q. Wang, X. Dong, Y. Qin, X. Wu, Y. Gao, and G. Hao, “Knowledge distillation facilitates the lightweight and efficient plant diseases detection model,” *Plant Phenomics*, vol. 5, p. 62, Jan. 2023.

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