Research on Wheat Disease Recognition Algorithm based on Deep Learning

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Abstract

In order to meet the demand for efficient detection and diagnosis of wheat diseases, this study proposes an improved YOLOv8-based object detection method. First, a dataset of 1,500 wheat disease images was collected and annotated. Subsequently, using the PyTorch framework, we modified and trained the YOLOv8 model by replacing the original Anchor-Free detection head with a dyhead-prune detection head, which incorporates attention mechanisms and pruning operations, and adopted Inner-Wise-GIoU as the loss function. Experimental results show that, compared to the baseline model, the improved model achieves a 1.5% increase in mAP50 while reducing the number of parameters by 2.5%, effectively enhancing both detection accuracy and operational efficiency. Finally, TensorRT was utilized for inference acceleration, enabling real-time disease detection. This research provides an efficient and feasible approach for the automatic recognition and timely prevention of wheat diseases, playing a crucial role in ensuring crop yield, reducing losses, and advancing the digital development of "Internet + Agriculture."

Keywords

YOLOv8; Wheat Diseases; TensorRT.

1. Introduction

Wheat is one of the three major grains, with a yield almost entirely for consumption, and plays a crucial role in world agriculture. One of the main factors affecting wheat yield is wheat pests and diseases, which have a wider range of harm and stronger transmission ability. Timely detection and accurate diagnosis of wheat diseases are of great practical significance for reducing the harm caused by wheat diseases in agricultural development[1].

Deep learning can solve key problems by using feature extraction methods, overcoming the shortcomings of traditional recognition algorithms that rely on manually designed features, and has received increasing attention from researchers. Among them, the most obvious advantage of deep learning is that it can automatically learn features from big data without human manipulation. The model is composed of multiple levels and has deep advantages, as well as strong self-learning ability and efficient feature expression ability. Nowadays, using object detection methods based on deep learning technology to intelligently detect crops can greatly improve the detection efficiency of crop diseases, effectively control the spread of crop diseases, and increase the yield of agricultural products.[2] Intelligent detection has far-reaching significance and value for promoting agricultural development, improving farmers' income, and promoting the digital agriculture policy of "Internet plus agriculture".

This project is to study wheat diseases based on deep learning. By using an improved YOLOv8 model and TensorRT for model detection acceleration, the detection accuracy and speed are improved, and

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wheat diseases are quickly and accurately identified. Corresponding preventive measures are taken for wheat disease problems in a timely manner, which is of great significance for improving crop yield and quality, reducing economic losses, and liberating labor.

The model of this system adopts the efficient and accurate YOLOv8 algorithm and improves it by replacing the traditional Anchor Free detection head with a dyhead scheme detection head. It uses attention mechanism to unify different object detection heads and prunes them to reduce the model coefficients. This model has also improved the loss function to Inner Wise GIOU. These improvements resulted in a 1.5% increase in mAP50 and a 2.5% reduction in parameter count for the model on the dataset[3]. This algorithm has excellent object detection capabilities and can accurately identify various diseases of wheat, greatly improving the efficiency and accuracy of detection.

Innovation in the application of deep learning algorithms in wheat disease detection: This work is the first to apply YOLOv8's improved algorithm to the field of wheat disease detection, bringing a new and efficient detection method for wheat diseases and promoting technological progress in the industry[4].

The introduction of dataset augmentation technology: Through data augmentation technology, the dataset has been successfully expanded, the generalization ability of the model has been improved, and it can cope with more complex and varied wheat disease situations.

The combination of disease detection and treatment opinions: This work not only achieves efficient detection of wheat diseases, but also analyzes the types of diseases, making it convenient for users to carry out targeted treatment of diseases. It helps agricultural workers optimize planting processes, improve product quality, reduce disease detection costs, and enhance market competitiveness.

2. System Analysis and Design

2.1 Wheat Disease Identification Algorithm based on YOLOv8

The design of wheat disease recognition algorithm based on YOLOv8 is as follows:

(1) Collecting a large number of images with wheat diseases to collect data as a dataset;

(2) Use the Labelme annotation tool to annotate the collected wheat disease images;

(3) Train the YOLOv8 model on the annotated data through five steps: loading data, forming a network model, drawing the model, loading a pre trained model, and calculating the loss function;

(4) Use the trained model for prediction and non maximum suppression operations, and draw a rectangular box for the target with the highest confidence as the wheat disease recognition result;

(5) Improve YOLOV8 to better identify wheat diseases;

(6) Identify the types of wheat diseases and propose solutions.

2.2 Functional Modules of Wheat Disease Identification System

The wheat disease recognition system is composed of two main modules: the Detection Module and the Data Analysis Module. The Detection Module serves as the system's core, leveraging a YOLOv8 model built on deep learning techniques. Through convolutional neural networks (CNNs), it extracts critical features from input images to accurately identify and locate diseased areas in wheat crops. Once an image is fed into the system-either uploaded by a user or captured by a camera-the model performs inference to produce bounding boxes, disease labels, and confidence scores, all of which are essential for subsequent processing[5].

Building on the outputs of the Detection Module, the Data Analysis Module provides deeper insights into the recognized diseases. It aggregates and visualizes statistics such as disease frequency, distribution, and overall severity through various graphical representations like bar charts and pie charts[6]. This facilitates easy identification of patterns and trends, enabling informed decision-making for agricultural professionals and managers. By storing detection results in a database or local files, historical data can be retrieved and compared. Furthermore, the system can be integrated with

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GIS or other agricultural platforms to examine spatial distribution patterns, ultimately enhancing the efficiency and effectiveness of wheat disease management[7].

2.3 YOLOv8 Basic Theory

The structural design of YOLOv8 mainly includes several key parts: the backbone network, neck, and head. The overall structure of YOLOv8 is shown in Fig. 1.

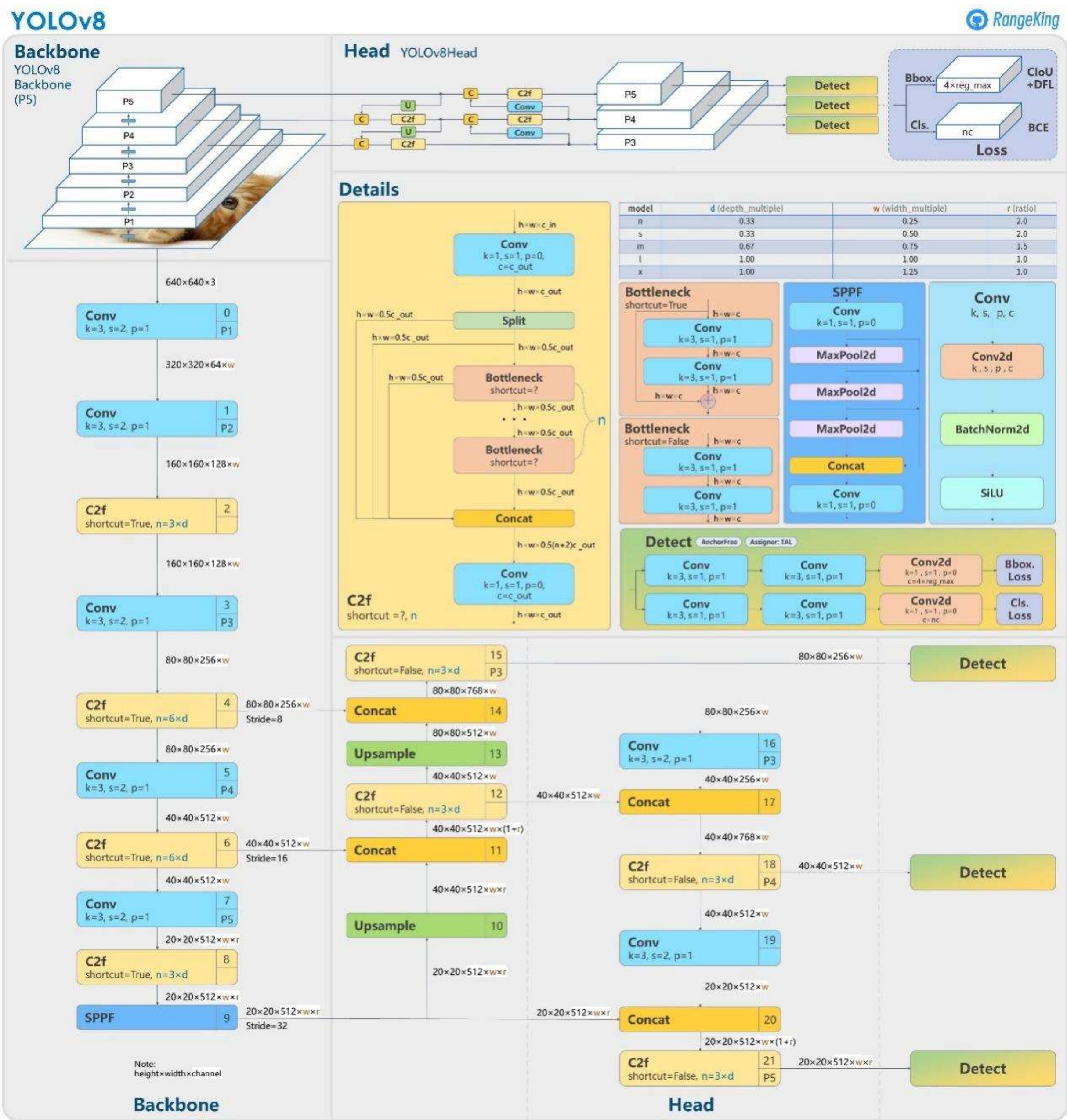

Fig. 1 YOLOV8 structural diagram

The backbone of YOLOv8 is the InceptionNext neural network structure, and InceptionNeXt is a perfect combination of Inception and ConvNeXt. This combination enables the network to learn features at different scales and abstraction levels simultaneously, thereby improving its ability to detect small targets. This is because the Inception module captures features of different scales through convolution kernels of different sizes and pooling operations, allowing the network to better adapt to targets of different scales. The main diagram of InceptionNext is shown in Fig. 2.

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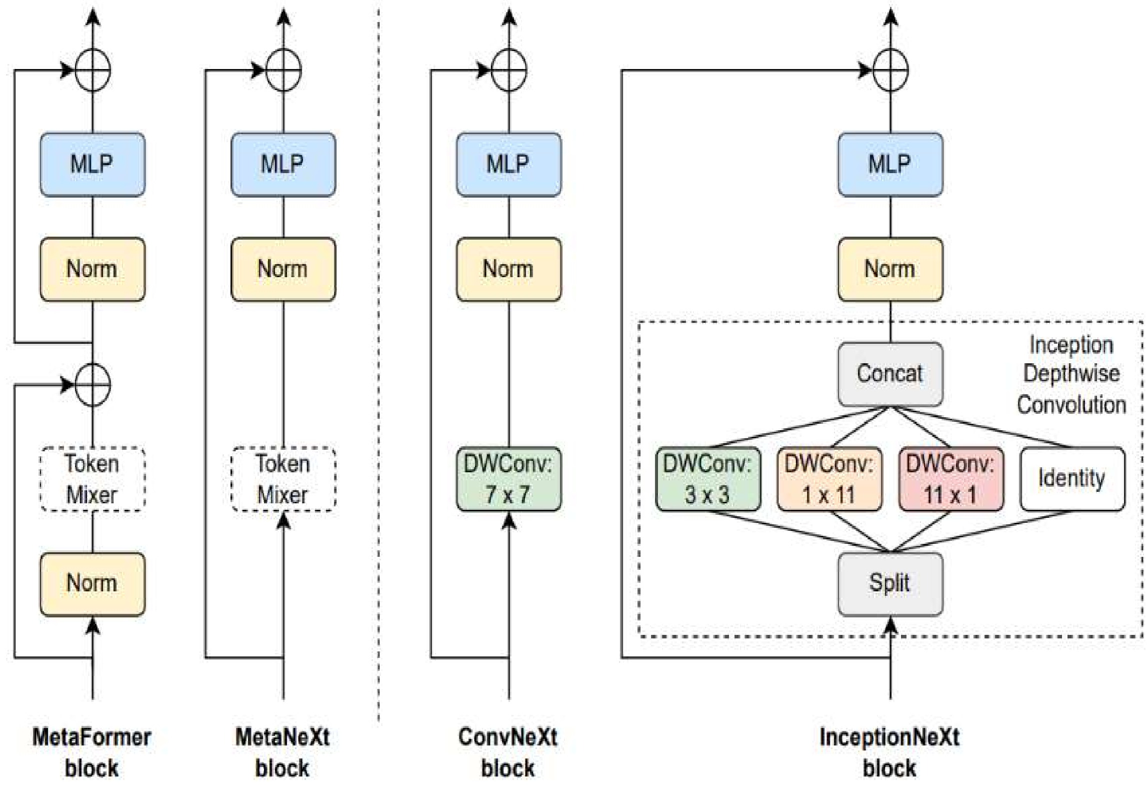

Fig. 2 InceptionNext Structure Diagram

In YOLOv8, the role of the neck is to further fuse and process the features extracted by the backbone network. Specifically, YOLOv8 adopts multiple C2f modules (i.e. Concentrated Convolutional Modules), which have more skip layer connections and additional Split operations, helping to enhance feature representation and model robustness. The C2f structure diagram is shown in Fig.3

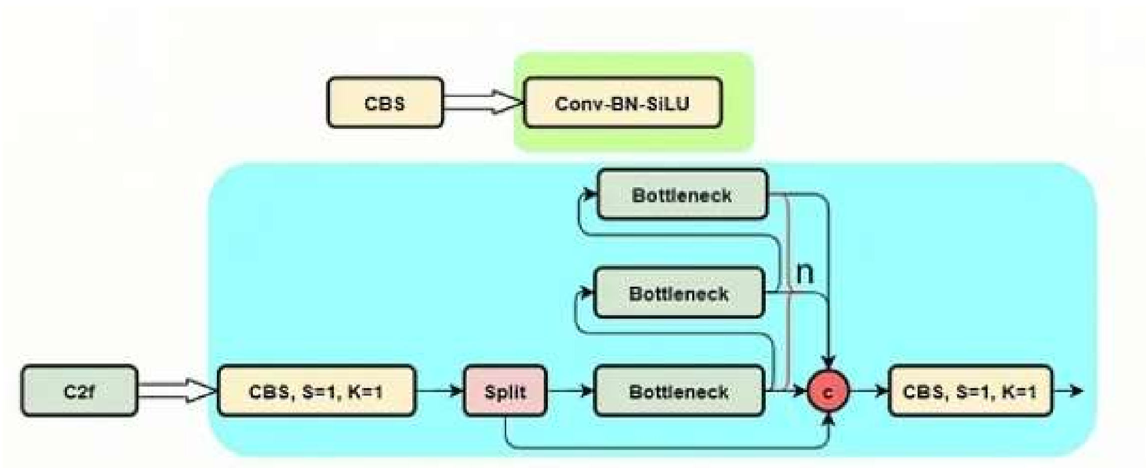

Fig. 3 C2f structure diagram

The head structure of YOLOv8 has two major characteristics. Firstly, it adopts the current mainstream Decoupled Head structure, which separates the classification and detection heads to improve the accuracy and efficiency of the model. Secondly, YOLOv8 also adopts an anchor free detection method, which means it directly predicts the center of the object rather than knowing the offset of the

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anchor box. This new method reduces the number of box predictions, thereby accelerating a very complex inference step - Non Maximum Suppression (NMS)[8]. The anchor free model is shown in Fig. 4

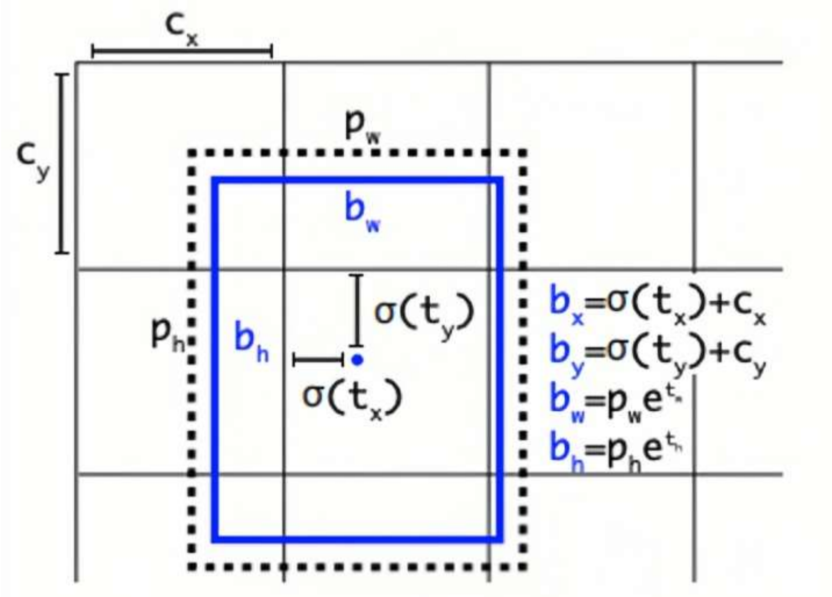

Fig. 4 Anchor free model diagram

3. Main Technical Indicators

Precision and recall are fundamental indicators for evaluating the performance of deep learning models. The YOLOv8 model mainly relies on accuracy and recall for model evaluation. Among them, TP represents the number of correctly detected wheat diseases, FP represents the number of wheat diseases incorrectly identified as non diseased parts, and FN represents the number of wheat diseases identified as non diseased parts[9].

The P of the P-R curve is precision (also known as precision), which refers to the probability of a sample being actually positive among all predicted positive samples.

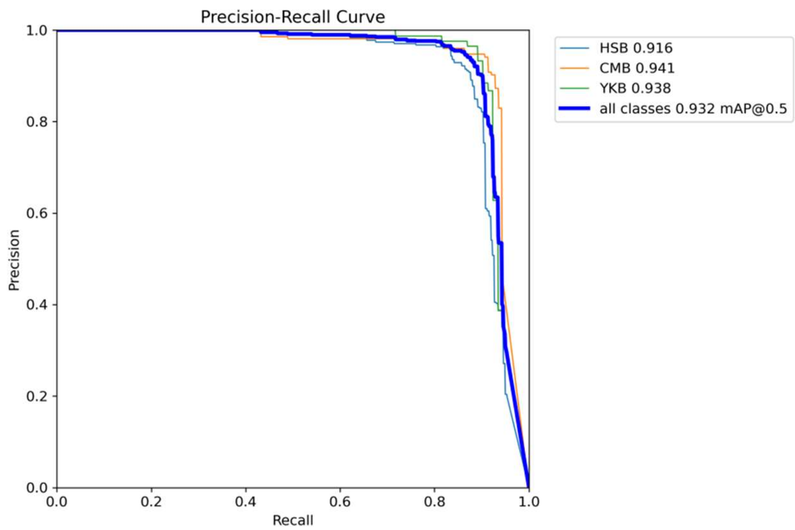

Fig. 5 Precision Recall plot of YOLOV8S model for wheat disease detection

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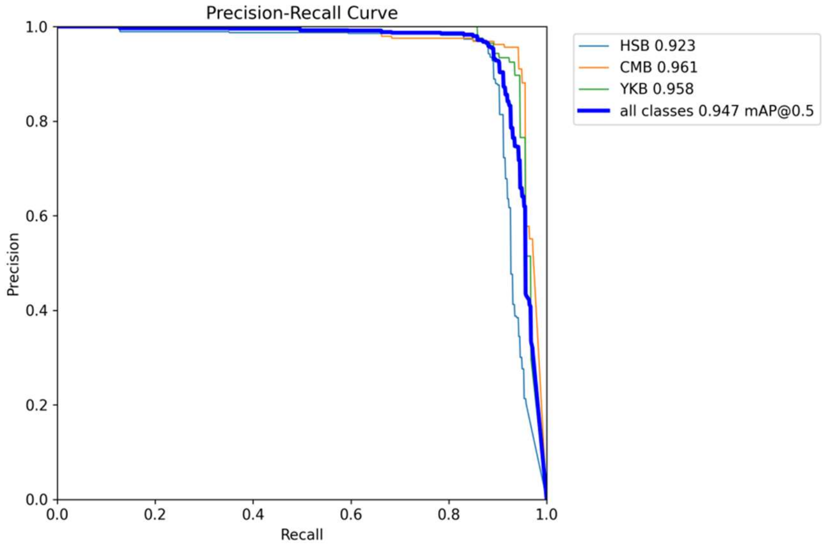

Fig. 6 Precision Recall plot of YOLOV8S-DYPIWG model for wheat disease detection

4. Summary

In today's rapidly evolving technological landscape, countless advanced techniques and methods are emerging. Among these, YOLOv8 has carved out a vital role in deep learning due to its practicality, clarity, and robust real-time performance. By leveraging deep learning theories and combining resources from literature and research platforms, over 3,000 wheat disease images were collected, labeled, and used for training. Continuous fine-tuning of disease classifications yielded a model capable of accurate recognition, disease-severity analysis, and provision of relevant recommendations. Through the implementation of these functionalities, both theoretical understanding and practical proficiency in deep learning have been significantly enhanced.

Strengthening technology-driven support for modern agriculture is of great importance. Automatic, efficient, and precise diagnosis of wheat diseases not only ensures grain yield and quality but also contributes to food safety and the sustainable development of the wheat industry. By focusing on rural development challenges and promoting modernization, a deep learning–based wheat disease system can effectively facilitate the precise detection of various diseases. This, in turn, allows for the application of different control strategies to mitigate damage, reduce the environmental impact of chemical usage, and boost farmers incomes.

Apart from detection, the system also analyzes disease severity and offers corresponding solutions. Future work can delve deeper into the agronomic aspects of wheat diseases, paving the way for a more scientifically rigorous and standardized disease analysis framework. Currently, the systems interface design and functionalities are relatively straightforward. Subsequent enhancements might include using a database to store detection outcomes, archiving historical records, and employing cloud-based data to forecast the likelihood of disease outbreaks. A lightweight mini-program version could further simplify usage for farmers, especially when integrated with cameras for real-time disease monitoring. Such timely detection in the early stages of an outbreak would enable immediate intervention and foster collaborative research efforts, ultimately supporting the development of targeted measures to reduce disease incidence.

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