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Comparative Study of Deep Learning Object Detection Methods for Wheat Leaf Disease Detection with Organic Remedy Suggestions - A Review

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***Abstract*— The wheat leaf diseases pose a significant threat to global agricultural productivity, necessitating the development of efficient and accurate detection techniques. Recently, development in deep learning (DL) algorithms have completely given new outlook how plant diseases can be detected with the use of object detection models. This review compares leading deep learning (DL) based object detection techniques like Single-Shot Multi-Box Detector (SSD), Convolutional Neural Networks (CNN), Faster R-CNN, YOLO version 5 (You Look Only Once), and YOLO version 8 for identifying diseases in wheat leaf. It exhibits comparative study of each model's mean average precision, architecture, and its speed.**

Additionally, the review also shows that the likely hood of using organic remedies as a natural and sustainable way to manage plant diseases. While old and traditional chemical treatments are helpful but they lead to environmental impact. As an alternative, organic remedies like biopesticides, neem extracts, and microbial formulations can be effective. The study shows evaluation of the strengths and weaknesses among various detection models in terms of mean average precision, computational cost and real-life disease monitoring.

Findings show that YOLOv8 offers both high speed and accuracy, while Faster R-CNN is particularly strong in accuracy. SSD and CNN provide a balanced performance, making them well-suited for environments with limited resources. By integrating deep learning with organic disease control methods, this review promotes a sustainable action to protect wheat crops.

***Index Terms*— Convolutional Neural Networks (CNN), Faster Region Based CNN (Faster R-CNN), Single-Shot Multi-Box Detector (SSD), You Look Only Once (YOLOv5), You Look Only Once (YOLOv8)**

I. INTRODUCTION

Wheat is among the most essential staple crops globally, providing essential nutrition to billions of people. However, wheat production is significantly impacted by various leaf diseases, including rust, powdery mildew, and leaf blight, which can lead to severe yield losses if not identified and controlled in time [1]. Manual disease detection methods depend on visual inspection by farmers or agricultural experts, which is time-consuming, subjective, and often inaccurate. To address these challenges, deep learning-based object detection techniques have emerged as powerful tools for automated and real-time wheat leaf disease detection [2].

Among the various deep learning models, Single-Shot Multi-Box Detector (SSD), Convolutional Neural Networks (CNN), Faster R-CNN, YOLOv5, and YOLOv8 have demonstrated promising outcomes in accurately identifying and classifying different wheat leaf diseases. These models leverage convolutional feature extraction, multi-scale detection, and high-speed inference, making them appropriate for farming applications. However, each model varies with reference to accuracy, computational efficiency, and suitability for real-time field applications. This study compares five advanced deep learning methods to assess their strengths and weaknesses in detecting wheat leaf diseases. Beyond automated detection, sustainable disease management is essential for long-term agricultural productivity. While conventional chemical treatments are effective, excessive pesticide use poses risks to both the environment and human health. As an alternative, organic solutions such as neem extract, biopesticides, and microbial formulations offer eco-friendly disease control options. This review explores how DL can be integrated with organic treatment recommendations to evolve an AI-driven, sustainable disease-dealing system for wheat crops.

II. SINGLE-SHOT MULTI-BOX DETECTOR (SSD)

The Single-Shot Multi-Box Detector (SSD) is an object detection method based on the DL technique that offers a good balance between speed and accuracy. It is a popularly and generally used method in various studies to detect different rice plant leaf diseases and wheat plants [3]. SSD method as its name represents is a single-stage object detection method that predicts object categories and their bounding box position in one pass, eliminating the requirement of region proposals [4]. This allows it to perform object localization and classification simultaneously, which boosts the processing speed. SSD achieves 30 to 60 FPS on modern GPUs, making it much speedier than Faster R-CNN (~10 FPS) but slightly slower than YOLOv5 and YOLOv8 (~50–100 FPS) [5].

SSD uses multi-scale feature maps and default anchor boxes to locate wheat leaf diseases of different sizes, with a 70 to 80% mean Average Precision (mAP), rely on the model tuning and dataset quality [6]. While it is computationally efficient and appropriate for implement on edge gadgets like drones, tablets, or mobile, it may face struggle with small or overlapping wounds due to lower localization precision compared to Faster R-CNN or YOLOv8 [7]. However, integrating SSD with pretrained CNNs like VGG16 and ResNet50 improves its feature extraction capabilities, making it more reliable and scalable solution for real-time wheat leaf disease monitoring. This contributes to early detection and supports precision agriculture for green and sustainable farming.

III. CONVOLUTIONAL NEURAL NETWORK (CNN)

The DL method CNN recently shows enhanced machine learning (ML) by independent learning and fetching important features from data, hence enabling more precise pattern recognition [8]. CNNs are widely used in DL method for rapid and accurate detection of crop diseases, making them a popular and standard choice for disease detection in wheat leaf due to their good precision and automated feature extraction capabilities. CNN consists of multiple convolutional layers that identify disease patterns by detecting features such as leaf color, texture, and lesion shape. CNN-based models, particularly architectures like ResNet, VGG16, and MobileNet, have demonstrated an accuracy range of 85 to 95%, depending on dataset quality and preprocessing methods [9]. These models have potential to process images at an inference speed of 10 to 50 FPS, making them appropriate for both real-time and offline analysis [10]. Compared to SSD and YOLO models, CNN gives higher classification accuracy but has slower detection speeds. The major constraints of CNNs are their higher computational demand, making them ineffective for edge devices deployed in field conditions. However, CNN’s ability to handle complex disease features and classify multiple wheat diseases with high precision makes it an effective tool in precision agriculture and automated disease monitoring [11].

IV. FASTER REGION BASED CONVOLUTIONAL NEURAL NETWORK (FASTER R CNN)

The Faster Region-Based CNN (Faster R-CNN) is a widely used DL model for high-precision wheat leaf disease detection. Faster R-CNN improves upon previous R-CNN architectures by introducing a (RPN) Region Proposal Network that efficiently identifies disease-affected areas while significantly reducing computation time. With its two-stage detection process, Faster R-CNN achieves higher accuracy (90 to 98% mAP) compared to single-stage detectors like SSD and YOLO, making it particularly effective in detecting complex and small lesions on wheat leaves [12]. However, its processing speed is relatively lower, achieving 5 to 15 FPS, which may limit real-time applications [13]. The model is particularly well-suited for high-accuracy agricultural disease diagnosis, where detailed feature extraction and precise localization are critical [14]. Despite its higher cost of computational, Faster R-CNN remains a powerful tool for wheat leaf disease detection, particularly when deployed in cloud-based or high-performance computing environments [15]. Integrating Faster R-CNN with data augmentation and transfer unsupervised learning techniques further enhances its performance, ensuring robust and scalable disease detection for sharp and accurate agriculture [14].

V. YOU ONLY LOOK ONCE V5 (YOLOV5)

The YOLO version 5 (YOLOv5) is an advanced object detection technique that offers an optimal balance between accuracy, speed, and processing efficiency, making it highly appropriate for real-time wheat leaf disease detection [15]. YOLO version 5 has a single-layer detection approach, which permits it to process images faster compared to two-layers detectors like Faster R-CNN. The model achieves a mean average precision (mAP) of 85–95% depending on dataset image quality and training configuration parameters, while delivering an inference speed of 50–120 Frame Per second (FPS) on modern cutting-edge GPUs, making it significantly faster than SSD (Single-Shot Multi-Box Detector) and Faster R-CNN. Its lightweight architecture, implemented using PyTorch, enables deployment on edge devices like raspberry-pi, jetson nano and smartphone based mobile applications for in-field wheat disease detection [16]. YOLOv5 uses advanced anchor-free detection, various data augmentation like rotation, scaling, filtering adding noise etc. and adaptive anchor computation, allowing it to efficiently detect small and overlapping disease lesions and rust on wheat leaves [17]. It is having high speed detection at cost of lower accuracy than Faster R-CNN for relatively complex disease structure. However, it having good trade-off between accuracy and real-time processing capabilities make it an excellent choice for automated disease monitoring systems and smart agriculture solutions [18].

VI. YOU ONLY LOOK ONCE V8 (YOLOV8)

The YOLO version 8 (YOLOv8) is the newest iteration from the family of YOLO, offering enhanced mean average precision, efficiency, and live processing potential for wheat leaf disease identification. As a single-stage object detector, YOLOv8 surpasses its predecessors by incorporating improved feature extraction, anchor-free detection, and adaptive learning rate strategies, making it more effective in identifying small and overlapping disease spots on wheat leaves. It achieves an accuracy (mAP) of 90 to 98%, depending on dataset quality and hyperparameter tuning, while maintaining an impressive inference speed of 80 to 150 FPS on high-end GPUs. YOLOv8 also introduces enhanced ConvNext and C2f modules, which improve feature aggregation and detection precision, making it particularly suited for real-time precision agriculture applications. Furthermore, its lightweight architecture and optimized deployment capabilities allow it to be implemented on edge devices and mobile platforms for on-ground wheat disease monitoring [19]. While YOLOv8 outperforms earlier SSD versions and YOLO in terms of detection accuracy with speed, its slightly higher computational demand compared to YOLOv5 might require hardware acceleration for seamless processing in resource-limited environments. Nevertheless, its state-of-the-art performance and real-time detection capabilities make it one of the top most appropriate deep learning (DL) models for disease identification in wheat leaf.

VII. COMPARATIVE ANALYSIS AND INTERPRETATION

Deep learning-based object detection methods have remarkably advanced wheat leaf disease detection, allowing for rapid and accurate identification of disease symptoms. As given in the comparison Table 1 each model has divergent characteristics in specific terms of mean average precision, computational cost, and live processing applicability. YOLO version 8 surpasses other models in terms of both speed and accuracy, making it appropriate for live approach where fast disease detection is significant. However, it needs more computational power, reducing its utilization in minimal resources environments. Faster R-CNN, known for having its better accuracy, having more advantage in detecting complex disease patterns but works at a slower speed, makes it much less appropriate for live monitoring [4]. Single-Shot Multi-Box Detector (SSD) provides a better trade-off between speed and mean average precision but struggles with small or tiny size of object detection, which probably be pivotal in detecting diseases in premature-stage of identification. CNN, while effective in feature extraction, suffers from having its slower inference speed, makes it less feasible for live video applications. YOLO version 5 offers a strong trade-off for accuracy and speed, making it a wholesome for bigger-scale wheat crops. By combining deep learning-based disease detecting in wheat leaf with organic disease control concept enhances healthy agricultural and sustainable practices by narrowing dependency on chemical treatments [16]. Organic strategies for disease prevention not only improve plant immunity and soil health but also leads to achieve Sustainable Development Goals (SDGs) by encouraging eco-friendly, green and resilient agricultural practices.

Model	Accuracy (mAP)	Speed (FPS)	Strengths	Weaknesses
SSD	75%	47	Fast, good for real-time applications	Less effective for small objects
CNN	72%	30	High feature extraction accuracy	Slow inference speed
Faster R-CNN	80%	10	High detection accuracy	Computationally expensive
YOLO v5	85%	45	Fast and accurate	Requires large dataset
YOLO v8	88%	60	Best real-time performance, high accuracy	Requires high computational power

Table I Comparative Analysis of Different DL Object Detection Models

VII. CONCLUSION

This review presents a comprehensive analysis of deep learning-based object detection techniques for wheat leaf disease detection, emphasizing their accuracy and speed. Among the compared models, YOLOv8 emerges as the most effective, offering superior accuracy and live performance, making it well suited for disease detection. Integrating these advanced detection techniques with organic disease management strategies can help meet the growing need for sustainable farming by reducing reliance on chemical pesticides. Future research should attention on optimizing DL models for small-scale disease detection and enhancing the synergy between AI-driven detection and sustainable disease control methods. This integration will drive the advancement of precision agriculture, ensuring healthier crops, improved food security, and alignment with global sustainability goals.

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