Wheat Fusarium Head Blight

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Fusarium has become a major impediment to stable wheat production in many regions worldwide. Infected wheat plants not only experience reduced yield and quality but their spikes generate toxins that pose a significant threat to human and animal health. There are two primary methods for effectively controlling Fusarium head blight (FHB): spraying quantitative chemical agents and breeding disease-resistant wheat varieties. The premise of both methods is to accurately diagnosis the severity of wheat FHB in real time.

deep learning wheat fusarium head blight image segmentation

1. Introduction

Wheat is the third largest grain crop after maize and rice around the world, and its cob and fruit parts are rich in large amounts of starch, protein and other nutrients, which can be consumed by humans and animals [1]. However, there are many destructive diseases in nature that seriously affect wheat production and threaten global food security [2]. Among them, Fusarium head blight (FHB), caused by *Fusarium graminearum Sehw*, is one of the epidemic diseases in wheat production [3]. The disease is prevalent in wheat fields of semihumid and humid regions and can reduce wheat yield losses by 10–70%, affecting more than 70,000 hectares of acreage [4]. Pathogenic fungi attack the spikes of wheat, resulting in a significant reduction in crop yield and quality. In addition, FHB can lead to a range of mycotoxins (e.g., deoxynivalenol and zearalenone) to be produced inside the grain, which can cause human and animal poisoning and pose a significant health risk to food safety [5]. In summary, research on the monitoring and warning of FHB is important for the development of scientific wheat production with high yield, high quality, and high efficiency.

For timely control of FHB in wheat, each sample plant needs to be monitored for disease. Traditionally, the assessment of FHB severity has relied on manual field sampling, where infected spikelets are counted and their percentage of total spikelets is calculated to assign a grade [6]. This method is simple to operate, but it is inefficient and costly in practice, and the accuracy of data is subjective, which seriously affects the efficiency of FHB control in wheat [7]. In recent years, imaging and spectroscopic methods including near-infrared spectroscopy (NIRS) and hyperspectral imaging (HSI) have also been rapidly developed in the field of disease surveillance [8][9]. However, such sensors can only sense the spectral characteristics of an object at a certain point and the computational data increase dramatically, which are not suitable for real-time analysis of large-scale wheat spikes in reality [10][11].

The novelty of this research is the development of an integrated multi-model fusion system for FHB severity assessment of wheat with deep learning. Taking wheat FHB as the research object, convolutional neural network

(CNN) and related algorithms of image processing are used to sequentially complete the integrated operations of wheat spike segmentation, extraction of disease color features, disease spot segmentation, and disease grade assessment. Eventually, accurate images of wheat spike and disease spot segmentation and grade information are obtained in the high-throughput wheat population, thus realizing the purpose of real-time monitoring. The exploratory contributions of the method can be summarized as follows:

- Using the multi-scale feature of Deeplab for wheat spike extraction.
- Fine-grained segmentation of disease spots using multi-resolution feature of Hrnet.
- The evaluation method was optimized by the HSV color features as weighting factor.
- Mobile terminal equipped with the all-in-one system to achieve real-time diagnosis.

2. Wheat Fusarium Head Blight

With the rapid development of computer vision technology, digital image processing based on deep learning has been widely applied to wheat crops [12][13][14]. The related research mainly includes four aspects: object segmentation, disease segmentation, disease feature extraction, and severity diagnosis system.

To accurately assess the severity of FHB in individual wheat spikes under field conditions, precise segmentation of each spike area within the complex background is crucial. Researchers worldwide have conducted extensive experiments and research on target segmentation methods, leveraging advancements in neural network performance and structure, resulting in promising achievements. Zhang, et al. [15] developed a pulse-coupled neural network (PCNN) based on the fully convolutional network (FCN) for segmenting wheat spikes infected with FHB. However, only one spike in the image was taken into consideration in the research, which was not practical for high throughput detection in the field environment. Su, et al. [16] and Qiu, et al. [17] developed Mask-RCNN for independent accurate segmentation of wheat spikes with recognition rates reaching 77.76% and 92.01%, respectively. In addition, more advanced deep learning models, such as Fast R-CNN, BlendMask, and YOLOv4, have also been applied to image segmentation of wheat spikes [18][19][20].

Based on the segmented wheat spikelet samples, it is important to effectively distinguish healthy spikelets in the wheat disease region. This step is crucial for accurately grading the severity of FHB in wheat and achieving precise disease classification. Su, Zhang, Yang, Page, Szinyei, Hirsch and Steffenson [16] adopted Mask-RCNN to segment FHB disease spots, whose detection rate was as high as 98.61%, but the related strategies still need to be optimized. Since the color of wheat spikes changes significantly after being infected with FHB, color features are extracted as an auxiliary basis for judging the severity level of erysipelas on top of spot segmentation. For example, Sarayloo and Asemani [21] extracted texture, color and shape features of infected wheat, processed them as effective features for identifying diseases, and finally obtained 98.3% recognition accuracy.

- In a recent study, HSV color threshold extraction was also used to assist the YOLO network in achieving improved accuracy and precision in wheat FHB detection [22].

For the task of estimating the severity of FHB, the deep convolutional neural network (DCNN) model built by Zhang, et al. [23] was successfully used to locate disease spots and to predict the grading with a high degree of accuracy. Furthermore, transfer learning was also used to assess the severity of FHB [24]. The approach can save time and partially address the overfitting problem, but pre-trained large models exhibited significant fluctuations in accuracy when evaluating imbalanced samples. With the growing demand for end devices, such as personal computers and smart agricultural equipment, the development of integrated intelligent diagnostic systems has gradually emerged as a current focal point [25]. Although satisfactory results are reported in the above studies based on deep learning models, there will be a problem in the practical application of disease severity diagnosing due to the high number of parameters, the large storage space, and computational consumption. Recent studies have also deployed light-weight GSEYOLOX-s models on mobile terminals to help farmers identify the severity of FHB in real time [26]. However, considering the small and subtle differences between different FHB severity levels, building a real-time accurate FHB all-in-one system is still a great challenge.

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