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Review of Wheat Disease Classification and Severity Detection Models

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Abstract: Wheat is an important cereal crop that feeds more than a third of the world's population. The yield of wheat depends on various factors. Among them, disease is an important factor affecting the yield and quality of wheat. To combat these diseases, researchers have been studying the use of advanced techniques such as deep plant disease learning and image processing methods for identification. In the current study, there are many researches for wheat disease classification, but less for wheat disease severity recognition or estimate. The existing wheat disease severity detection is basically achieved by classification. Moreover, the same disease shows different symptoms at different periods or at different degrees of infection, which increases the difficulty of disease identification. In order to fully grasp the core technology of wheat disease recognition, this paper reviews the research of deep learning technology in wheat leaf disease classification and wheat disease severity. Special attention is paid to the application of image segmentation technology in wheat disease severity recognition. This paper mainly aims to explain deep learning-based wheat diseases identification algorithm, and to discuss the benefits and drawbacks of present wheat disease detection approaches. The main conclusion is that the classification of wheat diseases and the severity of wheat diseases have made good progress, but they are still in the state of independent research. Hybrid algorithm is a new way and a new challenge to link the two tasks.

Keywords: Classification; Deep learning; Disease severity; Review; Segmentation; Wheat disease.

1. INTRODUCTION

Wheat is one of the world's most important grain crops, providing food for more than 40% of the world's population. Wheat is one of the most important crops in China and has been cultivated in China for more than 5,000 years. Its cultivation area and yield account for more than a quarter of total grain output, while the annual purchase, sale, and inventory of national commodity wheat account for over one-third of total grain [1]. However, many people in the world still face hunger because they do not have enough food. Therefore, new scientific methods are needed to increase wheat yields to meet the growing demand. In agricultural production, disease is a main factor directly affecting plant yield and quality. Wheat diseases seriously affect the yield and quality of wheat [2, 3, 4]. According to the statistics of the Agricultural Research Institute, 6-7% of the annual decline in wheat grain quality is caused by wheat diseases [5]. Wheat diseases not only affect the normal growth of wheat, but also reduce the yield and quality of agricultural products and bring food security problems.

In the computer-aided diagnosis of plant diseases, it is not only necessary to predict the types of diseases, but also to distinguish the severity of diseases. Most of the existing plant disease recognition focuses on the classification of plant diseases. Similarly, the wheat disease classification task can only identify different disease types and cannot detect the severity of the disease. But severity detection researches are all detect one disease. Therefore, the previous wheat disease classification and severity recognition are independent. Whether the classification of diseases and the detection of disease severity can be combined into a model is a problem to be studied. At present, there is no perfect method to accurately and quickly identify the severity of multiple diseases. The integrated application of disease identification and severity still faces some challenges. Although severity detection for multiple diseases is involved in many researches [6, 7, 8, 9], but they are concerned with diseases of different plants. The algorithms used in these studies are designed to classify the severity of different diseases with significant differences between classes and are not suitable for diagnosing multiple disease types with low similarity in a single plant and detecting the fine-grained severity of multiple diseases simultaneously.

Image segmentation assigns a specific category to each pixel. Therefore, image segmentation techniques have a great impact on the performance of any disease detection and classification model [1]. Vishwas *et al.* presents a novel approach for the multi-classification of Wheat Stripe Rust (WSR) disease into five different severity levels using the You Only Look Once version 4 (YOLOv4) model [10]. The model was trained on a dataset of 5000 images and achieved a mean average precision (MAP) score of 0.85 and overall accuracy of 85.98%, demonstrating high accuracy and performance across all severity levels. By quantifying the severity of loose smut in wheat using Mask Region-based Convolutional Neural Networks (MRCNN), Deepak *et al.* [11] achieved a 97.8% F1 score for loose smut identification with bounding boxes. The severity of loose smut has been calculated through the disease severity index. With the help of Disease Severity Index (DSI), a total of 63% severity for loose smut has been estimated in different wheat spikelet.

In this study, relevant techniques for identifying plant diseases based on deep learning and image processing methods are reviewed and a comprehensive analysis is conducted to evaluate their effectiveness in practical applications. In order to detect wheat disease and severity more effectively, the focus of this study is to study the existing classification and segmentation algorithms, and investigate the methods of classification and segmentation fusion to obtain the optimal comprehensive model.

The main contribution of this paper has two aspects. First, the methods of improving model accuracy and lightweight in wheat leaf disease classification literature were compared and analyzed, which provided a theoretical basis for the design of hybrid model with high precision and lightweight at the same time. Second, the existing methods of wheat leaf disease severity were compared and analyzed. The two methods are label classification and area segmentation. The discussion and analysis in this paper are the preparation for the subsequent design of a more accurate multi-disease severity recognition model.

The rest of this systematic literature review is divided into four parts: Section 2 outlines the research background and the types and characteristics of wheat diseases. Section 3 summarizes the main methods and key technologies of deep learning in wheat disease detection. Section 4 focuses on the identification and evaluation methods of disease severity. Lastly, the conclusion of the review and the recommendations on future trends are demonstrated in Section 5.

2. WHEAT DISEASE

The main cause of wheat grain quality loss is damage to the leaf structure, resulting in a decrease in chlorophyll and water concentration in the leaves [12]. There are 38 common wheat diseases, such as powdery mildew, rust, and fusarium head blight (Scab) [4]. Rust is divided into leaf rust, stripe/yellow rust and stem rust. Stripe rust can lead to total output loss of up to 40% [13]. If not controlled and prevented, the wheat rust pathogen can affect 50% to 100% of the crop area [14]. Global losses from rust pathogens are estimated at $5.5 billion per year [15]. Wheat powdery mildew is one of the three most common and devastating diseases in the middle and late stages of the growth and development of wheat. It is characterized by rapid spread, difficulty in prevention and control, and severe yield decline.

The impacts of several illnesses on wheat production were investigated based on the time of disease incidence, the location of disease beginning, and the primary features of disease spots. Table 1 shows an overview of some common wheat leaf diseases and their symptoms characteristics. Wheat diseases have serious impacts on the yield, mild symptoms can cause 10% to 30% reduction, severe symptoms can cause 40% to 50% reduction. The symptoms of various diseases are reflected on the leaves, so observing the leaves is a good way to help us identify different diseases. For example, rust and powdery mildew are different in color, rust is generally yellow and brown; powdery mildew is generally white. In addition to color, the most important and most difficult to distinguish is the shape of the disease spot. Different disease spot shape represents different diseases. Therefore, the shape of the lesion is an important feature to distinguish different diseases. But sometimes, even with the same disease, the shape of the plaques varies greatly at different levels of severity. Here, rust disease is taken as an example for detailed explanation. Leaf rust spots are small spots in the early stage, but it will evolve into a large area in the middle and late stages. At the same time, different rust diseases are very similar in colour and shape, which is the more difficult part of the identification. Therefore, a strong learning ability is needed to be trained on more sample data.

To reduce the impact of disease on crop yield loss, it is becoming increasingly important to recognize, identify, evaluate, and control crop diseases. It has been noticed that over the past decade, image processing has made significant strides. It has been exciting to see how deep learning has been applied to plant disease recognition, particularly through CNN in plant disease imaging. The success in this area has been impressive. AlexNet have achieved a 99.35% accuracy rate in identifying crops and disease types in the Plant Village dataset. In addition, there have been recent advances in the performance of CNNs for diagnosing plant diseases.

3. ADVANCEMENTS OF RESEARCH ON WHEAT DISEASE RECOGNTION

Compared with the early plant disease recognition methods, plant disease recognition based on deep network can automatically preprocess the image, and no longer need to manually process the image, so the efficiency of disease recognition is improved. At the same time, with the increase of network depth, the learning ability of the model is stronger, and the extracted features are richer. However, due to the increase of network depth, the training process will consume a lot of time, and there may be overfitting problems during training. Many researchers try to use CNN-based deep neural networks in plant disease recognition to improve the accuracy of recognition. Over the years, researchers have created several algorithms and strategies for wheat leaf disease detection, and these efforts have generated some very effective applications.

Table 1. The common diseases of wheat and their characteristics

Disease		OccurTime	DiseaseSite	Characteristics	Yield Reduce
Stripe /yellow Rust		During growth period, most serious in the late growth and maturity of the plant	Stem, Leaves and vaginae	Small yellow or orange round spots gradually expand and form large yellow-brown rust spots	up to 50% or more
Leaf/brown Rust		growth period, most serious in the late growth and maturity of the plant	Leaves	Scattered small circular rust spot, yellow orange to brownish red, 0.5-2 millimeter. In severe infections, the entire leaf may be covered with rust spots	up to 40%
Stem/black Rust		spring and autumn	Leaves	Parallel yellow to orange-yellow rust spots, which are usually narrow and appear as long strips	30%-40%
Powdery Mildew		growth period, most serious in the late growth and maturity of the plant	Leaves, stem, ear, and sheath	A white to off-white powdery layer of mycelium appears on the leaves	10%-30%
Septoria Leaf Blotch		growth period, especially in jointing period and grouting period	Leaves	Brown spots, these spots usually appear as small circles or ovals, about 1-3 millimeter in diameter	10%-30%
Tan Spot		growth period, especially in jointing period and grouting period	Leaves	Brown spots, 2-10 millimeter in diameter, these spots may join into strips, overall leaves may be covered with brown	10%-30%
Bacterial Leaf Streak		growth period, especially in jointing period and grouting period	Leaves	Streaks of yellow to brown, may be wavy or form distinct lines, centimeters in length and have blurred edges	15%-20%
Fusarium Head Blight (Scab)		during the flowering stage	wheat spikes	The infected wheat spikes develop bleached or white heads with salmon-pink to orange discoloration at the base.	50%-60%

3.1 Wheat Disease Classification

Thakur *et al.* analyzed 148 literatures on plant diseases and it has been found that deep learning algorithms used in nearly 70% of plant disease identification and classification, in which CNNs contribute about 38% [16]. It is observed in Table 2, the accuracy based on improved CNN is nearly 10 percentage points higher than that of machine learning. It can be seen from the type of disease, most disease detections were based on leaves, because disease changes can be observed easiest on leaves. Various diseases reflect leaves at the early stage. So, it will facilitate early disease detection.

The publicly available diseased leaf datasets are LWDCD2020 [24], WFD2020 [26], Yellow-Rust-19 [14] and CGIAR Dataset [23]. 70% of studies use custom datasets. Part of the data collected from network, and other part was collected on field by camera or phone. Field data can increase the usefulness of the model, and public data can better validate the performance of the model.

Table 2. Related research on wheat disease recognition

Ref	Year	Methodology	Dataset	Accuracy	Disease
[17]	2023	R-CNN, SVM	Customize (1000 images)	96.63%	Leaf Spot
[18]	2023	Xception, U2Net, ResNet -50	Wheat-Stripe-Rust-Dataset (2000 images)	96%	Yellow Rust
[19]	2020	RF, SVM, BPNN	Customize	87.1%	Stripe Rust
[20]	2022	CNN, SGDR-S (stochastic gradient descent with warm restarts)	Customize	-	Wheat Rust
[21]	2023	KM(K-means), Feature, Selection	Data from Iraq DiyalaBaquba Vb	92%	Stripe Rust
[22]	2023	SPA (sub-window permutation analysis) Algorithm, Regressi on	Customize	82.35%	Powdery Mildew
[23]	2021	DCNN	CGIAR Dataset	97%	Leaf Rust, Stripe Rust, Stem Rust
[1]	2021	Watershed, Grab Cut, U2Net	Wheat Stripe Rust	96.19%	Stripe Rust
[24]	2021	SVM, KNN, Random Forest (RF), Decision Tree (DT)	LWDCD2020	97.88%	Leaf and spike
[25]	2021	VGG16, Resnet50, VGG19, InceptionV3,	Customize	99.38%	Leaf Rust, Stripe Rust, Stem Rust
[26]	2021	EfficientNet	WFD2020	94.20%	Leaf Rust, Stripe Rust, Stem Rust, Powdery Mildew
[27]	2022	CNN	Customize	92.30%	Yellow Rust
[28]	2022	CNN, VGG16, ResNet50	Wheat Leaf Rust, Wheat stripe Rust	99.07%	Leaf Rust, Stripe Rust, Stem Rust
[14]	2021	Yellow-Rust-Xception	Yellow-Rust-19	91%	Yellow Rust
[29]	2021	VGG, Mask RCNN	Customize	90.63% (F1)	Stripe Rust
[30]	2020	SVM, VGG16, GoogleNet	Customize	98%	Leaf Rust, Tan Spot
[31]	2020	C-DenseNet	WSR grading Image Dataset	97.99%	Stripe Rust

3.2 Lightweight and Attention Mechanism in Wheat Disease Classification

Lightweight network models are specifically designed for mobile and other low-power devices, thus with low memory requirements and operational complexity. Due to their low model size and computational complexity, they can be trained and inferred on faster computational devices, thus shortening the training time and inference time. The representative ones include MobileNet, ShuffleNet and EfficientNet. However, lightweight networks suitable for mobile deployment are difficult to obtain high precision classification results. The advantage of attentional memory is that it can focus on important image areas and suppress irrelevant information, thus improving the robustness of the model against complex backgrounds and noise. As can be seen from the previous application of lightweight networks, the adoption of attention mechanisms allows lightweight networks to improve accuracy while maintaining a small number of parameters and reasoning time, as shown in Table 3. The recognition accuracy of the improved network is higher than 95%, while attention mechanism was integrated into the MobileNet network. Convolutional block attention module (CBAM) and Squeeze-and-Excitation (SE) are the most frequently used attention machines. While models using Densent and ResNet combined with the attention mechanism achieve greater accuracy, these dense networks are not easy to deploy on mobile devices because of the large number of parameters and computations. Therefore, the combination of lightweight network and attention mechanism is more appropriate.

Through the comparative analysis of the above studies, the current wheat disease research mainly focuses on the symptoms of leaves. CNN, lightweight network model and attention mechanism have been widely used, but few studies have integrated attention mechanism and lightweight model in these studies. In dozens of relevant literatures, only [38, 42] deal with the integration of lightweight model and attention mechanism. Therefore, there are still great research prospects in satisfying both high precision and light weight.

Table 3. Summary of related researches on wheat disease recognition Characteristics

Ref	Year	Methodology	Dataset	Accuracy
[32]	2022	Modified CBAM, residual, Inception	Plant Village	99.55%
[33]	2022	WheCNet (a combination of VGG-16 and a capsule network)	-	98%
[34]	2021	WheatNet (a truncated MobileNetV2)	publicly available wheat database from Global wheat head detection (gwhd) dataset [35]	MAE and RMSE of 3.85 and 5.19
[36]	2020	Self-Attention Convolutional Neural Network (SACNN)	9214 leaf images in 6 classes	95.33%
[37]	2022	(YOLOv4) and MobileNet	866 wheat images stored in the Joint Photographic Experts Group (JPEG) format. the model size was also compressed to 1/5 of the state-of-the-art model	93.69%
[38]	2020	SE, MobileNet	444 images in 25 classes obtained from Rice Dataset. 1645 images in 11 classes from PVD	99.33% 99.78%
[39]	2021	SimpleNet CBAM	total of 568 wheat ear images	94.1%
[27]	2020	DenseNet CBAM	WSR (wheat stripe rust) grading Dataset 5,242 wheat leaves with 6 levels of wheat stripe rust infection.	97.90%
[40]	2022	Attention dense learning (ADL) mechanism	contains 10,851 real-world RGB leaf images of 17 plant species for classifying their 44 distinguished health conditions.	97.33%
[41]	2023	Multi-dilated-CBAM-DenseNet (MDCDenseNet)	PlantVillage and 278 images of leaf blight, 263 of anthracnose, and 315 of healthy.	98.84%
[42]	2021	Deep Fusion of the SE and Depth-Wise Separable Convolution	A total of 2975 images containing 5 kinds of diseased and healthy leaves.	97.01%
[43]	2023	Improved GhostNetV2	Yellow-Rust-19	95.44%

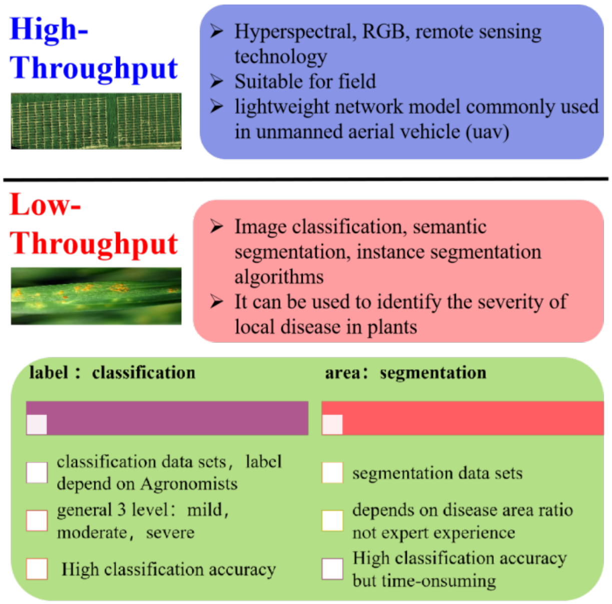

Figure 1. Different methods of disease severity estimate

4. WHEAT DISEASE SEVERITY

The severity classification or disease severity detection in wheat is crucial for effective disease management and cultivar resistance [31]. Currently, the identification of wheat leaf diseases is done through an artificial method that relies on the experience of plant pathology experts through visual inspection [39]. However, this method is both expensive and inefficient, which hinders the progress of modern agriculture [44]. The use of pesticides also becomes problematic due to the slow progress of disease control [31]. To ensure wheat quality and yield, it is necessary to have an effective disease recognition and classification algorithm that accurately identifies wheat leaf diseases and their severity. Conventional deep learning networks cannot achieve the desired performance due to the small and subtle differences between wheat leaves with different infection levels. Therefore, more studies should be done to assess the severity of the disease.

4.1 Evaluation of Wheat Disease Severity

The study on the severity of plant diseases mainly includes two aspects, namely high throughput and low throughput, as shown in Figure 1. Among them, the high-throughput disease research mainly adopts hyperspectral technology, partly adopts the Unmanned Aerial Vehicle (UAV) equipped with cameras to acquire data, and partly adopts remote sensing data. 90% of the studies used offline detection methods, and less than 10% of the studies reported real-time online monitoring, of course, it is very demanding for algorithms and equipment. The second category is based on local images of plants, such as leaves. This type of research can be divided into two ways, one is to use the classification algorithm, the other is to use the segmentation algorithm.

4.2 Application of Segmentation Techniques in Wheat Diseases Detection

The monitoring of wheat yellow rust disease [45] with multispectral RGB images has been monitored through the UNet segmentation technique. The authors [5] use VIA tool for creating masks of leaves. The proposed method utilizes customized UNet model for segmentation followed by convolutional network for classifying the segmented images to ten categories. The accuracy of 98.12%. In [11], a system that achieves a 97.8% F1 score for loose smut identification with bounding boxes was proposed. Hayit *et al.* [14] proposed Yellow-Rust-Xception mode to determine the severity level of yellow rust in wheat among six different severity levels. It is a six-way classification ConvNet model, the model accuracy was 91%. Pan *et al.* [46] proposed an identification method of wheat yellow rust based on UAV images. The method adopted PSPNet semantic segmentation model and weakly supervised learning method to effectively solve the sample labeling problem, and the recognition accuracy reached 98%. In [47], proposed model may have a great potential in stem rust severity estimation with higher accuracy and much less computational cost. The training and testing accuracy of the model reached 98.41% and 96.42% respectively. Gao *et al.* propose a method for wheat stripe rust severity identification that combines Simple Linear Iterative Clustering (SLIC) superpixel segmentation and a random forest algorithm [48]. This method first employs SLIC to segment subregions of wheat stripe rust, automatically constructs and augments a dataset of wheat stripe rust samples based on the segmented patches. Then, a random forest model is used to classify the segmented subregion images, achieving fine-grained extraction of wheat stripe rust lesions. The Random Forest model performs the best, with a classification accuracy of 93.22% and a cross-validation score of 90.47%.

Through reviewing a large number of literatures, it is found that there are few studies on the severity of wheat diseases. Among the 16 literatures found so far, the studies on wheat disease severity mainly focused on Fusarium Head Blight (FHB), Stripe/Yellow Rust, Stem Rust, Powdery Mildew, Wheat Leaf Spot, and Ear Blast, as shown in Table 4.

Table 4. Related researches on wheat disease severity detection

Ref	Year	Algorithm	Disease	Disease severity	Method	Accuracy
[49]	2022	Mask-RCNN (Region based Convolutional Neural Network) + Resnet50 + FPN (Feature Pyramid Network)	FHB	4: healthy, mild, moderate and severe	Area: use segmentation to obtain disease area rate	91.80%
[45]	2020	Mask-RCNN + Resnet101 + FPN		15 FHB severity grades: 0-14	Area: use segmentation to obtain disease area rate	77.9%
[50]	2021	AlexNet + transfer learning + feature fusion		6 levels based on the ratio (R) of wheat ear lesion	Area: use segmentation to obtain disease area rate	90%
[51]	2019	IABC (improved artificial bee colony)-K-PCNN (pulse-coupled neural network with K-means)	Yellow rust / Stripe rust	6 grades: 0-5	Area: use segmentation to obtain disease area rate	92.5%
[14]	2021	Xception + transfer learning		6: 0, R, MR, MRMS, MS, S	Label: make classification labels according to expert experience	91%
[27]	2022	GLCM-LBP (Gray Level Co-occurrence Matrix Local Binary Patterns) machine learning		10: 0 to 9 level 3: healthy, resistant, susceptible	Area: use segmentation to obtain disease area rate	92.3%
[13]	2021	SRGANs (Super Resolution Generative Adversarial Network)		3: healthy, resistant, susceptible	Label: make classification labels according to expert experience	83%%
[31]	2000	C-DenseNet		6: 0-5 level	Label: make classification labels according to expert experience	97.99%
[10]	2023	YOLOv4		5: low, moderate, high, very high, Extreme	make classification labels according to expert experience	85.98%
[18]	2023	U2 Net ResNet-50	Stem rust	4: healthy, resistant, moderate, susceptible	Label: make classification labels according to expert experience	96%
[47]	2021	Proposed a CNN (6 cnov + 5 maxpool + 2 fc)	Stripe rust, powdery m ildew	4: healthy stage, early stage, middle stage, and end stage	Label: make classification labels according to expert experience	96.42%
[52]	2021	Elliptical-Maximum Margin Criterion (E-MMC) metric learning	Leaf diseases	3: mild, moderate, severe	Label: make classification labels according to expert experience	94.16%

[53]	2021	ResNet101 + transfer learning	Spike blast	3: 0%, 0.1–20%, 20.1–100%	Area: use segmentation to obtain disease area rate	94.1%
[5]	2023	Faster R-CNN and SVM	Wheat leaf spot	5: 0-4	Label: make classification labels according to expert experience	96.33%
[11]	2022	Mask RCNN	Powdery mildew	Percentage: 0% – 100%	Area: use segmentation to obtain disease area rate	-
[54]	2020	Machine Learning		3: healthy (level 0, DS < 5%), slight (level 1, 5% < DS < 0%) and serious (level 2, DS > 0%).	Area: use segmentation to obtain disease area rate	93.33%

From the current research results, the accuracy of the severity detection method graded according to expert experience is higher than the accuracy of the segmentation algorithm to calculate the lesion area ratio. The main reason is that in the labeling and grading method based on expert experience, the severity of the disease is generally divided into 3-5 levels, which is relatively rough. The adoption of area ratio classification needs to consider three aspects. First, the accuracy of the segmentation network. Second, there will be some errors in the annotation of the segmentation data set, because many disease spots themselves are relatively small, which is not easy to accurately mark. Third, if there are more levels, the average accuracy will inevitably decrease.

In addition, almost all diseases have small lesions at the initial stage, and there is a large error rate in segmentation and classification, which is also a major challenge we are facing at present. The same analysis and conclusion are also mentioned in several literatures. For example. Su *et al.* [45] divided FHB into 15 grades with an accuracy of only 77.9%, while in other expert classification studies, the accuracy reached 97.99% [31], 85.98% [10], 96% [18], 96.42% [47], 94.16% [39]. In addition, 15 of the 16 articles rated the severity of one of the diseases.

4.3 Discussion of Disease Area Calculate and Disease Severity Evaluation

In terms of disease severity assessment, deep learning techniques can use image segmentation models to precisely locate and quantify disease regions. By segmenting the images of infected plant leaves, the size and density of the damaged area can be calculated to assess the severity of the disease. This quantitative evaluation method is more objective and accurate than the traditional subjective evaluation method, which is helpful for decision makers to formulate targeted disease management programs. Therefore, it is necessary to design a more accurate segmentation model to detect the severity of wheat disease.

In contrast, label classification method is that the disease severity is labeled according to the experience of agronomic experts. Area segmentation method is that segmentation algorithm segmented the spots from the leaves, and then calculate the proportion of the spots. But the label method is not as accurate as the area method. We focused on diseases in wheat leaves. So, the above articles, which most relevant were retained. 58.3% of them adopted label depending on expert experience. From the perspective of accuracy results, the accuracy is relatively high which use label method. As it is only a classification method.

When the area method is used, the following steps are used: segment, calculate Disease Severity (DS) and assign labels according to DS. Even if the accuracy is low, the result is very reliable. After all, it has been segmented at the pixel level. Therefore, the first finding is that the method of area must be adopted if it is to be accurately identified. The second finding is that in previous studies, the severity detection models based on segmentation algorithm are all targeted at one disease.

In addition to wheat, researchers have made great progress in detecting the severity of other plant diseases. For example, fruits (apples, strawberries, pears are mainly for fruit detection; grape, lemon, citrus are for leaf detection), vegetables (tomatoes, potatoes, cassava, cucumbers, beets, etc.), crops (corn, rice, soybeans, etc.) and others (coffee, tea). Among them, the classification method for most of the diseases is similar to that of wheat, which mainly adopts the classification method of direct definition label and the method of segmentation in calculating the area. In addition, the prediction and evaluation are conducted directly by the percentage of disease spots [55].

As in Table 5, most studies use area, or pixels, to calculate the severity of disease. The first step is to obtain the number or area of pixels of the lesion site using segmentation techniques, and then the severity level is obtained by interval classification in the second step. A common phenomenon in these studies is that the accuracy rate is higher in moderate to severe cases than in mild cases. This is also a vulnerability of the current algorithm, that is, the recognition accuracy of small targets is low, and the recognition accuracy of different scale targets is inconsistent. However, in many actual images, the identified objects tend to vary in size and vary greatly. Therefore, how to ensure the recognition accuracy of different scale targets at the same time is a meaningful topic.

Table 5. Disease segmentation, area calculate and disease severity evaluation

Ref	Year	Plant Disease	Grade/Level	CNN Model	Accuracy	Calculation Formula
[52]	2021	Wheat Stripe rust, Powdery mildew	3 levels: Mild, Moderate, Severe	--	94.16%	Elliptic maximum margin criterion (E-MMC) $max \sum_{(x_i, x_j \in D)} d_E(x_i, x_j)^l$ $s.t. \begin{cases} \sum_{(x_i, x_j \in S)} d_E(x_i, x_j) \leq 1 \\ M > 0 \end{cases}$
[53]	2021	Wheat Spike Blast	3: no disease (0% severity, Category 1); moderate severity (0.1–20%, Category 2); high severity (20.1–100%, Category 3).	deep CNNs model	82%	$DS = \frac{A_{Diseased}}{A_{Total}} \times 100$ $A_{Diseased}$ is the proportion of the area of spike that is diseased divided by the total area of the spike A_{Total}.
[56]	2022	Strawberry gray mold disease	Percentage:0%–100%	UNET	98.2%	Disease Severity (%): $DS = \frac{\sum_{i=1}^{n} d_i}{\sum_{j=1}^{m} l_i} \times 100$
[57]	2022	Apple Alternaria leaf blotch	5 grades: Healthy: 0, Early:0–0.95%, Mild:0.95–1.75%, moderate:1.75–3.00% severe :3.00–100%	confusion matrix and the Lin's correlation coefficient	96.41%	$P = \frac{S_D}{S_L}$
[58]	2022	Grape black measles	3 levels: Mild, Medium, Severe	DeepLabV3+ ResNet50 Fuzzy Logic	97.75%	$POI = \frac{Disease\ leaf\ area}{Total\ leaf\ area} \times 100$ $POI = \frac{Pixel\ size\ of\ symptoms\ or\ injuries}{Pixel\ size\ of\ total\ leaf} \times 100$ $S = \begin{cases} S_{little}(x) = (5-x)/5, & 0 < x \leq 5 \\ S_{medium}(x) = \begin{cases} x/5, & 0 < x \leq 5 \\ (10-x)/5, & 5 < x \leq 10 \end{cases} \\ S_{much}(x) = (x-5)/5, & 5 < x \leq 10 \end{cases}$
[59]	2020	Rice Blight, Brown Spot and Leaf Smut	Percentage: 0%–100%	MobileNet UNet	85.7%	Severity (%) = $\frac{Area\ of\ Diseased\ spots}{Area\ of\ leaf} \times 100$
[60]	2023	Rice brown spot, blast, and bacterial blight	6 levels: 0-5	EfficientNet-B0	96.43%	Severity Quantification (%) = $\frac{\sum Disease\ of\ fected\ bounding\ box\ area(TDA)}{\sum Total\ leaf\ bounding\ box\ area(TLA)} \times 100$
[49]	2021	Potato late blight	Percentage: 0%–70%	SegNet	-	AUDPC (area under disease progression Curve) = $\sum_{i=0}^{3} A_{(i+1)}*(A_{(i+1)}-A_{(i)})$
[61]	2021	Cucumber leaf disease	6 levels: L0-L5 L0: P =0, L1: 0<P<0.05, L2: 0.05<P<0.1, L3: 0.1<P< 0.25, L4: 0.25<P<0.5, L5: 0.5<P<1.	DeepLabV3+ and U-Net	92.85%	$P = \frac{S_{Diseased}}{S_{Leaf}}$ $PA = \frac{\sum_{i=0}^{k} P_{ii}}{\sum_{i=0}^{k} \sum_{j=0}^{k} P_{ij}}$ while $k = 1$, segment leaves from the background.

[62]	2016	Betel Leaf Rot	percentage	Otsu segmentation	Precision 100 % recall 83.33%	Calculated by applying Otsu method on 3H′ component of HVS color space for image segmentation. Segmented binary image is consisting of the rotted area in white pixels.
[63]	2019	maize	percentage 3 levels: low POI, Medium POI, High POI	Segmentation and Fuzzy Logic	-	$POI = \frac{D_{LA}}{T_{LA}} \times 100$
[64]	2022	Pear Appearance quality	3 levels: A B C	Mask R-CNN, DeepLabV3+ and Resnet50 ResNet50, VGG16 and MobileNetV3	99.58% 95.97%	$P = \frac{S_{Diseased}}{S_{pear}}$ $RPA = \frac{\sum_{i=0}^{k} P_{ii}}{\sum_{i=0}^{k}\sum_{j=0}^{k} P_{ij}}$
[55]	2022	Maize Bipolaris maydis	5 levels:0-4	DISENet Multi-Scale Attention Mechanism	97.12%	$k = \frac{A_1}{A} = \frac{N_1}{N}$ A is the whole leaf area of the crop, A_1 is the lesion area, N is the number of pixels of the whole leaf, and N_1 is the number of pixels of the lesion area.
[65]	2021	Cucumber	percentage	lightweight deep learning architecture with Modified ReLU	93.75%	$\text{Extend} = \frac{\sum_i P_{i,diseased}}{\sum_i P_{i,diseased} + \sum_i P_{i,green}} \times 100$

After getting the proportion of disease spots, the next step is how to get the mapping relationship between the proportion of lesions and the level of severity. The existing mapping relationships can be summarized as direct mapping, user-defined segmentation mapping, fuzzy logic mapping, etc., according to various representations in table 5. However, it does not matter whether the simple mapping such as direct mapping and piecewise mapping or the complex mapping such as fuzzy logic rules, the mapping relationship is not convenient to modify when used in different situations, especially when fuzzy logic is applied to other fields, new rules need to be defined. Therefore, other mappings can be considered simpler and can be easily modified according to the actual situation.

5. CONCLUSION

This study provided an overview of wheat leaf disease categorization and severity identification algorithms. To detect wheat diseases quickly and accurately, previous researches have proposed various computer vision-based methods, such as machine learning and deep learning, which have been proven to be highly effective in detecting these diseases quickly and accurately. However, there are three problems that need to be solved in the existing wheat disease recognition.

a) The previous wheat disease severity detection and disease classification tasks are stand alone. Comprehensive identification and detection have a certain role in promoting the high degree of automation of smart agriculture.
b) Neither a single segmentation algorithm nor a multi-label classification algorithm can achieve accurate disease classification and pixel-level accurate assessment of severity at the same time.
c) The existing deep learning algorithms involve many parameters and slow reasoning speed, which are not suitable for mobile terminal deployment. However, lightweight networks suitable for mobile deployment are difficult to obtain high-precision classification results. Therefore, it is necessary to make comprehensive use of the advantages of different network models to improve accuracy while keeping the number of parameters small and the inference time.

The public and local custom data sets have been compared and analyzed in this paper. The methods of improving model accuracy and lightweight in literature are presented. The present wheat leaf disease severity recognition approaches were discussed, and the two primary disease severity recognition methods, as well as their benefits and drawbacks, were analyzed and summarized. In summary, research on disease identification and severity recognition of wheat diseases faces many challenges. Overcoming these problems will require fuse computer vision, deep learning, and related technologies, combined with practical application requirements, to achieve accurate, efficient, interpretable, and applicable plant disease diagnosis systems.

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DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest with respect to the research and publication of this article.

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