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Disease Detection In Rice And Wheat Leaves: A Comparative Study On Various Deep Learning Techniques

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ABSTRACT

Rice and wheat are considered as the most significant foods in agriculture all over the globe. Around 50% of all calories consumed in the human diet are rendered by both rice and wheat. Rice is a rich source of carbohydrates that is the main energy source of the human body. Wheat, which comprises vitamins and minerals, is a staple food source. Also, wheat is extensively used as flour to make a variety of food products. However, the disease that occurs in the leaves of rice and wheat could decelerate the production of these two food sources. Thus, timely detection of disease that occurs within the rice and wheat leaves is very significant. To detect Rice Leaf Diseases (RLD) and Wheat Leaf Diseases (WLD), numerous conventional methods are established. Specifically, You Only Look Once (YOLO), Faster Region-based Convolutional Neural Network (FRCNN), and Single Shot Detector (SSD) are extensively implemented in various works to detect diverse leaf diseases in rice and wheat plants. Therefore, in this review, the merits and demerits of the traditional Object Detection (OD) models in RLD and WLD detection are provided systematically. The robustness of the Deep learning (DL) techniques in detecting various kinds of leaf diseases in rice and wheat plants with a classification accuracy of 99% and a precision of 98% is proved by the analysis outcomes.

Key words: Rice Leaf Diseases (RLD), Wheat Leaf Diseases (WLD), Leaf disease detection, Comparative study, Classification models, Deep learning techniques, and Object detection.

1. INTRODUCTION

Agriculture is the backbone and vital source of income for many people in India and numerous global countries; also, the global food systems are highly interconnected among those countries [1]. The major food sources of the global food systems for human survival are plants and crops. Hence, taking care of plants and crops is very significant [2]. The most important factor of the global food system is Food Security (FS), which also states that “all people have physical, social, and economic access to sufficient and nutritious food to meet their dietary needs for an active and healthy life at all times” [3]. More than half of the global population consumes rice as the primary food source. Rice is a major staple food. Moreover, wheat, which is utilized as a raw material for numerous food industries worldwide, is another major staple food [4]. Wheat is enriched with vitamins and minerals and rice is enriched with carbohydrates that are crucial for the human body [5]. Nevertheless, rice and wheat plants are easily susceptible to several diseases and pests. A significant factor that also affects the growth of the paddy and wheat crops is climatic changes, namely unseasonal rainfall and temperature variations.

To protect healthy plants from diseased plants, quick detection of diseased plants is very important [6]. For sustainable and correct agriculture, the timely detection of plant disease is significant. Majority of the plant diseases display visible symptoms; some plant diseases do not have any visible symptoms [7]. Therefore, manual detection of plant diseases is a slow and inaccurate process. Hence, numerous Machine Learning (ML) and DL techniques have been developed in the last 10 years for an early, quick, and accurate diagnosis and detection of plant diseases [8]. In the following Figure 1, the process of the plant disease detection models is displayed.

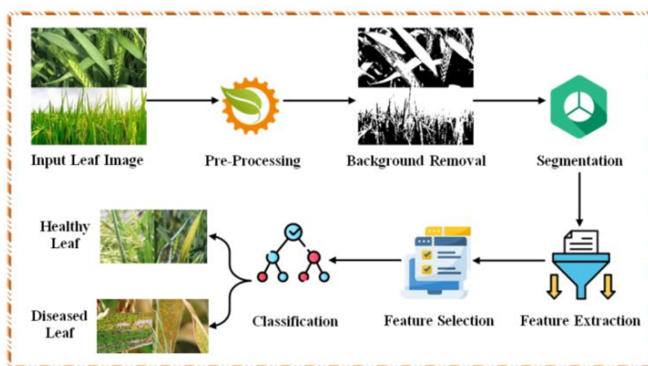

Figure 1: Process of Plant disease detection

Some of the OD algorithms utilized to detect numerous types of plant diseases are some prevailing techniques, namely YOLO, Convolutional Neural Network (CNN), Region-based CNN (RCNN), FRCNN, EfficientNet, and SSD [9]. These established models categorized healthy and diseased plants efficiently by modifying the prevailing models and processing them centered on the optimal features from the sample images [10]. Nevertheless, they had problems, such as some models being only effectual for small areas, inadequate data availability, varying image quality, and augmented training time. For addressing all these difficulties, in this study, the prevailing OD models are surveyed and a brief description of the pros and cons of the diverse plant disease detection models is provided. Figure 2 presents this comparative study's architecture.

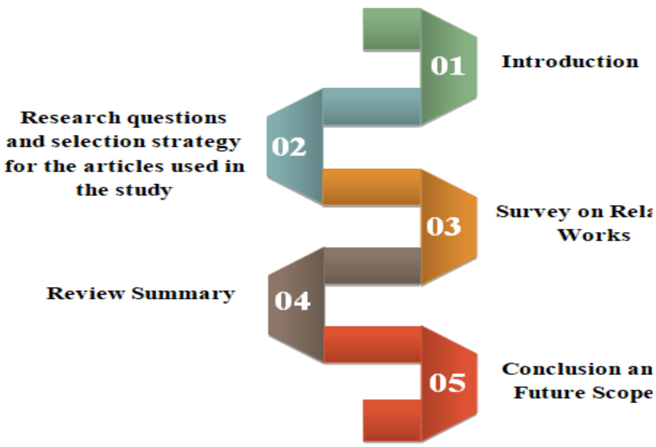

Figure 2: Architecture of the study

2. RESEARCH QUESTIONS AND SELECTION STRATEGY FOR THE ARTICLES USED IN THE STUDY

This comparative study is performed in a way to understand the merits and demerits of the numerous plant disease detection mechanisms. All the research questions are also taken in a way that signifies the study's objective. To answer the research questions, the prevailing models' articles are chosen. The selection strategy renders various criteria to choose the articles that are utilized in the study.

2.1. Research questions

- Describe various leaf diseases occurring in rice and wheat plants.
- How leaf diseases in rice and wheat plants are a threat to global FS?
- What are the numerous inputs taken to detect diseases in rice and wheat leaves?
- State some databases utilized to assess leaf disease detection mechanisms in rice and wheat plants.
- How OD models are utilized to detect diseases in rice and wheat leaves?
- What are the different DL mechanisms used for detecting RLD and WLD?
- Which is an effective OD approach in detecting leaf diseases in rice and wheat plants?

2.2. Article selection strategy

The inclusion criteria for selecting articles are as follows:

- The articles associated with the study's objective are taken for the survey.
- All the articles are selected centered on the appropriate keywords associated with the study's objective.
- The articles are chosen centered on the synonyms of the objective and the keywords of the survey.
- The articles are collected from standard search engines like IEEE, Springer, and Elsevier, as well as from article sources in Google Scholar.
- For the survey, the articles published between the time period of 2017 and 2023 were only selected.
- Only English-written articles are chosen for the analysis.

The exclusion criteria for the article selection process are:

- The articles published before 2017 were neglected for the survey.
- Other than the English language articles are not chosen for the analysis.
- The articles without the objective of the rice and wheat plant leaf disease detection mechanism are omitted.

In Figure 3, the graphical representation of the selection strategy of the articles for the study is rendered.

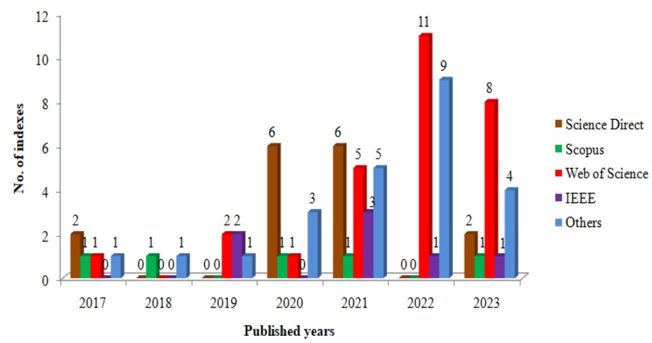

Figure 3: Graphical representation of article selection strategy

3. LITERATURE SURVEY

To detect leaf diseases occurring in rice and wheat plants, several methods were implemented. The overview of diverse diseases occurring in the rice and wheat leaves is presented in Section 3.1, the impact of leaf diseases in rice and wheat plants on global FS is discussed in Section 3.2, the numerous inputs taken to detect RLD and WLD are explained in Section 3.3, the details about the datasets used to evaluate leaf disease detection mechanisms are provided in Section 3.4, some OD approaches utilized in RLD and WLD detection mechanisms are stated in Section 3.5, various DL methodologies utilized to detect RLD and WLD are described in Section 3.5.1, and the overall performance and comparison evaluation of the OD techniques in RLD and WLD detection are presented in Section 3.5.2.

3.1. Overview of different diseases that occur in rice and wheat leaves

The major reason for the reduction in the quality and quantity of rice and wheat production is crop diseases [11]. Pests and fungal, viral, and bacterial diseases threaten and affect agriculture and forestry [12]. In general, diseases occur on any crop at any time; thus, continuous monitoring may aid in preventing the crops from diseases and pests [13]. For reducing the severity of the diseases, it is essential to detect diseases in the early stage [14]. In this segment, the overview of some popular leaf diseases that occur in rice and wheat plants is explained.

Md. Ashiqul Islam *et al.* [15] established an automated paddy leaf disease detection technique with Deep-CNN. The developed Deep-CNN handled the feature extraction and classification. 4 paddy diseases, such as Brown spot, Leaf blight, Leaf smut, and Bacterial leaf blast were classified by the developed model. As per the analysis, this model achieved efficient accuracy in detecting paddy leaf diseases. Nevertheless, the developed model detected only 4 different RLDs, which reduced the model's efficiency than top-notch models.

Usha Kiruthika *et al.* [16] propounded a paddy leaf disease detection and classification model utilizing DL approaches. The framework was initiated by preprocessing the input image, followed by recognizing the disease types like brown spots, leaf blasts, and bacterial blight utilizing the Gray Level Co-occurrence Matrix (GLCM) and Artificial Neural Network (ANN). As per the experimental investigation, the developed model was an effective model for detecting paddy diseases. However, the developed model's training time was higher, making the model infeasible to detect the disease symptoms.

M.N. Abu Bakar *et al.* [17] presented an integrated method to detect rice leaf blast disease utilizing an image processing method. By image segmentation, the developed model extracted the Region of Interest (ROI); also, the pattern recognition was centered on a multi-level thresholding technique. According to the analysis, the framework detected the rice leaf blast disease successfully; however, the model was inefficient in detecting the other diseases, which also had similar features. Table 1 describes the analyses of different leaf diseases occurring in rice and wheat plants.

Table 1: Analyzing different rice and wheat leaf diseases

Reference	**Crops**	**Techniques**	**Diseases identified**	**Accuracy (%)**	**Demerits**
Tolga Hayit *et al.* [18]	Wheat	SVM and KNN	Wheat yellow rust	92.4	The model's efficacy is affected by capturing only grayscale images.
Ruoling Deng *et al.* [19]	Rice	CNN and ensemble model	False smut, leaf blast, neck blast, bacterial stripe disease, sheath blight, and brown spot	91	The ensemble approach had more processing parameters, affecting the disease identification speed.
Megan Long *et al.* [20]	Wheat	CerealConv model and CNN	Yellow rust, brown rust, powdery mildew, and Septoria leaf blotch	97.05	High calculation load.
Zhihui Li *et al.* [21]	Wheat	GhostNet V2	Wheat yellow rust	95.44	Trained with a limited number of samples.
Long Tian *et al.* [22]	Rice	SVM	Rice leaf blast	95	Utilized an ineffective feature extractor, which was not robust over physical changes.
Habib Khan *et al.* [23]	Wheat	RFC	Brown and yellow wheat rust	99.8	Misclassification problem.
Mikhail A. Genaev *et al.* [24]	Wheat	EfficientNet-B0 neural network	Stem rust, leaf rust, yellow rust, Septoria, and powdery mildew	94.2	Lower sensitivity.
Tianxiang Zhang *et al.* [25]	Wheat	Ir-UNet	Wheat yellow rust	97.13	Augmented computational load and less robustness.
N. Bharanidharan *et al.* [26]	Paddy	MLOA	Rice blast, brown leaf spot,	90	Limited area coverage.

			leaf folder, hispa, and bacterial leaf blight		

In Table 1, different leaf diseases and the techniques utilized for detecting the leaf diseases in rice and wheat plants are presented. Here, the achievements and disadvantages of diverse leaf disease detection techniques were discussed. Support Vector Machines (SVM), Random Forest Classification (RFC), Modified Lemurs Optimization Algorithm (MLOA), K-Nearest Neighbors (KNN), Irregular Segmentation U-Shape Network (Ir-UNet), CNN, and ensemble model are the leaf disease detection methods that are used.

Anting Guo *et al.* [27] established an identification model for detecting wheat yellow rust utilizing the hyperspectral images' spectral as well as texture features. The healthy and yellow rust-infected samples were detected by SVM, which used 6 optimum wavebands, 4 vegetation indices, and 4 textural features. As per the analysis, this model significantly achieved effective accuracy in identifying the wheat yellow rust. However, the cost and complexity of utilizing the developed model were higher.

Yang Lu *et al.* [28] presented an RLD detection methodology centered on image classification techniques and a Weight Cooperative Self-Mapping Chaos Optimization Algorithm (WOACW). Centered on the WOACW-SimpleNet, the framework detected rice blasts, bacterial leaf blight, brown spot disease, sheath blight, and tungro diseases. According to the analysis outcomes, the developed model performed better than the other top-notch models by achieving dynamic detection accuracy and F1-score. However, the developed system's hyperparameters affected the model's efficiency.

3.2. Impact of leaf diseases in rice and wheat plants on global food security

Global FS has 4 dimensions, such as availability, accessibility, utilization, and stability. Global food insecurity is caused by instability in food production [29] [30]. In this section, the impact of the RLD and WLD on global FS is explained.

Zhiwen Mi *et al.* [31] established a wheat stripe rust detection model by DL with an attention mechanism. The wheat stripe rust posed serious threats to FS by affecting the wheat-yielding ratio and quality. To detect wheat stripe rust, a Convolutional block attention module-DenseNet (C-DenseNet) was implemented by the framework. As per the analysis outcomes, this system attained a more robust performance compared to other top-notch disease detection models. Nevertheless, the developed model's significance was considerably decreased under a complex background.

Chowdhury R. Rahman *et al.* [32] introduced an identification and recognition model for disease as well as pest detection in rice plants. The FS of the global population was affected by rice diseases. For detecting and recognizing rice diseases and pests, the framework used Visual Geometry Group-16 (VGG16) and InceptionV3. According to the performance analysis, efficient detection accuracy was achieved by the developed model. However, the system could lose the symptom classes while training.

Ahmed Elaraby *et al.* [33] established a DL approach for wheat plant disease detection. The framework utilized AlexNet for feature extraction and Particle Swarm Optimization (PSO) for feature selection. The plant diseases were a serious threat to FS through huge crop loss and reducing the crop yield's quality and quantity. The system's robustness was exhibited by this system's experimental analysis. Yet, owing to the varying image sizes, the developed model had a higher inference time.

3.3. Different inputs taken for detecting rice and wheat leaf diseases

The detection mechanisms to identify various diseases in the rice and wheat leaves were centered on diverse inputs. From natural field images, hyperspectral Unmanned Aerial Vehicles (UAV) images, and grayscale images, the sample inputs were taken [34]. Here, the analysis for different leaf disease detection models grounded on their input samples is discussed.

Wenxia Bao *et al.* [35] established a WLD and its severity level identification model by utilizing the elliptical-maximum margin criterion. By utilizing the Otsu method, the framework segmented the disease spot centered on the WLD images. The developed model's superiority was stated by the experimental analysis outcomes. But, for training and assessment, the framework did not use any standard databases.

Meenakshi Aggarwal *et al.* [36] introduced a lightweight federated learning for the RLD classification centered on non-independent and identically distributed images. To effectively select the features for disease classification, EfficientNetB3 was implemented by the framework. As per the performance analysis, the developed model attained significantly higher accuracy in disease classification. However, this model's implementation in the real-time application was complex.

Uferah Shaf *et al.* [37] established a framework to classify wheat yellow rust disease. Primarily, by utilizing mobile cameras, the yellow rust disease wheat's grayscale images were gathered. After that, by using a Decision Tree, RFC, Light Gradient Boosting Machine (LightGBM), Extreme Gradient Boosting (XGBoost), and CatBoost, the yellow rust was classified. According to the analysis outcomes, the framework was obtained with effective classification accuracy. Nevertheless, since the texture features did not render sufficient information for the classification, the utilization of texture features only reduced the developed model's performance efficiency. The evaluation of different leaf disease detection models based on their utilized input samples is presented in Table 2.

Table 2: Evaluation of different leaf disease detection model based on their inputs

References	**Methods**	**Inputs**	**Detection accuracy (%)**	**Challenges**
Xin Zhang *et al.* [38]	DCNN	Hyperspectral UAV Images	85	The number of learning parameters was augmented with the number of layers, which led to exploding gradients in the training process.
Yang Lu *et al.* [39]	CNN	Natural images of diseased and healthy rice leaves	95 .48	The model's convergence speed was slower, which resulted in local minima.
Anting Guo *et al.* [40]	Partial Least-Squares Regression (PLSR)	UAV-based hyperspectral images	82	The developed model's accuracy in the early stages was lower, which was ineffective in preventing diseases.

3.4. Different datasets utilized for the evaluation of rice and wheat leaf disease detection mechanisms

Centered on some standard datasets, the RLD and WLD detection systems were trained and assessed. For training, testing, and evaluation purposes of the classification models, the datasets render samples [41]. This phase discusses numerous plant disease datasets used in different RLD and WLD detection models.

Prabira Kumar Sethy *et al.* [42] established deep feature-centric RLD detection utilizing SVM. To identify RLD, the framework utilized some features that were extracted from 11 Deep-CNN (DCNN) models. The performance analysis was employed with the on-field dataset with 5932 diseased rice leaf images. The developed model's efficacy over other top-notch models was stated by the analysis outcomes. Nevertheless, the developed model was ineffective for large crop areas.

Md. Sazzadul Islam Prottasha and Sayed Mohsin Salim Reza [43] introduced a classification model to identify rice plant diseases utilizing CNN. Through fine-tuning eight top-notch CNN architectures, the framework detected 12 types of rice plant diseases. The framework's performance was evaluated centered on the Rice leaf Disease Dataset (RDD) and attained significant accuracy in diagnosing rice plant diseases. However, the model was a slow-processed model. Table 3 indicates numerous datasets utilized to evaluate leaf disease detection models.

Table 3: Describing different datasets used in rice and wheat leaf disease detection

Author	**Purpose**	**Dataset**	**Image samples**	**Challenges**
Ahmed S. Almasoud *et al.* [44]	Paddy leaf disease detection and classification	RDD	120	Higher training time.
SK Mahmudul Hassan and Arnab Kumar Maji [45]	Plant diseases identification	PV dataset, RDD, and cassava dataset	PV- 54306 RDD- 5932 cassava-5656	Required a larger amount of labeled data for training.
Maryam Saberi Anari [46]	Leaf disease detection	PV dataset	90,000	Increased execution time.
Vinay Gautam *et al.* [47]	Paddy leaf disease identification	PV dataset	1500	Higher complexity.
Yasamin Borhani *et al.* [48]	Automated plant disease classification	Wheat rust classification dataset, RDD, and PV dataset	Wheat rust classification-3679 RDD-120 PV- 54306	Ineffectual after some iterations.

Jiang Lu *et al.* [49] established an infield automatic wheat disease diagnosis model with an infield image dataset and wheat disease database in 2017. To diagnose wheat diseases, the deep multiple instances learning system was used along with 2 conventional CNN architectures. As per the outcomes of the experimental analysis, the developed model performed better than the conventional CNN structures. However, the model suffered in capturing relative spatial information for the diagnosis.

Shivani Machha *et al.* [50] introduced a classification model for the WLD diagnosis system. For the classification of WLD, MobileNet was used. The experimental analysis was done by utilizing the PlantVillage (PV) dataset, and it led to accurate outcomes for the diagnosis of WLD. But, owing to varying sample sizes, the developed model had overfitting problems.

3.5. Purpose of object detection techniques in rice and wheat leaf disease detection

In the RLD along with WLD detection, the OD algorithms were used for locating the instances of the diseases in the sample images. In this segment, some of the extensively utilized OD algorithms in RLD and WLD detection are investigated, which is exhibited in Figure 4.

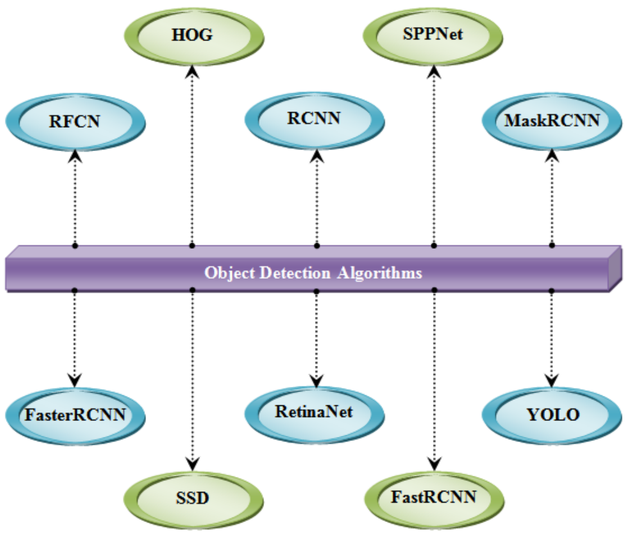

Figure 4: Object detection algorithms

(i). YOLO: It was used for its speed and accuracy in detecting objects in images. The image is divided into a grid system by YOLO, which also detects the objects within the grids. YOLO performs the detection and classification simultaneously and has less error than other OD models [51]. The YOLO has diverse types of architecture, which are discussed further with its benefits and challenges.

Kantip Kiratiratanapruk *et al.* [52] presented an automatic detection model for rice diseases based on different leaf sizes. To automatically estimate the sizes of the leaves in the sample images, YOLOv4, a single-shot CNN-based OD model, was integrated with the image tiling technique. According to the analysis, the developed YOLOv4 model enhanced the RLD detection's mean Average Precision (mAP) effectively. However, owing to the processing of various parameters, the memory consumption by the developed model was higher.

Liangquan Jia *et al.* [53] introduced an enhanced YOLOv7 algorithm for rice pests as well as disease recognition. The framework used a lightweight network MobileNetV3 and attention mechanisms for extracting features and enhancing detection accuracy, respectively. As per the performance analysis, the developed model attained significantly higher accuracy and mAP in detecting RLD. Nevertheless, for processing tiny objects and too many objects in an image, the model's efficiency was slightly reduced.

Siddhi Jain *et al.* [54] established an automatic rice disease detection framework in the form of a Smartphone application termed E-crop Doctor. To detect brown spots, leaf blasts, and hispa in rice leaves, the efficiency of YOLOv3 tiny and YOLOv4 tiny algorithms was investigated. As per analysis outcomes, the developed system's performance was considerably higher. However, YOLOv3 tiny had possibilities for missing some diseases during detection.

Nilamadhab Mishra *et al.* [55] proffered an ant lion-centric YOLOv5 model for the prediction and classification of paddy leaf diseases. For extracting form, texture, and color features from the input image, the grey-level co-occurrence matrix was utilized. As per the performance analysis, the developed model performed better than the conventional models with its robust accuracy. Nevertheless, owing to augmented parameters, the developed model had a higher false detection rate.

(ii). FRCNN: The FRCNN is a 2-stage DL-based OD model. Primarily, the FRCNN identified the images' ROI. After that, for the disease classification, output feature maps were passed via SVM [56]. The purpose of FRCNN in RLD and WLD detection was investigated as follows,

Bifta Sama Bari *et al.* [57] established a real-time diagnosis model for RLD utilizing a DL-based FRCNN framework. To clearly address the object location, the developed FRCNN used regional proposal network architecture. According to the experimental analysis, the developed model could effectively identify healthy leaves and detect the three classes of RLD. Yet, in the developed model, the hispa's tiny portions were not detected, thus significantly decreasing the model's efficiency.

Rutuja Rajendra Patil *et al.* [58] propounded an artificial intelligence-based RLD detection and severity estimation model. For the evaluation of the area of the leaf instance and infected region, the framework utilized the FRCNN. The analysis of the developed model's performance stated the developed model's robustness by achieving significant accuracy, sensitivity, and specificity in disease detection. However, due to gradient explosion parameters, the developed model's computational cost was higher.

WU Wei *et al.* [59] presented a detection model for wheat diseases centered on FRCNN. For the development of FRCNN, the developed model utilized a TensorFlow framework. The framework was trained with diverse input images in a complex background. As per the analysis outcomes, the developed model was less error-prone but computationally expensive than the other top-notch models.

Guoxiong Zhou *et al.* [60] implemented a rapid rice disease detection model centered on the fusion of Fuzzy C-Means and K-Means (FCM-KM) clustering algorithms and FRCNN. For determining the different sizes of the target frames in the image, the FCM-KM was used. According to the experimental analysis, the developed approach was more capable of detecting rice diseases with reduced detection time. However, the developed model had local optimum problems. In Table 4, some other OD algorithms were investigated.

Table 4: Analyzing different OD algorithms in rice and wheat leaf diseases

Reference	**Algorithms**	**Objects detected**	**Achievements**			**Drawbacks**
			mAP (%)	**Accuracy (%)**	**Recall (%)**	
Faruq Aziza and Ferda Ernawan [61]	SSD and FRCNN	Detecting RLD	89	94	83	Less accurate with higher surrounding interference.
Dr. J A Shaikh and Dr. K. P. Paradeshi [62]	Histogram of oriented gradient	Texture and color feature extraction	-	98.85	-	Ineffective for large-scale RLD detection.
Riki Ruli A. Siregar *et al.* [63]	YOLO	Predict bounding boxes and identify objects	69	94	-	Higher false positive rate.
Denghao Pang *et al.* [64]	RetinaNet	Detect and locate wheat spider mites	81.7	-	90.2	Augments the amount of computation and parameters.
Md Ershadul Haque *et al.* [65]	YOLOv5	RLD classification and detection	76	-	67	Time-consuming model.
Sitao Liu *et al.* [66]	Mask RCNN	Recognition of insects and pests	92.72	-	89.28	Temporal information was not efficiently explored.
V Senthil Kumar *et al.* [67]	YOLOv5	Detect and classify RLD	82.8	94.87	75.81	The small objects in the image were not detected.
Jingbo Li, Changchun Li *et al.* [68]	RetinaNet and FRCNN	Predict WLD	-	82	-	Class imbalance problem.

3.5.1. DL techniques for detecting rice and wheat leaf diseases

To detect numerous diseases that affect the rice and wheat plant's growth and production, DL techniques were used [69]. Regarding the accurate identification of the RLD and WLD, the DL techniques achieved effective performance [70]. The DL techniques render early diagnosis of the disease, which is very effective for taking preventive measures [71]. The conventional DL techniques were investigated and assessed further.

Feng Jiang *et al.* [72] established an image recognition model for RLD detection based on DL and SVM. Initially, for the extraction of the image features, the CNN was utilized in the developed model. Thereafter, for the detection of the specific RLD, the SVM was utilized. According to the analysis outcomes, the developed model's performance was considerably higher when compared to conventional models. Yet, the segmentation results from the developed model were not satisfactory.

Rafia Mumtaz *et al.* [73] introduced integrated digital image processing methods and DL techniques for wheat stripe rust disease detection. Single-band and dual-band processing, image segmentation, and image cropping were the image processing methods. As per the performance analysis, the developed model attained an effective performance in detecting wheat stripe rust. However, for training and processing, the developed model needed a large amount of computational requirements. In Table 5, the analysis of DL techniques in detecting different RLDs and WLDs is presented.

Table 5: Analysis of DL techniques in detecting rice and wheat leaf diseases

References	**DL techniques**	**Objective**	**Datasets**	**Detection accuracy (%)**	**Demerits**
Lakshay Goyal *et al.* [74]	DCNN	Wheat leaf and spike disease detection	Large Wheat Disease Classification Dataset 2020	98.62	Overfitting problem.
Wenxia Bao *et al.* [75]	Lightweight CNN	Wheat disease detection	PV	94.1	Large processing data was required.
Mengping Dong *et al.* [76]	Differential amplification CNN	WLD identification	WLD dataset	95.18	Need higher execution requirements.

Rahul Sharma *et al.* [77]	CNN	RLD diagnosis and classification	RDD	99.58	Inaccurate with highly similar diseases.
Ghazanfar Latif *et al.* [78]	DCNN	Detection of rice plant diseases	RDD	96.08	Expensive model for its complex architecture.
Mariela Fernandez-Campos *et al.* [79]	DCNN	Wheat spike blast disease detection	Wheat spike image classification dataset	90.1	Time-consuming model.

Shankarnarayanan Nalini *et al.* [80] established a paddy leaf disease detection model by utilizing an enhanced Deep Neural Network (DNN). The classification error in the DNN model was mitigated by optimizing the weights along with biases utilizing the Crow search algorithm. This model's robustness in the paddy leaf disease was stated by the analysis outcomes. Nevertheless, the developed model attained significantly lower performance in real-time applications compared to the training time performance.

3.5.2. Performance evaluation of different object detection techniques in rice and wheat leaf disease detection

The robust OD model is estimated by the prevailing models' overall performance assessment. In this segment, some effective OD algorithms used in the detection of RLD and WLD are indicated, and their performances are tabulated in Table 6.

Table 6: Performance evaluation of existing works

Techniques	mAP (%)
YOLOv7[54]	97.36
FRCNN[58]	92
SSD and FRCNN[61]	89
RetinaNet[64]	81.7
MaskRCNN[66]	92.72

In Table 6, the overall performance evaluation of OD algorithms based on mAP obtained for detecting RLD and WLD is described. The OD algorithms like YOLOv7 [54], FRCNN [58], SSD and FRCNN [61], RetinaNet [64] and MaskRCNN [66] have been investigated. The YOLOv7 [54] achieved the highest mAP of 97.36% in the above analysis, whereas the MaskRCNN [66] obtained a mAP of 92.72% in detecting leaf disease. Next, FRCNN [61] attained the next highest mAP rate of 92%. Lastly, the SSD and FRCNN [61] and RetinaNet [64] have the lowest mAP of 89% and 81.7%, respectively. In Figure 5, the graphical representation of the comparison evaluation of the traditional works is presented.

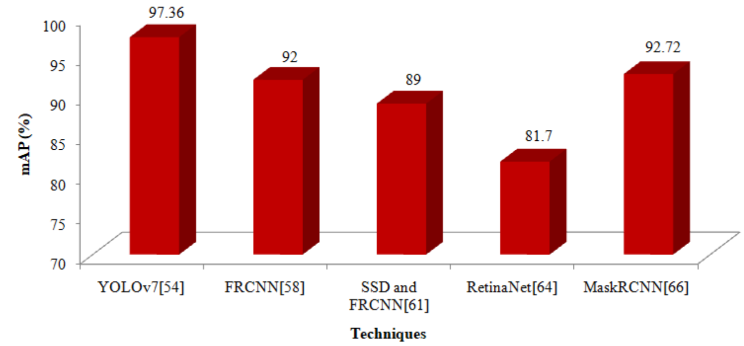

Figure 5: Comparison evaluation of the existing works

In Figure 5, the comparison assessment of the existing OD methodologies utilized to detect RLD and WLD is described. It is clear from the figure that in RLD and WLD detection, the YOLOv7 [54] achieved the highest mAP of 97.36%. Hence, in the analysis, the efficacy of the developed YOLOv7 is proved.

4. REVIEW SUMMARY

Rice and wheat are considered as the major food crops and consistent food sources for humans globally. These food sources are a significant factor, which ensures global FS. However, rice and wheat plants are easily susceptible to more fungal, viral, and bacterial diseases and numerous pest attacks. The crops' overall growth and yield are affected by the diseases and pests. The global food system is severely affected by the reduction in crop production. Thus, early and timely diagnosis and identification of RLD and WLD are very crucial. In this comparative study, several DL-centric OD algorithms in RLD and WLD detection models are effectively explained. The merits and demerits of the traditional leaf disease detection models are studied under 7 research questions; also, the whole study is performed in a way to answer the seven questions. Initially, in section 3.1, the different RLD and WLD are overviewed, which is under research question one. Next, in section 3.2, the impact of the RLD and WLD on global FS is discussed to render a response to the second question. After that, the third question is taken to know about various inputs used to detect plant diseases, which is explained in section 3.3. Thereafter, to understand different datasets employed for the evaluation of the disease detection models, the fourth question is used, and it is described in section 3.4. Then, in section 3.5, different OD algorithms are analyzed and compared to know the robustness OD model. Afterward, in section 3.5.1, different DL techniques were investigated. Lastly, in section 3.5.2, the performances of the OD algorithms are analyzed. As per overall performance, the YOLOv7 [54] had the highest mAP (97.36%). Then, the second-highest mAP (92.72%) in detecting leaf diseases is obtained by MaskRCNN [66]. After that, the next highest mAP (92%) is attained by FRCNN [61]. Finally, FRCNN [61] attained the next highest mAP of 92%. Finally, the SSD and FRCNN [61] and RetinaNet [64] have the lowest mAP of 89% and 81.7%, respectively. Hence, the effective approaches for leaf disease detection models are assessed, and those models's robustness is proved in the performance analysis.

5. CONCLUSION

In this survey, the detection of RLD and WLD by utilizing DL-based OD algorithms is studied. Numerous DL and OD algorithms, which are used for the detection of RLD and WLD, are briefly investigated in this study. The developed models' experimental analysis is centered on utilizing some standard datasets, namely PV, RDD, and WLD classification datasets. The assessment outcomes stated the developed models' efficacy with accuracy of 99%, precision of 98%, recall of 90.2%, and mAP of 97.36% for leaf disease detection. According to the overall performance evaluation, since YOLOv7 attains an mAP of 97.36% in detecting RLD and WLD, it is the robust OD model. Hence, the pros and cons of the different DL techniques and OD algorithms in the detection of RLD and WLD are rendered by the whole survey.

FUTURE RECOMMENDATIONS

In the analysis, the effective detection of RLD and WLD by using the developed model is explained. However, the major issues in most of the developed works are higher time consumption and misclassification. Thus, works will be developed in the future in a way to enhance the model's efficiency by finding the spreading characteristics of the diseases caused by plant pathogens.

REFERENCES

1. Gudeta W Sileshi and Solomon Gebeyehu, "**Emerging infectious diseases threatening food security and economies in Africa**", Global Food Security, vol. 28, pp. 1-9, 2021.
2. Yousef Methkal Abd Algani, Orlando Juan Marquez Caro, Liz Maribel Robladillo Bravo, Chamandeep Kaur, Mohammed Saleh Al Ansari and Kiran Bala B, "**Leaf disease identification and classification using optimized deep learning**", Measurement: Sensors, vol. 25, pp. 1-6, 2023.
3. Savary S, Bregaglio S, Willocquet L et al., "**Crop health and its global impacts on the components of food security**", Food Security, vol. 9, pp. 311-327, 2017.
4. Hridoy Ul Awall Rezvi, Md Tahjib-Ul-Arif, Md Abdul Azim, Toufica Ahmed Tumpa, Mohammad Monirul Hasan Tipu, Farhana Najnine, Mona FA Dawood, Milan Skalicky and Marian Brestic, "**Rice and food security: Climate change implications and the future prospects for nutritional security**", Food and Energy Security, vol. 12, no. 1, pp. 1-17, 2022.
5. Surabhi Lingwal, Komal Kumar Bhatia and Manjeet Singh Tomer, "**Image-based wheat grain classification using convolutional neural network**", Multimedia Tools and Applications, vol. 80, pp. 35441-35465, 2021.
6. Swathika R, Srinidhi S, Radha N and Sowmya K, "**Disease identification in paddy leaves using CNN based deep learning**", Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 04-06 February, Tirunelveli, India, 2021.
7. Umit Atila, Murat Ucar, Kemal Akyol and Emine Ucar, "**Plant leaf disease classification using EfficientNet deep learning model**", Ecological Informatics, vol. 61, pp. 1-17, 2020.
8. Aziiba Emmanuel Asibi, Qiang Chai and Jeffrey A Coulter, "**Rice blast: A disease with implications for global food security**", Agronomy, vol. 9, no. 8, pp. 1-14, 2019.
9. Nanehkaran YA, Defu Zhang, Junde Chen, Yuan Tian and Najla Al-Nabhan, "**Recognition of plant leaf diseases based on computer vision**", Journal of Ambient Intelligence and Humanized Computing, pp. 1-18, 2020. https://doi.org/10.1007/s12652-020-02505-x
10. Hassan Raza Bukhari, Rafia Mumtaz, Salman Inayat, Uferah Shafi, Ihsan Ul Haq, Syed Mohammad Hassan Zaidi and Maryam Hafeez, "**Assessing the impact of segmentation on wheat stripe rust disease classification using computer vision and deep learning**", IEEE Access, vol. 9, pp. 164986-165004, 2021.
11. Waleej Haider, Aqeel-Ur Rehman, Nouman M Durrani and Sadiq Ur Rehman, "**A generic approach for wheat disease classification and verification using expert opinion for knowledge-based decisions**", IEEE Access, vol. 9, pp. 31104-31129, 2021.
12. Juliano P Goncalves, Francisco AC Pinto, Daniel M Queiroz, Flora MM Villar, Jayme GA Barbedo and Emerson M Del Ponte, "**Deep learning architectures for semantic segmentation and automatic estimation of severity of foliar symptoms caused by diseases or pests**", Biosystems Engineering, vol. 210, pp. 129-142, 2021.
13. Harshadkumar B Prajapati, Jitesh P Shah and Vipul K. Dabhi, "**Detection and classification of rice plant diseases**", Intelligent Detection Technology, vol. 11, no. 3, pp. 357-373, 2017.
14. Gayathri Devi T and Neelamegam P, "**Image processing based rice plant leaves diseases in Thanjavur, Tamil Nadu**", Cluster Computing, vol. 22, pp. 13415-13428, 2018.
15. Ashiqul Islam, Nymur Rahman Shuvo, Muhammad Shamsojjaman, Shazid Hasan, Shahadat Hossain and Tania Khatun, "**An automated convolutional neural network based approach for paddy leaf disease detection**", International Journal of Advanced

Computer Science and Applications, vol. 12, no. 1, pp. 280-288, 2021.

16. Usha Kiruthika, Kanagasuba Raja S, Jaichandran R and Priyadharshini C, "**Detection and classification of paddy crop disease using deep learning techniques**", International Journal of Recent Technology and Engineering, vol. 8, no. 3, pp. 4353-4359, 2019.
17. Abu Bakar MN, Abdullah AH, Abdul Rahim N, Yazid H, Misman SN and Masnan MJ, "**Rice leaf blast disease detection using multilevel colour image thresholding**", Journal of Telecommunication, Electronic and Computer Engineering, vol. 10, no. 1-15, pp. 1-6, 2018.
18. Tolga Hayit, Hasan Erbay, Fatih Varcin, Fatma Hayit and·Nilufer Akci, "**The classification of wheat yellow rust disease based on a combination of textural and deep features**", Multimedia Tools and Applications, vol. 82, pp. 47405–47423, 2023.
19. Ruoling Deng, Ming Tao, Hang Xing, Xiuli Yang, Chuang Liu, Kaifeng Liao and Long Qi, "**Automatic diagnosis of rice diseases using deep learning**", Frontiers in Plant Science, vol. 12, pp. 1-15, 2021.
20. Megan Long, Matthew Hartley, Richard J Morris, James KM Brown, "**Classification of wheat diseases using deep learning networks with field and glasshouse images**", Plant Pathology, vol. 72, no. 3, pp. 536-547, 2022.
21. Zhihui Li, Xin Fang, Tong Zhen and Yuhua Zhu, "**Detection of wheat yellow rust disease severity based on improved GhostNetV2**", Applied Sciences, vol. 13, no. 17, pp. 1-19, 2023.
22. Long Tian, Bowen Xue, Ziyi Wang, Dong Li, Xia Yao, Qiang Cao, Yan Zhu, Weixing Cao and Tao Cheng, "**Spectroscopic detection of rice leaf blast infection from asymptomatic to mild stages with integrated machine learning and feature selection**", Remote Sensing of Environment, vol. 257, pp. 1-16, 2021.
23. Habib Khan, Ijaz Ul Haq, Muhammad Munsif, Mustaqeem, Shafi Ullah Khan and Mi Young Lee, "**Automated wheat diseases classification framework using advanced machine learning technique**", Agriculture, vol. 12, no. 8, pp. 1-20, 2022.
24. Mikhail A Genaev, Ekaterina S Skolotneva, Elena I Gultyaeva, Elena A Orlova, Nina P Bechtold and Dmitry A Afonnikov, "**Image based wheat fungi diseases identification by deep learning**", Plants, vol. 10, no. 8, pp. 1-21, 2021.
25. Tianxiang Zhang, Zhiyong Xu, Jinya Su, Zhifang Yang, Cunjia Liu, Wen-Hua Chen and Jiangyun Li, "**Ir-UNet: Irregular segmentation U-shape network for wheat yellow rust detection by UAV multispectral imagery**", Remote Sensing, vol. 13, no. 19, pp. 1-20, 2021.
26. Bharanidharan N, Sannasi Chakravarthy SR, Harikumar Rajaguru, Vinoth Kumar V, Mahesh TR and Suresh Guluwadi, "**Multiclass paddy disease detection using filter-based feature transformation technique**", IEEE Access, vol. 11, pp. 109477-109487, 2023.
27. Anting Guo, Wenjiang Huang, Huichun Ye, Yingying Dong, Huiqin Ma, Yu Ren and Chao Ruan, "**Identification of wheat yellow rust using spectral and texture features of hyperspectral images**", Remote Sensing, vol. 12, no. 9, pp. 1-17, 2020.
28. Yang Lu, Xinmeng Zhang, Nianyin Zeng, Wanting Liu and Rou Shang, "**Image classification and identification for rice leaf diseases based on improved WOACW_SimpleNet**", Frontiers in Plant Science, vol. 13, pp. 1-18, 2022.
29. Alexander Johannes, Artzai Picon, Aitor Alvarez-Gila, Jone Echazarra, Sergio Rodriguez-Vaamonde, Ana Díez Navajas and Amaia Ortiz-Barredo, "**Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case**", Computers and Electronics in Agriculture, vol. 138, pp. 200-209, 2017.
30. Chinna Gopi Simhadri and Hari Kishan Kondaveeti, "**Automatic recognition of rice leaf diseases using transfer learning**", Agronomy, vol. 13, no. 4, pp. 1-24, 2023.
31. Zhiwen Mi, Xudong Zhang, Jinya Su, Dejun Han and Baofeng Su, "**Wheat stripe rust grading by deep learning with attention mechanism and images from mobile devices**", Frontiers in Plant Science, vol. 11, pp. 1-11, 2020.
32. Chowdhury R Rahman, Preetom S Arko, Mohammed E Ali, Mohammad A Iqbal Khan, Sajid H Apon, Farzana Nowrin and Abu Wasif, "**Identification and recognition of rice diseases and pests using convolutional neural networks**", Biosystems Engineering, vol. 194, pp. 112-120, 2020.
33. Ahmed Elaraby, Walid Hamdy and Madallah Alruwaili, "**Optimization of deep learning model for plant disease detection using particle swarm optimizer**", Computers, Materials & Continua, vol. 71, no. 2, pp. 4019-4031, 2022.
34. Ammar Kamal Abasi, Sharif Naser Makhadmeh, Osama Ahmad Alomari, Mohammad Tubishat and Husam Jasim Mohammed, "**Enhancing rice leaf disease classification: A customized convolutional neural network approach**", Sustainability, vol. 15, no. 20, pp. 1-18, 2023.
35. Wenxia Bao, Jian Zhao, Gensheng Hu, Dongyan Zhang, Linsheng Huang and Dong Liang, "**Identification of wheat leaf diseases and their severity based on elliptical-maximum margin criterion metric learning**", Sustainable Computing: Informatics and Systems, vol. 30, pp. 1-9, 2021.
36. Meenakshi Aggarwal, Vikas Khullar, Nitin Goyal, Abdullah Alammari, Marwan Ali Albahar and Aman

Singh, "**Lightweight federated learning for rice leaf disease classification using non independent and identically distributed images**", Sustainability, vol. 15, no. 16, pp. 1-20, 2023.

37. Uferah Shafi, Rafia Mumtaz, Ihsan Ul Haq, Maryam Hafeez, Naveed Iqbal, Arslan Shaukat, Syed Mohammad Hassan Zaidi and Zahid Mahmood, "**Wheat yellow rust disease infection type classification using texture features**", Sensors, vol. 22, no. 1, pp. 1-21, 2022.
38. Xin Zhang, Liangxiu Han, Yingying Dong, Yue Shi, Wenjiang Huang, Lianghao Han, Pablo González-Moreno, Huiqin Ma, Huichun Ye and Tam Sobeih, "**A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images**", Remote Sensing, vol. 11, no. 13, pp. 1-16, 2019.
39. Yang Lu, Shujuan Yi, Nianyin Zeng, Yurong Liu and Yong Zhang, "**Identification of rice diseases using deep convolutional neural networks**", Neurocomputing, vol. 267, pp. 378-384, 2017.
40. Anting Guo, Wenjiang Huang, Yingying Dong, Huichun Ye, Huiqin Ma, Bo Liu, Wenbin Wu, Yu Ren, Chao Ruan and Yun Geng, "**Wheat yellow rust detection using uav-based hyperspectral technology**", Remote Sensing, vol. 13, no. 1, pp. 1-22, 2021.
41. Basavaraj S Anami, Naveen N Malvade and Surendra Palaiah, "**Deep learning approach for recognition and classification of yield affecting paddy crop stresses using field images**", Artificial Intelligence in Agriculture, vol. 4, pp. 12-20, 2020.
42. Prabira Kumar Sethy, Nalini Kanta Barpanda, Amiya Kumar Rath and Santi Kumari Behera, "**Deep feature based rice leaf disease identification using support vector machine**", Computers and Electronics in Agriculture, vol. 175, pp. 1-9, 2020.
43. Sazzadul Islam Prottasha and Sayed Mohsin Salim Reza, "**A classification model based on depth wise separable convolutional neural network to identify rice plant diseases**", International Journal of Electrical and Computer Engineering, vol. 12, no. 4, pp. 3642-3654, 2022.
44. Ahmed S Almasoud, Abdelzahir Abdelmaboud, Taiseer Abdalla Elfadil Eisa, Mesfer Al Duhayyim, Asma Abbas Hassan Elnour, Manar Ahmed Hamza, Abdelwahed Motwakel and Abu Sarwar Zamani, "**Artificial intelligence-based fusion model for paddy leaf disease detection and classification**", Computers, Materials & Continua, vol. 72, no. 1, pp. 1391-11407, 2022.
45. Mahmudul Hassan SK and Arnab Kumar Maji, "**Plant disease identification using a novel convolutional neural network**", IEEE Access, vol. 10, pp. 5390-5401, 2022.
46. Maryam Saberi Anari, "**A hybrid model for leaf diseases classification based on the modified deep transfer learning and ensemble approach for agricultural AIoT-based monitoring**", Computational Intelligence and Neuroscience, vol. 2022, pp. 1-15, 2022.
47. Vinay Gautam, Naresh K Trivedi, Aman Singh, Heba G Mohamed, Irene Delgado Noya, Preet Kaur and Nitin Goyal, "**A transfer learning-based artificial intelligence model for leaf disease assessment**", Sustainability, vol. 14, no. 20, pp. 1-19, 2022.
48. Yasamin Borhani, Javad Khoramdel and Esmaeil Najafi, "**A deep learning based approach for automated plant disease classification using vision transformer**", Scientific Reports, vol. 12, no. 1, pp. 1-10, 2022.
49. Jiang Lu, Jie Hu, Guannan Zhao, Fenghua Mei and Changshui Zhang, "**An in-field automatic wheat disease diagnosis system**", Computers and Electronics in Agriculture, vol. 142, pp. 369-379, 2017.
50. Shivani Machha, Nikita Jadhav, Himali Kasar and Sumita Chandak, "**Crop leaf disease diagnosis using convolutional neural network**", International Research Journal of Engineering and Technology, vol. 7, no. 2, pp. 2558- 2561, 2020.
51. Riki Ruli A Siregar, Teuku Rifki Dhulul Fata and Indrianto, "**Detection of brown spot and leaf blight in rice with the you only look once (YOLO) algorithm**", Jurnal Pengkajian dan Penerapan Teknik Informatika, vol. 16, no. 1, pp. 117-130, 2023.
52. Kantip Kiratiratanapruk, Pitchayagan Temniranrat, Wasin Sinthupinyo, Sanparith Marukatat and Sujin Patarapuwadol, "**Automatic detection of rice disease in images of various leaf sizes**", arXiv, pp. 1-28, 2022. https://arxiv.org/pdf/2206.07344.pdf
53. Liangquan Jia, Tao Wang, Yi Chen, Ying Zang, Xiangge Li, Haojie Shi and Lu Gao, "**MobileNet-CA-YOLO: An improved YOLOv7 based on the MobileNetV3 and attention mechanism for rice pests and diseases detection**", Agriculture, vol. 13, no. 7, pp. 1-18, 2023.
54. Siddhi Jain, Rahul Sahni, Tuneer Khargonkar, Himanshu Gupta, Om Prakash Verma, Tarun Kumar Sharma, Tushar Bhardwaj, Saurabh Agarwal and Hyunsung Kim, "**Automatic rice disease detection and assistance framework using deep learning and a Chatbot**", Electronics, vol. 11, no. 14, pp. 1-18, 2022.
55. Nilamadhab Mishra, Seetha J, Arra Ganga Dinesh Kumar, Supriya Menon M, Ananda Ravuri, "**Design an ant lion-based Yolo-V5 model for prediction and classification of paddy leaf disease**", International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 6, pp. 599-612, 2023.
56. Faruq Aziz and Ferda Ernawan, "**Object detection for diagnosis rice leaf diseases using YOLO method**",

Communications in Science and Technology, pp. 1-7, 2023. https://repository.nusamandiri.ac.id/repo/files/243342/download/CST_Object-Detection-for-Diagnosis-Rice-Leaf-Diseases-Using-YOLO-Method.pdf

57. Bifta Sama Bari, Nahidul Islam, Mamunur Rashid, Jahid Hasan, Mohd Azraai Mohd Razman, Rabiu Muazu Musa, Ahmad Fakhri Ab Nasir and Anwar PP Abdul Majeed, "**A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework**", PeerJ Computer Science, vol. 7, pp. 1-27, 2021.
58. Rutuja Rajendra Patil, Sumit Kumar, Shwetambari Chiwhane, Ruchi Rani and Sanjeev Kumar Pippal, "**An artificial-intelligence-based novel rice grade model for severity estimation of rice diseases**", Agriculture, vol. 13, no. 1, pp. 1-19, 2023.
59. Wu Wei, Yang Tian-Le, Li Rui et al., "**Detection and enumeration of wheat grains based on a deep learning method under various scenarios and scales**", Journal of Integrative Agriculture, vol. 19, no. 8, pp. 1998-2008, 2020.
60. Guoxiong Zhou , Wenzhuo Zhang, Aibin Chen, Mingfang He and Xueshuo Ma, "**Rapid detection of rice disease based on FCM-KM and Faster R-CNN fusion**", IEEE access, vol. 7, pp. 143190-143206, 2019.
61. Yunusa Haruna, Shiyin Qin and Mesmin J Mbyamm Kiki, "**An improved approach to detection of rice leaf disease with GAN-based data augmentation pipeline**", Applied Sciences, vol. 13, no. 3, pp. 1-22, 2023.
62. Ashutosh Kumar Singh, SVN Sreenivasu, USBK Mahalaxmi, Himanshu Sharma, Dinesh D Patil and Evans Asenso, "**Hybrid feature-based disease detection in plant leaf using convolutional neural network, Bayesian optimized SVM, and random forest classifier**", Journal of Food Quality, vol. 2022, pp. 1-16, 2022.
63. Shaikh JA and Paradeshi KP, "**Faster R-CNN based rice leaf disease detection method**", Telematique, vol. 21, no. 1, pp. 5890-5901, 2022.
64. Denghao Pang, Hong Wang, Peng Chen and Dong Liang, "**Spider mites detection in wheat field based on an improved RetinaNet**", Agriculture, vol. 12, no. 12, pp. 1-14, 2022.
65. Ershadul Haque, Ashikur Rahman, Iftekhar Junaeid, Samiul Ul Hoque and Manoranjan Paul, "**Rice leaf disease classification and detection using YOLOV5**", arXiv, pp. 1-16, 2022. https://doi.org/10.48550/arXiv.2209.01579
66. Sitao Liu, Shenghui Fu, Anrui Hu, Pan Ma, Xianliang Hu, Xinyu Tian, Hongjian Zhang and Shuangxi Liu, "**Research on Insect pest identification in rice canopy based on GA-Mask R-CNN**", Agronomy, vol. 13, no. 8, pp. 1-18, 2023.
67. Senthil Kumar V, Jaganathan M, Viswanathan A, Umamaheswari M and Vignesh J, "**Rice leaf disease detection based on bidirectional feature attention pyramid network with YOLO v5 model**", Environmental Research Communications, vol. 5, pp. 1-18, 2023.
68. Jingbo Li, Changchun Li, Shuaipeng Fei, Chunyan Ma, Weinan Chen, Fan Ding, Yilin Wang, Yacong Li, Jinjin Shi and Zhen Xiao, "**Wheat ear recognition based on RetinaNet and transfer learning**", Sensors, vol. 21, no. 14, pp. 1-21, 2021.
69. Qian Pan, Maofang Gao, Pingbo Wu, Jingwen Yan and Shilei Li, "**A deep-learning-based approach for wheat yellow rust disease recognition from unmanned aerial vehicle images**", Sensors, vol. 21, no. 19, pp. 1-17, 2021.
70. Zhongqi Lin, Shaomin Mu, Feng Huang, Khattak Abdul Mateen, Minjuan Wang, Wanlin Gao and Jingdun Jia, "**A unified matrix-based convolutional neural network for fine-grained image classification of wheat leaf diseases**", IEEE Access, vol. 7, pp. 11570-11590, 2019.
71. Yang Li, Tianle Qiao, Wenbo Leng et al., "**Semantic segmentation of wheat stripe rust images using deep learning**", Agronomy, vol. 12, no. 12, pp. 1-11, 2022.
72. Feng Jiang, Yang Lu, Yu Chen, Di Cai and Gongfa Li, "**Image recognition of four rice leaf diseases based on deep learning and support vector machine**", Computers and Electronics in Agriculture, vol. 179, no. pp. 1-9, 2020.
73. Rafia Mumtaz, Muhammad Hassan Maqsood, Ihsan ul Haq, Uferah Shafi, Zahid Mahmood and Mustafa Mumtaz, "**Integrated digital image processing techniques and deep learning approaches for wheat stripe rust disease detection and grading**", Decision Analytics Journal, vol. 8, pp. 1-14, 2023.
74. Lakshay Goyal, Chandra Mani Sharma, Anupam Singh and Pradeep Kumar Singh, "**Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture**", Informatics in Medicine Unlocked, vol. 25, pp. 1-8, 2021.
75. Wenxia Bao, Xinghua Yang, Dong Liang, Gensheng Hu and Xianjun Yang, "**Lightweight convolutional neural network model for field wheat ear disease identification**", Computers and Electronics in Agriculture, vol. 189, pp. 1-15, 2021.
76. Mengping Dong, Shaomin Mu, Aiju Shi, Wenqian Mu and Wenjie Sun, "**Novel method for identifying wheat leaf disease images based on differential amplification convolutional neural network**", International Journal of Agricultural and Biological Engineering, vol. 13, no. 4, pp. 205-210, 2020.
77. Rahul Sharma, Amar Singh, Kavita, Jhanjhi NZ, Mehedi Masud, Emad Sami Jaha and Sahil Verma, "**Plant disease diagnosis and image classification**

using deep learning", Computers, Materials & Continua, vol. 71, no. 2, pp. 2125-2140, 2022.

78. Ghazanfar Latif, Sherif E Abdelhamid, Roxane Elias Mallouhy, Jaafar Alghazo and Zafar Abbas Kazimi, **"Deep learning utilization in agriculture: Detection of rice plant diseases using an improved CNN model**", Plants, vol. 11, no. 17, pp. 1-17, 2022.
79. Mariela Fernandez-Campos, Yu-Ting Huang, Mohammad R Jahanshahi, Tao Wang, Jian Jin, Darcy EP Telenko, Carlos Gongora-Canul and Cruz CD, "**Wheat spike blast image classification using deep convolutional neural networks**", Frontiers in Plant Science, vol. 12, pp. 1-14, 2021.
80. Shankarnarayanan Nalini, Nagappan Krishnaraj, Thangaiyan Jayasankar, Kalimuthu Vinothkumar, Antony Sagai Francis Britto, Kamalraj Subramaniam and Chokkalingam Bharatiraja, "**Paddy leaf disease detection using an optimized deep neural network**", Computers, Materials & Continua, vol. 68, no. 1, pp. 1117-1128, 2021.