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Rice Leaf Diseases Detection Using YOLOv8

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Abstract

The development of rice plants holds immense importance today as it impacts crucial aspects of life such as food security, agricultural advancement, and the economy of nations. Consequently, research on disease detection in rice plants, particularly using machine learning, is gaining popularity. Several diseases pose a threat to rice leaves, with Leaf Blast, Leaf Folder, and Brown Spot being the most common ones, directly affecting crop cultivation and causing yield loss. In this study, we propose the utilization of deep learning, the state-of-the-art image processing solution, to address this issue. Our proposed method consists of two steps: first, collecting reliable dataset by approaching and capturing direct images of rice leaf diseases in the fields, and second, designing and training an Artificial Intelligence (AI) model using the YOLOv8 algorithm to detect and classify the three aforementioned diseases. The data set used in this study includes 3175 images, divided into three parts, of which the training part is 2608 images, the validation part is 326 images and the test part is 241 images. Our experimental results demonstrate an accuracy up to 88.9% for the proposed model.

Keywords: Leaf Blast, Leaf Folder, Brown Spot, YOLOv8, deep learning.

1. Introduction

Rice stands as a cornerstone of global nutrition, supporting billions of people worldwide. In the face of climate change, Vietnam confronts a dual challenge: adapting to shifting environmental conditions and combatting the increasing threat of rice diseases. The nation's agriculture, deeply intertwined with rice cultivation, grapples with altered rainfall patterns, rising temperatures, and the amplified risk of extreme weather events. Concurrently, diseases like *Leaf Blast*, *Brown Spot*, and *Leaf Folder* exert escalating pressure on rice yields. This intersection of climatic shifts and disease escalation underscores the urgency of early detection mechanisms. Early identification becomes a linchpin for devising responsive strategies that safeguard crops against the mounting threats. As the climate continues to evolve, the application of advanced technologies, including artificial intelligence for swift disease detection, assumes a critical role in securing the future of rice farming in Vietnam and addressing the global challenge of food scarcity.

Several notable studies in this research area include study involving the detection of diseases in cucumber plants based on the application of the YOLOv4 network for leaf image analysis [1]. This study achieved an accuracy rate of over 80% with more than 7,000 images. However, since this research only utilized the Convolutional Neural Network (CNN) model, the accuracy is still limited. Additionally, other studies have focused on diseases in tea leaves using YOLOv7 [2], and the model was evaluated on metrics including accuracy, precision, recall, mAP, and F1-score, and the results are 97.3%,96.7%, 96.4%, 98.2% and 0.965 respectively. The application of disease detection in bell pepper leaves utilize YOLOv5 is also mentioned [3] covering the bacterial spots that appear on the paper leaves, and the classification of apple tree health conditions through leaf analysis using EfficientNet and DenseNet [4]. Although these studies achieved high accuracy, they do not specifically address individual diseases. Moreover, for rice plants, Krishnamoorthy N *et al*. [5] utilized the InceptionResNetV2 convolutional neural network model with transfer learning methods to identify diseases with reasonable accuracy. Furthermore, Ruyue Li *et al*. in [6] combined deep learning methods with genomic, physiological, and biochemical factors to identify multiple diseases in rice leaves.. YOLOv5 was utilized in the study [7, 8] to identify a few common varieties of rice leaf diseases.

These methods can achieve high accuracy, as demonstrated by the previously mentioned papers, but their practical applications are limited. In addition to being highly applicable to rice, our suggested approach can also be extended to other plants and crops.

In our paper, we suggest employing the YOLOv8 model to detect leaves affected by three prevalent rice diseases in Vietnam: *Leaf Blast*, *Leaf Folder*, and *Brown Spot*.

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1.1. Leaf Blast

Leaf Blast, induced by the fungus Magnaporthe oryzae, has the potential to impact various components of a rice plant's aerial structures, encompassing the leaf, collar, node, neck, specific regions of the panicle, and occasionally the leaf sheath. Symptoms of *Leaf Blast* disease will appear on leaves and leaf collars. Leaf Symptoms are when leaf lesions are diamond-shaped, ranging from 0.39 to 0.58 inches (1.0–1.5 cm). They have a gray/white center and brown/reddish-brown border, with variations in color and size based on plant factors. *Leaf Blast* may lead to the death of young plants up to the tillering stage, peaking early in the season and declining later. Leaf Collar Symptoms are when infections at the leaf blade-sheath junction cause brown "collar rot." Severe cases may result in complete leaf death. (Fig. 1)

Fig. 1. Leaf Blast.

1.2. Leaf Folder

Leaf Folder (Fig. 2) is made by *Leaf Folder* caterpillars. Recognizing the leaf folder involves noting the flat, oval-shaped eggs with a yellowish-white tint. During the larval stage, the insect adopts a greenish, translucent appearance, and in adulthood, the moth presents a yellowish-brown hue marked by dark wavy lines at the center and a pronounced dark band along the wing margin.

Damage indicators from the *Leaf Folder* include the distinctive behavior of larvae, which longitudinally fold leaves while remaining concealed inside. Furthermore, the larvae scrape green tissues, leading to a whitening and drying effect. In severe cases, widespread infestations result in the entire field exhibiting a scorched appearance.

Fig. 2. Leaf Folder.

1.3. Brown Spot

Brown Spot is a fungal disease that affects rice plants, causing infection in the leaves, sheaths, and shoots. One of the distinctive symptoms of this disease is the formation of multiple large lesions on the leaves, which can lead to leaf mortality. In cases where the infection occurs in seeds, incomplete seed development or the presence of discolored and spotted seeds may be observed.

Fig. 3 illustrates the characteristic features of *Brown Spot*, depicting small round lesions of yellow-brown or brown color on young rice plants. As the plants mature, larger brown lesions with a gray center and reddish-brown borders become apparent on the leaves. These lesions can induce wilting in susceptible rice varieties, while on resistant varieties, they are smaller and brown in color. To effectively manage and control *Brown Spot*, meticulous monitoring and appropriate control measures are crucial.

Fig. 3. Brown Spot.

2. Proposed Method

2.1. Overview of YOLOv8 Model

From [9-11] we can see in the Table 1 are the performance of three different types of architectures that ran on Jetson AGX Orin:

Table 1: Performance of different models

	Image Size	Parameter (M)	FLOPs (B)	FPS
YOLO v8n	640	3.2	8.7	383
YOLO v5n	640	1.9	4.5	370
YOLO v7-tiny	640	6.2	13.8	290

From the table, while YOLOv7 is clear unfit for low-cost devices, the other two is more eligible for these types of hardware, take note that although having higher parameters, YOLOv8 is still able to perform better, and for this advantage we decided to dive deeper into the research of YOLOv8

2.2. Data Preparation

The Vietnam National University of Agriculture (VNUA) rice field provided the dataset for this study. In all, 1634 photos were taken in the university's experimental field. This number is somewhat low because the field's primary objective was to test rice plant variations rather than diseases. Three diseases-*Leaf Folder, Leaf Blast*, and *Brown Spot*-that are frequently seen in Vietnamese rice fields are depicted in the dataset. The diseases in the dataset have been verified by the university's experts (Fig. 4). Both cloudy and light rainy conditions as well as sunny weather with temperatures between 39 and 40 degrees Celsius were present when the photos were taken. However, the dataset lacks images that were captured on heavy windy days, and the images will sometimes be blurry because they were captured when the camera position was against the light, this can make the images extremely blurry.

There are three sections in our dataset which include the training set, validation set, and test set, each part has 2608, 326, and 241 images respectively. In total there are 3175 images, in these images, there are 1634 images that were taken from the field of VNUA and the rest was taken from the internet. The dataset includes 1237 leaves that have *Brown Spot* disease, 1231 leaves that have *Leaf Folder* disease, and 1377 leaves that have *Leaf Blast* disease, although *Leaf Blast* have slightly more samples than other classes, this does not severely affect model training process. The images of the test, validation, and training are completely separate.

Fig. 4. Verifying and labelling the dataset with the agricultural expert.

Fig. 5. Examining the rice diseases on the field with the expert.

2.3 Data Augmentation

The augmentation methods that we used in this paper are shown in the Table 2 below.

Table 2. Augmentation hyperparameters

No.	Name	Fraction
1	Hsv_h	0.015
2	Hsv_s	0.7
3	Hsv_v	0.4
4	Translate	0.1
5	Scale	0.5
6	Flipud	0.5
7	Fliplr	0.5
8	Mosaic	1.0

To explain the meaning of each hyperparameter implemented in YOLOv8, a brief description of each method is presented as the followings.

- *Hsv_h*: Refers to the Hue channel in the HSV color space. HSV stands for Hue, Saturation, and Value which are the three components that make up the HSV color model. The Hue channel represents the color information and is typically represented as a value between 0 and 360 degrees. It encodes the dominant wavelength or color tone of a pixel, ranging from red at 0 degree, through yellow, green, cyan, blue, magenta, and back to red at 360 degrees.

- *Hsv_s*: Saturation is typically represented as a value between 0 and 1, where 0 indicates a completely grayscale color and 1 indicates the highest saturation of the most vibrant and pure color.
- *Hsv_v*: The value channel is typically represented as a value between 0 and 1, where 0 indicates black or no light, and 1 represents the maximum brightness or the brightest possible color.
- *Translate*: Shifting an image in different directions, either on the horizontal axis or on the vertical axis. helps the model learn object localization and robustness to object position changes.
- *Scale*: Changing the scale of an image can result in different distances and zoom levels. Scaling can be performed by zooming in or out.
- *Flipud*: Flipping an image horizontally.
- *Fliplr*: Flip an image vertically.
- *Mosaic*: In this method, several images from the original dataset are randomly selected and arranged in a grid-like pattern to form a new image. The purpose of this augmentation method is to introduce more complex and diverse backgrounds into the training dataset. By combining different images, the model learns to recognize objects in the presence of various backgrounds.

2.3. YOLOv8

The block diagram of the YOLOv8 model is shown in Fig. 6. It is composed of three components: backbones, neck, and head.

2.3.1. Backbones

YOLOv8 and YOLOv5, its predecessor, are quite similar. *C2f*, a combination of the C3 module from YOLOv5 and the ELAN (Efficient Long-Range Attention Network) model concept-which itself takes influence from the CSP (Cross-Stage-Partial-connections) strategy and VoVNet-replaces the C3 module seen in YOLOv5 in YOLOv8 [12].

2.3.2. Neck

The SPPF (Spatial Pyramid Pooling Fast) technique is again pass down from YOLOv5 to YOLOv8. The predecessor of SPPF is SPP (Spatial Pyramid Pooling), and both of these techniques have the same functionality in which is used for feature fusion. The SPPF version yield better execution speed which is a reference for the name SPP Fast. There are changes of the SPPF compared to SPP, in which the use of different kernel size of maxpooling layer and series connection is abandoned in SPPF to be replaced with same kernel size and parallel connection.

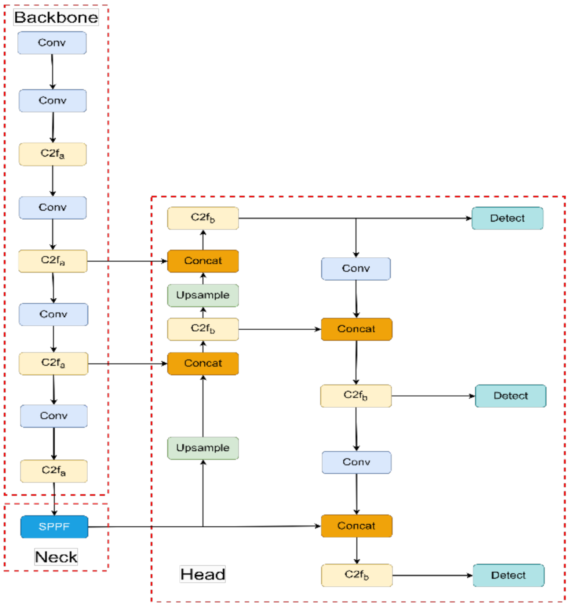

Fig. 6. YOLOv8 architecture.

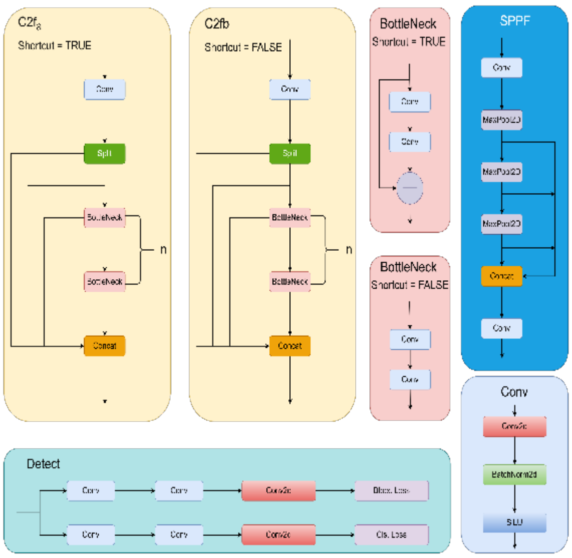

Fig. 7. YOLOv8 blocks detail.

2.3.3. Head

In the head component of the YOLOv8, *C2f* and *Conv* still remain the main blocks, along with them, a few other techniques are also added in this part which are the *Concat* and the *Upsample*. Two new techniques which are the *Decouple Head* and *Anchor-Free* are also introduced while the techniques of Anchor-Based and Couple-Head are removed. The method from the paper [13] name Task Alignment Loss is also brought to YOLOv8, the formular of this method can be described as:

$$t = s^{\alpha} \times u^{\beta} \quad (1)$$

t represents the alignment metric while classification score and IoU (Intersection over Union) score are denoted by *s* and *u*, respectively. Alpha and Beta regulate the impact of these two elements.

2.3.4. Loss function

The loss function of YOLOv8 is made of three different functions, each of them are weight differently. These functions focus on three task, classification, box, distribution focal loss, the formular of the loss function of YOLOv8 can be seen as follows:

$$Loss = l_1 L_{cls} + l_2 L_{box} + l_3 L_{DFL} \tag{2}$$

Classification loss

The classification loss of YOLOv8 utilizes the BCE with logit loss, the formular can be demonstrated as:

$$\ell_c(x, y) = L_c = \{l_{1,c}, \dots, l_{N,c}\}^{\top}$$
$$l_{n,c} = -w_{n,c}[p_c y_{n,c} \cdot \log \sigma(x_{n,c}) + (1 - y_{n,c}) \cdot \log(1 - \sigma(x_{n,c}))] \tag{3}$$

Box loss

To calculate the box loss, the author of YOLOv8 use CloU loss (Complete loU loss [14]), same as in YOLOv5. The formular are shown as below:

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \tag{4}$$

$$\alpha = \frac{v}{(1 - IoU) + v} \tag{5}$$

$$v = \frac{4}{\pi^2}\left(arctan\frac{w^{gt}}{h^{gt}} - arctan\frac{w}{h}\right)^2 \tag{6}$$

DFL(Distribution Focal Loss) loss

Stands as a part of GFL (General Focal Loss) in paper [15], the author of YOLOv8 uses this function to replace the old objectness loss. The formula of DFL can be described as follows:

$$DFL(S_i, S_{i+1}) = -\left((y_{i+1} - y)\log(S_i) + (y - y_i)\log(S_{i+1})\right) \tag{8}$$

$$S_i = \frac{y_{i+1} - y}{y_{i+1} - y_i}, S_{i+1} = \frac{y - y_i}{y_{i+1} - y_i} \tag{9}$$

3. Result and Discussion

In this project, to be able to evaluate the performance of the model, we take into account the following metrics: *Precision, Recall, F1-score, Map@50*. The following formula of these metrics are given:

$$Recall = \frac{TP}{(TP + FN)} \times 100\% \tag{10}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{11}$$

$$Precision = \frac{TP}{(TP + FP)} \times 100\% \tag{12}$$

$$F_1 - score = \frac{2 * Precision * Recall}{(Precision + Recall)} \tag{13}$$

$$AP = \textstyle\sum_{k=0}^{k=n-1}[Recalls(k) - Recalls(k+1)] * Precision(k) \tag{14}$$

where *P* stands for precision, and *R* stands for recall. The number of correctly identified cases of diseased leaves is known as TP (True Positive). The leaves that are diseased but are labeled as healthy is known as false positives, or FPs. The number of leaves that are disease-free but have been diagnosed are called FN (False Negative) leaves. *n* stands as the total number of IoU thresholds. Represent for the mean precision is AP and AP_i denotes the mean precision of class i^{th}. The number of classes represented in *N*.

The Table 3 and PR-Curve in Fig. 8 below display the final findings of the rice disease detection process using YOLOv8. This outcome was obtained in the test set that included 84 leaves with brown spot disease, 95 leaves with blast disease, and 95 leaves with folder disease. The YOLOv8n model, the nano version of YOLOv8, was used to get this outcome.

Table 3. Evaluation results

YOLOv8	Precision	Recall	F1	Map@50
All	89.6	83.5	86.4	88.9
Leaf Folder	93.9	88.4	91.1	91.7
Leaf Blast	86.7	90.5	88.6	91.2
Brown Spot	88.2	71.5	79.0	84.0

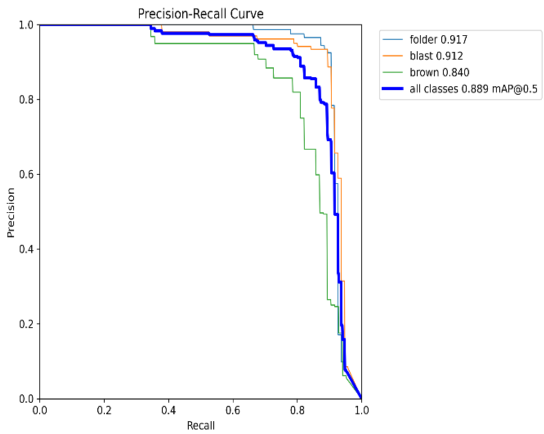

Fig. 8. P-R curve.

Fig. 9. Leaf Folder disease detection.

Fig. 11. Brown Spot disease detection.

Fig. 10. Leaf Blast disease detection.

Fig. 9, 10, 11 above are the inference result of our model. Take note that the first, second, and third bounding box represent the *Leaf Folder*, *Leaf Blast* and *Brown Spot* respectively, with the confidence of the model on each image are 74% on *Leaf Folder* in Fig. 9, 88% on *Leaf Blast* in Fig. 10, and 75% on *Brown Spot* in Fig. 11. In terms of class *Leaf Blast* and *Brown Spot*, our model yields 91.2% and 84% accuracy compares to 80.3% and 55.4% of [8] and also surpass 69.4% of *Leaf Blast* accuracy of [7]. From the Bacterial Blight pictures of [7], it is likely that the author has labeled *Leaf Folder* as bacterial blight, because of this we assume that the class Bacterial Blight in [7] is *Leaf Folder*, which means that our model is able to provide better accuracy for *Leaf Folder*, 91.7% compared to 65% of [7]. In terms of YOLOv7 of [16], which is one of the State-of-the-art models, our model increases by 21.7% and 20.5% for *Leaf Folder* and *Leaf Blast* respectively. As a result, YOLOv8 surpassed the accuracy of YOLOv7 while still maintaining fewer parameters. With YOLOv5, while it has fewer parameters than YOLOv8, YOLOv8 is still able to achieve higher accuracy and inference speed, as mentioned in Table 1.

Despite the high accuracy of our suggested method, there are still certain shortcomings. For the class *Leaf Blast* and *Brown Spot*, the model sometimes mistakes these two together, the main reason is that these two diseases sometimes have disease marks that are quite difficult to distinguish. For the *Leaf Folder* disease, in sunny conditions, the background object can be mistaken for being leaf that contains the disease. Possible consequences might be the farmer gives the wrong solution to contain the spread of the diseases. For both problems, the solution is to increase the images in the dataset, in particular, we aim to increase the number of images of *Leaf Blast* and *Brown Spot* that are hard to distinguish, and images that contain leaves contain *Leaf Folder* disease in strong light conditions. Also, with *Leaf Folder* disease images, we can further increase the brightness of the images during the augmentation process.

In the future, we would like to implement our model into a low-cost hardware system because the model we use in this research is the lightest version of YOLOv8, YOLOv8 nano. In this case, we would like to implement our model on a Raspberry Pi 4 model B, a version for a cheap mini-PC.

3. Conclusion

In this paper, the synthetic dataset was used, part of which comes from sources published on the internet, part of which we took from real data sources at the Vietnam National University of Agriculture - where we have incorporated expert knowledge about rice diseases into the dataset. Our proposed method is able to achieve an accuracy of 88.9% on the test set of this dataset, which is a promising achievement for the future application of the model in the real world. With this result, we hope to implement it in the low-cost hardware with user-friendly components in the future to provide the farmers a solution to detect the diseases without the professional knowledge. The method of using deep learning, in this case YOLOv8 can help the task of detecting and spotting rice disease become automatically while still being able to yield decent accuracy compared to traditional method. This will benefit the time saving problem for the farmers. So, this can help the researchers reduce time and money to obtain data in the future and, provides a model to detect *Leaf Folder* diseases which is a disease that rarely appear in the research about rice diseases.

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References

[1] Q. U. Ngo, T. D. Ngo, A. S. LE, D. T. Bui, A novel automatic detecting system for cucumber disease based on the convolution neural network algorithm, GMSARN International Journal, vol. 16, no. 3, pp. 295-301, 2021.

[2] Md. J. A. Soeb, Md. F. Jubayer, T. A. Tarin, M. R. A. Mamun, F. M. Ruhad, A. Parven, N. M. Mubarak, S. L. K., I. Md. Meftaul, Tea leaf disease detection and identification based on YOLOv7 (YOLO-T), Nature, Scientific Report, 6078, 2023

[3] M. P. Mathew, T. Y. Mahesh, Leaf-based disease detection in bell pepper plant using YOLO v5, springer, Signal, Image and Video Processing, vol. 16, pp. 841 – 847, 2021. https://doi.org/10.1007/s11760-021-02024-y

[4] P. Bansal, R. Kumar, S. Kumar, P. Pathology, Disease detection in apple leaves using deep convolutional neural networks: apple leaves disease detection using EfficientNet and DenseNet, MDPI, Agriculture, Vol. 11, issue 7, 617, 2021. https://doi.org/10.3390/agriculture11070617

[5] N. Krishnamoorthy, L.V. N. Prasad, C.S. P. Kumar, B. Subedi, H. B. Abraha, V. E. Sathishkum, Rice leaf diseases prediction using deep neural networks with transfer learning, Environ Res. ,198:111275, 2021. https://doi.org/10.1016/j.envres.2021.111275

[6] R. Li, S. Chen, H. Matsumoto, M. Gouda, Y. Gafforov, M. Wang, Y. Liu, Predicting rice diseases using advanced technologies at different scales: present status and future perspectives, Springer, aBIOTECH, vol. 4, pp.359 – 371, 2023. https://doi.org/10.1007/s42994-023-00126-4

[7] M. E. Haque, A. Rahman, I. Junaeid, S. U. Hoque, M. Paul, Rice leaf disease classification and detection using YOLOv5, arXiv:2209.01579v1,2022. https://doi.org/10.48550/arXiv.2209.01579

[8] J. J. Muhammad, A. S. Riaz, A. S. Noor, R. Samina, H. A. Rafaqat, H. C. Ghulam, Q. B. Abdul, S. Hidayatullah, H. S. Kashif, Deep learning-based rice leaf diseases detection using Yolov5, Sukkur IBA Journal of Computing and Mathematical Science – SJCMS, vol. 6, no. 1, pp. 49-61, 2022. https://doi.org/10.30537/sjcms.v6i1.1009

[9] G. Jocher, A. Chaurasia, J. Qiu.YOLOv8. Ultralytics. Feb.3,2024. [Online] Available: https://docs.ultralytics.com/models/yolov8/

[10] G. Jocher and S. Waxmann. YOLOv7: Trainable bag-of-freebies. Ultralytics. July. 1,2024. [Online] Available: https://docs.ultralytics.com/models/yolov7/

[11] Performance benchmark of YOLOv5, YOLOv7 and v8. Jan. 12,2023. [Online] Available: https://www.stereolabs.com/blog/performance-of-yolo-v5-v7-and-v8

[12] Y. Lee, J.W. Hwang, S. Lee, Y. Bae, An energy and GPU-computation efficient backbone network for real-time object detection, arXiv:1904.09730v1, 2019. https://doi.org/10.1109/CVPRW.2019.00103

[13] C. Feng, Y. Zhong, Y. Gao, M.R. Scott, W. Huang, TOOD: Task-aligned one-stage object detection, arXiv:2108.07755v3, 2021. https://doi.org/10.1109/ICCV48922.2021.00349

[14] Z. Zheng, P. Wang, D. Ren, W. Liu, R. Ye, Q. Hu, W. Zuo, Enhancing geometric factors in model learning and inference for object detection and instance Segmentation, IEEE Transactions on Cybernetics, vol. 52, no. 8, pp. 8574-8586, Aug. 2022. https://doi.org/10.1109/TCYB.2021.3095305

[15] X. Li, W. Wang, L. Wu, S. Chen, X. Hu, J. Li, J. Tang, J. Yang, Generalized Focal Loss: Learning qualified and distributed bounding boxes for dense object detection, arXiv:2006.04388v1, 2020. https://doi.org/10.1109/CVPR46437.2021.01146

[16] H. Ershadul, P. Manoranjan, R. Ashikur, T. Faranak, Md. Islam, Rice leaf disease detection and classification using lightly trained YOLOv7 active deep learning approach, Digital Image Computing: Techniques and Applications (DICTA), 2023.