Date of publication DEC-31, 2024, date of current version JUL-27, 2024.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.23.4.3773

Real-time Identification of Rice Leaf Diseases using Convolutional Neural Networks

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ABSTRACT Rice is one of the most important crops worldwide, serving as a primary food source for millions of people. However, this crop is threatened by diseases such as Rice Blast, Brown Spot, and Bacterial Blight, which manifest in the leaves of the plant. The characteristics of these diseases, captured in digital images, can be utilized in computer vision techniques for their detection and classification. In this study, two Convolutional Neural Networks, YOLO version 8 and Faster R-CNN, were compared to detect and classify the diseases Blast and Brown Spot in a dataset comprising 3636 images with 7915 annotations indicating the location of the disease on the rice leaves. The model trained using YOLO version 8 achieved an accuracy of 92.98% and a recall of 92.45%, while the model trained with Faster R-CNN achieved an accuracy of 91.99% and a recall of 87.78%. YOLO has lower inference times compared to Faster R-CNN due to its more efficient approach and simpler architecture.

KEYWORDS rice disease; CNN; YOLO; Faster R-CNN.

I. INTRODUCTION

RICE is one of the most important crops in the world, serving as the staple food for more than half of the global population [1]. However, like any other crop, rice is susceptible to a range of diseases that can impact its quality and yield, leading to economic losses for farmers [2]. Rice diseases typically manifest in its leaves, which are crucial for photosynthesis, thus affecting the plant's ability to produce its food. Among the most common diseases found in rice leaves are Blast, Brown Spot [3], Bacterial Blight, and Tungro [4]. These diseases are caused by fungi, bacteria, and viruses that can spread from plant to plant through air, water, or insects. The prevention and control of these diseases are essential for maintaining the health of rice plants [5]. Currently, control methods include the use of fungicides, bactericides, and agricultural practices such as crop rotation. These methods help to maximize production, thereby contributing to agricultural development and its impact on national economies [6].

Diseases affecting rice crops often manifest in the plant's leaves, making them a key indicator for identification. With technological advancements, methods for analyzing digital images using computer vision techniques have been developed to detect these diseases [7, 8]. Notably, feature-based classifiers [9] and deep learning techniques such as Convolutional Neural Networks (CNN) [10] have been employed. These techniques enable the detection and classification of specific diseases with greater accuracy than traditional visual inspection.

In the literature review, research based on machine learning and image recognition was found to have been used for analyzing rice leaves. Classification models such as CNN and Deep Maxout Network (DMN) have been employed to detect diseases like Blast, Brown Spot, and Hispa, achieving an accuracy of 96% [11]. Deep CNN models have been used to identify Bacterial Blight, Blast, Brown Spot, and Tungro with an accuracy of 93.87% [12]. Classification methods based on Random Forest and transfer learning with the deep Faster R-CNN architecture have been used to identify Bacterial Blight, Brown Spot, and Leaf Smut, achieving an accuracy of 97.3% [13]. Deep Convolutional Neural Networks (DCNN) have been used to detect diseases in rice leaves, such as Narrow Brown Spot, Leaf Scald, Blast, Brown Spot, and Bacterial Blight, achieving an accuracy of 96.08% [10].

Machine learning and deep learning techniques have made significant advancements in recent years with their ability to process digital images and their application in the field of computer vision. Applications such as biometric recognition using CNN and disease detection using CNN have been developed. However, these techniques still rely on extensive datasets to function efficiently, which means their learning process remains slow [14].

CNNs are used in image and video processing for object detection, image classification, image segmentation, pattern recognition, image generation, and other specialized applications [15]. There are various CNN architectures for object detection, among the most well-known are Region-based Convolutional Neural Networks (R-CNN), Fast R-CNN [16], Faster R-CNN [17], You Only Look Once (YOLO) [18], and Single Shot Multibox Detector (SSD). Each has its advantages and disadvantages, and the choice of architecture depends on the specific context of the project [19]. Research has been conducted in agricultural crops using the YOLO architecture for various applications such as plant detection and counting [20], weed detection [21], disease identification in tea leaves [22], and rice disease detection and classification [23]. Additionally, other studies have employed the Faster R-CNN architecture for disease detection in guava and mango [24], diseases in tomato plants [25], and the diagnosis of diseases in rice leaves [26].

In this study, two CNN architectures, YOLO version 8 and Faster R-CNN, were compared with the aim of detecting the rice diseases Blast and Brown spot. A dataset of digital images of rice leaves was used, and manual labeling was performed by annotating the location of the visual characteristics of the disease on the leaves, assigning a class to each disease: Brown Spot (class 0) and Blast (class 1). To expand the dataset and combat overfitting, data augmentation techniques such as rotation, horizontal flips, and vertical flips were employed. The trained models demonstrate capabilities for detecting and classifying Blast and Brown spot in rice plants.

II. MATERIALS AND METHODOLOGY

Two convolutional neural networks, YOLO and Faster R-CNN, were trained using a dataset of rice images for real-time identification of diseases affecting rice leaves, specifically Blast and Brown spot. The trained models were evaluated using precision, recall, and F1 Score metrics. The flowchart of this study is shown in Figure 1.

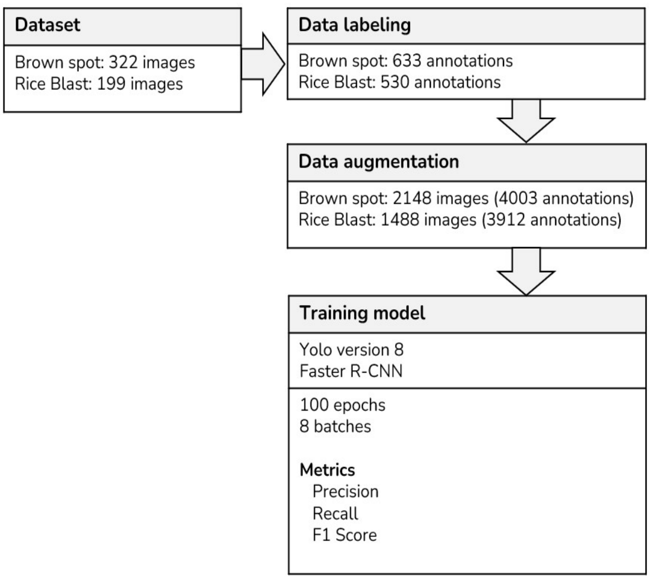

Figure 1. Process diagram for training and testing of the models.

A. DATASET

A previously presented dataset [28] containing 5932 photographs of rice plant leaves was used. These include images of rice leaves affected by Bacterial blight, Blast, Brown spot, and Tungro, with a resolution of 300 px × 300 px and in jpg format. From this dataset, only 322 images of rice with Brown spot and 199 images with Blast were selected.

Among the main diseases in rice crops are:

Blast: This is a severe rice disease caused by the fungus Magnaporthe oryzae, also known as *Pyricularia oryzae* [27]. Symptoms include lesions that can be found on all parts of the plant, with diamond-shaped lesions on the leaves being the most common symptom (Figure 2a).

Bacterial blight: This disease is caused by the bacterium *Xanthomonas oryzae* PV. It is characterized by lesions that exude milky sap and then dry out and turn yellowish. Subsequently, grayish-white lesions appear on the leaves, indicating an advanced phase of the infection that ultimately leads to the desiccation and death of the foliage within approximately 2-3 weeks [7] (Figure 2b).

Brown spot: This disease, caused by the fungus *Helminthosporium oryzae*, initially manifests as small brown spots on the leaves, which later transform into cylindrical or oval to circular lesions [7] (Figure 2c).

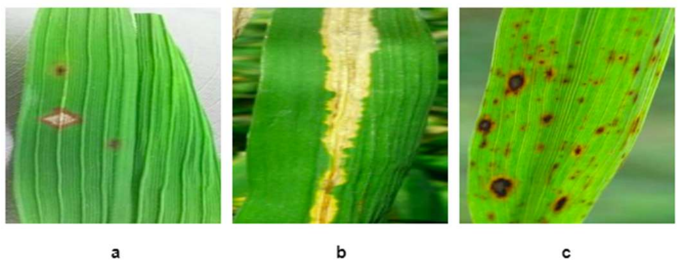

Figure 2. Examples of images of rice leaf diseases. (a) Blast, (b) Bacterial blight, (c) Brown spot.

B. DATA LABELING

The selected images were manually labeled (ground truth) using the LabelImg program, considering the format required by YOLO (Figure 3). The location (bounding boxes) of the visual characteristics of the disease on the rice leaf was annotated, classifying them into two available classes: Brown spot (class 0) and Blast (class 1). In the YOLO format, the coordinates of the bounding boxes are typically defined as the coordinates of the center of the bounding box, along with its width and height relative to the dimensions of the image.

To use the Faster R-CNN algorithm, taking into account the image size, the annotations were converted to Pascal VOC format (Figure 3), where "x_min" and "y_min" are the coordinates of the upper left corner, and "x_max" and "y_max" are the coordinates of the lower right corner of the bounding box.

Table 1 provides the details of the images and the annotations made for each rice leaf disease.

In Figure 4, we can see examples of rice leaf images with bounding boxes around the object of interest that identifies the disease.

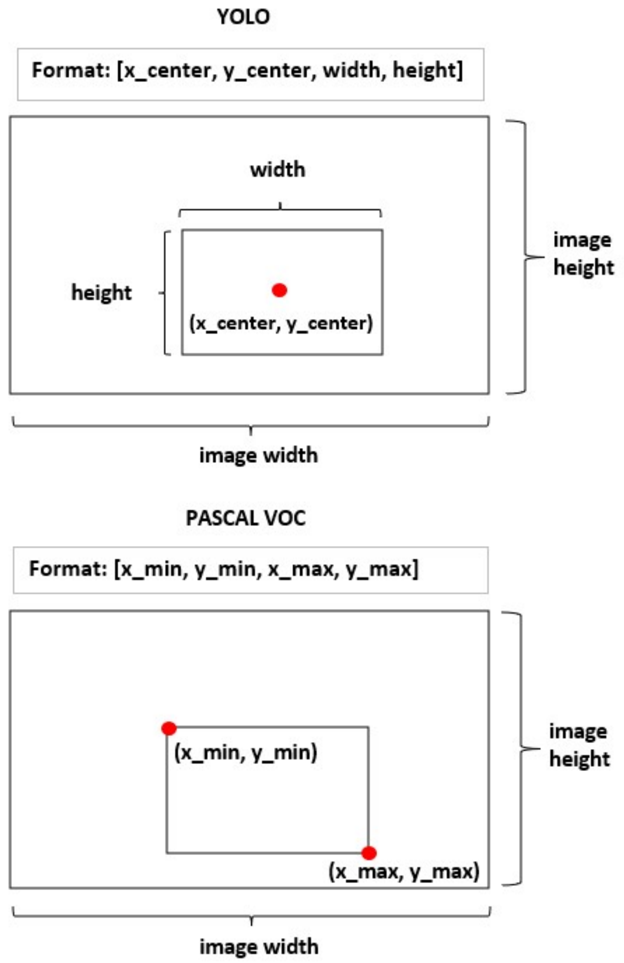

Figure 3. Structure of the YOLO and Pascal VOC format.

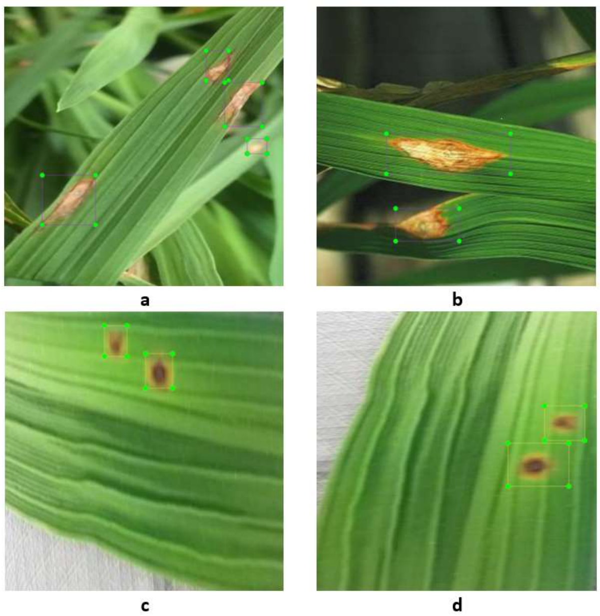

Figure 4. Manually labeled image samples. (a, b) Blast, and Brown spot (c, d).

Annotations were made by assigning a class to each disease, with Brown Spot (class 0) and Blast (class 1). Table 1 shows 633 annotations for the disease Brown Spot and 530 annotations for Blast.

C. DATA AUGMENTATION

Data augmentation was performed by applying various transformations to the original images: horizontal flip (left to right), vertical flip (top to bottom), and 90-degree rotation both clockwise and counterclockwise. Table 1 presents the total number of resulting images after applying these data augmentation techniques.

Table 1. Details of annotated images

Leaf disease	Original images		Data augmentation	
	Images	Annotations	Images	Annotations
Brown spot	322	633	2148	4003
Rice blast	199	530	1488	3912
Total	521	1163	3636	7915

D. TRAINING MODEL

The training of the YOLO and Faster R-CNN architectures was conducted over 100 epochs, with each epoch representing a complete training cycle using a batch size of 8. This batch size was chosen to balance computational efficiency and the model's generalization ability.

To train and evaluate the model, the dataset was divided into three sets: training (70%), validation (15%), and testing (15%). This division was performed randomly to ensure that all three sets represented the distribution of the original dataset.

E. EVALUATION METRICS

The detection of diseases in rice leaves can be categorized as true positive (TP) or true negative (TN) when correct detections are made in the plants, while they are classified as false positive (FP) or false negative (FN) in the case of incorrect detections.

Precision (P): Measures the accuracy of the model in classifying a leaf as diseased. A high precision indicates that the model makes few errors in identifying diseases in rice leaves. It can be calculated using Formula (1).

$$P = \frac{TP}{TP+FP} . \quad (1)$$

Recall (R): Measures the ability of the model to correctly identify all diseased leaves. A high recall indicates that the model detects most cases of diseases in rice leaves.

$$R = \frac{TP}{TP+FN} . \quad (2)$$

F1 Score (F): Harmonic mean of precision and recall, provides a balanced measure of the model's performance. A high F1 Score indicates that the model has both high precision and high recall, which is crucial for the effective detection of diseases in rice leaves.

$$F = 2 * \frac{P \; x \; R}{P + R} . \quad (3)$$

III. RESULTS

The training was conducted on Google Colab, utilizing a graphical processing unit (GPU) environment. The dataset described in Table 1 was used for this purpose. Training was carried out over 100 epochs, dividing the images into groups of 16, known as batches, and processing each batch in each iteration. Upon completion of the model training using YOLO version 8 and Faster R-CNN, precision, recall, and F1 Score values were obtained. These results are presented in Table 2.

Table 2. Comparison of detection performance.

Model	Precision (%)	Recall (%)	F1 Score (%)
YOLO version 8	92.98	92.45	92.71
Faster RCNN	91.99	87.78	89.83

These trained models can receive a test image to detect diseases in rice leaves. Figure 5 shows several test images with prediction labels and confidence scores.

Figure 5. Detection of diseases of the trained model.

A. YOLO version 8

The detection model trained with YOLO version 8 demonstrates strong performance in identifying and classifying Blast and Brown Spot diseases in rice leaf images. Figure 6 shows the results of the model trained over 100 epochs. With an accuracy of 92.98%, the model achieves a high proportion of correct predictions among all detections made. A recall of 92.45% indicates the model's ability to identify the vast majority of positive instances in the dataset. Finally, the F1 Score of 92.71% combines precision and recall into a single metric, indicating a solid balance between the model's precision and completeness.

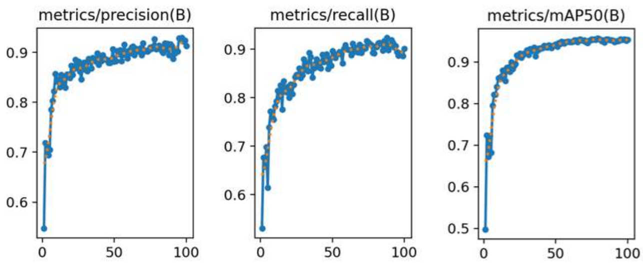

Figure 6. Results of the model trained with Yolo version 8 for 100 epochs.

The combined precision and recall graph of the model trained with YOLO (Figure 7) shows that the value for Brown Spot disease is 0.983 and for Blast disease is 0.920, indicating that the model performs better in detecting Brown Spot. The average value for detecting these two classes is 0.952.

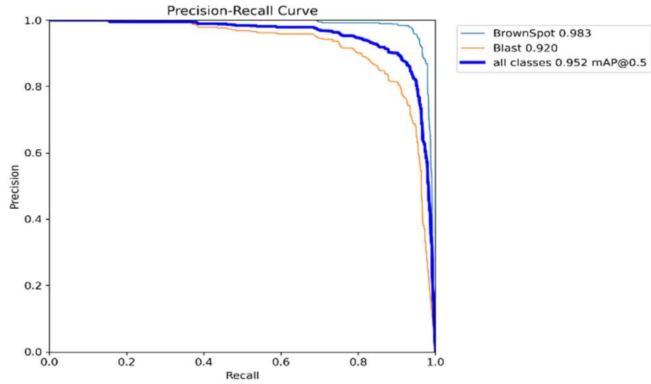

Figure 7. Precision and Recall Curve using YOLO.

B. Faster R-CNN

The detection model trained with Faster R-CNN has a precision of 91.99%, a recall of 87.78%, and an F1 Score of 89.83%. This model performs less effectively than the model trained with YOLO. Figure 8 shows the results of the model trained with Faster R-CNN over 100 epochs.

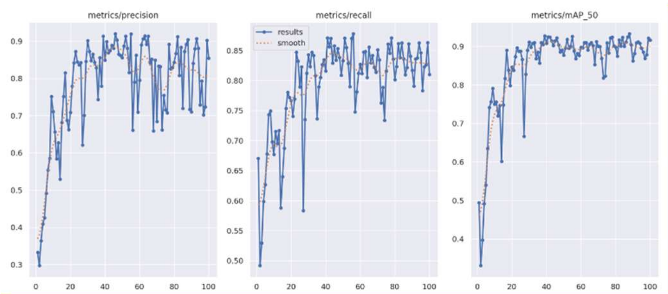

Figure 8. Results of the model trained with Faster R-CNN for 100 epochs.

The combined precision and recall chart of the model trained with Faster R-CNN (Figure 9) shows that the value for Brown Spot disease is 0.925 and for Blast disease is 0.908. The average value for detecting these two classes is 0.916.

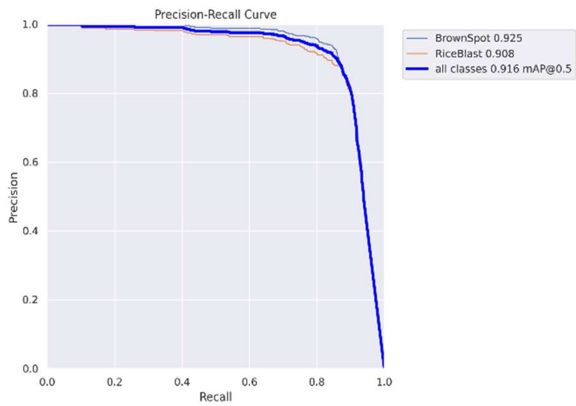

Figure 9. Precision and Recall Curve using Faster R-CNN.

IV. CONCLUSIONS

Given that rice is one of the most widely consumed foods globally, it is essential to leverage technologies to detect and control diseases that could affect it and reduce its production. Moreover, in the face of the challenges posed by global warming, it is crucial to evaluate and mitigate future problems that could impact rice cultivation.

In the present research, YOLO version 8 and Faster R-CNN architectures were compared to train models for detecting and classifying rice leaf diseases: Blast and Brown spot. A dataset comprising 3,636 images and 7,915 annotations indicating the locations of diseases on the leaves was used. Of this dataset, 75% was used for training, with the remaining 15% utilized for validation and testing. The experimental results demonstrate that the model trained using the YOLO architecture exhibits superior performance, with an accuracy of 92.98% and a recall of 92.45%, achieving up to 98.3% in the detection of Brown spot. Additionally, the YOLO model has an inference time of 26.0 ms, making it suitable for real-time applications.

In future work, this model could be employed for real-time detection of Brown spot and Blast in rice crops by implementing the proposed approach in an intelligent embedded system. This would provide farmers with an advanced tool to improve the productivity of their crops, facilitating the timely identification and management of diseases in the field.

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