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RICE DISEASES DETECTION AND CLASSIFICATION USING YOU ONLY LOOK ONCE AND CONVOLUTIONAL NEURAL NETWORK

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Abstract- Rice is one of the crops that is planted the most all over the world. Food safety and production may be impacted by the rice plant's diseases and a significant decrease in the quality and output of agricultural products. Therefore, plant disease diagnosis and identification automation are essential in the agricultural industry. Many solutions have been put up for this issue, with deep learning emerging as the most practical due to its excellent performance. The strategy that is suggested for classifying and diagnosing ten different types of rice diseases. A literature survey indicates that YOLOv5 outperforms other deep learning approaches regarding results. The YOLO family of algorithms, which have extreme precision and superior speed, have been employed in many scene identification tasks to design rice leaf disease monitoring systems due to improved object detection techniques. Because of this, the suggested system consists of two stages: the first stage uses a model called You Only Look Once (YOLO) version5 detection to determine whether the rice is healthy or not, and the second stage involves extracting and classifying diseases using a Convolutional Neural Network (CNN) from the affected area into nine classes of diseases. YOLOv5s is used to identify the rice diseases from the provided image. Each bordered area that separates the discovered diseases from the remainder of the image is clipped. The CNN model classified 97.28% of the test data, while the YOLOv5s had a detection accuracy of 94.60%. The proposed method successfully resolves many of the researcher's difficulties; however, it may result in decreased accuracy. Compared to earlier research of a similar type, the proposed technique is anticipated to provide favorable and beneficial outcomes.

Keywords: Rice Diseases, Deep Learning, Detection, Classification, Convolutional Neural Network, You Only Look Once YOLO.

1. INTRODUCTION

Rice is considered one of the most widely consumed foods in the world [1]. The Food and Agricultural Policy Research Institute predicts that during the next 25 years, rice consumption will rise by 26% [2]. Therefore, protecting rice plants from diseases is essential. Farmers, however, cannot manually patrol the enormous rice fields daily due to the farms' size; even if they did, they could not check each plant separately. Even if it were feasible, having farmers check on rice plants daily would be an expensive task that was also prone to human error and would have many other harmful impacts that would ultimately cause more harm than good.

An automated technique for identifying rice disease outbreaks could provide advice on preventing and treating the diseases, minimizing financial loss, and improving the quality and output of agricultural products [3]. Machine learning-assisted tasks and processes play essential roles in pattern recognition, particularly in image detection and classification, as well as intelligent quality control and maintenance [4]. Artificial intelligence techniques and machine learning methods used to help farmers and researchers in multiple fields of agriculture in the early diagnosis of rice diseases is one of the most recent advances in that researchers are looking to establish such a system [5]. Infections in rice are limited to the leaves, and leaf diagnosis can help farmers decide whether to spray their crops. In this work, CNN was used to categorize diseases, while Yolov5 was used to detect rice diseases.

2. RELATED WORK

In the domain of identifying and categorizing rice diseases, numerous researchers were interested. Rice disease detection and categorization are essential to identifying rice diseases. Following the removal of the region of interest (ROI) from the diseased rice leaves, the diseases are categorized. Some researchers describe a method for identifying rice diseases using machine learning methods. The dataset consists of three types of rice diseases; it is used to train several machine learning algorithms where the decision tree method generated outcomes on the test dataset with an accuracy of more than 97% [6]. In another study, features from images of rice leaf diseases were extracted using the Support Vector Machine method and CNN. The dataset used in this study contained 8911 images: normal leaves images 2274 and 6637 rice with four different types of diseases. According to the experimental results, the accuracy was 96.8% [7].

Additionally, ResNets and DenseNets were used to categorize five different rice diseases on the dataset known as K5RD, the experimental show that the suggested system can achieve excellent accuracy, averaging more than 95% [8]. While there have been attempts to use the deep learning model YOLOv5 to develop a straightforward model for the identification of rice diseases, where the dataset contains 400 images of four different rice diseases, the study findings demonstrate that the deep learning model performed at its max with 62% mean average precision (mAP) [9]. Another study used a method combining YOLOv4 object detection and image tiling method to examine 4,960 images of 8 different forms of rice diseases where the prediction performance of mAP for YOLOv4 was 91.14% [10].

Additionally, annotate 1500 images of four distinct disease categories and suggest a YOLOv5 algorithm for disease detection in rice. 76% was the mAP value [11]. Researchers provided a paradigm for detecting and classifying rice diseases of three different diseases, which was taken from the UCI Machine Learning Repository dataset; the efficient Residual Neural Network approach produced an accuracy of roughly 95.83% [12]. Different classification systems for rice leaf diseases are discussed in another study. Using Otsu's approach, images of four different forms of rice plant disease are segmented. Numerous features are extracted from the segmented area using Local Binary Patterns LBP and Histogram of Oriented Gradients HOG; after applying an SVM to classify the attributes, the model achieved 94.6% accuracy [13].

3. YOLO INTRODUCTION

Object detection is the greatest problem in computer vision [14]. Localizing various items in a scene and giving the bounding boxes of those objects' labels are the objectives of object detection. Assigning labels to bound boxes in a scene using already-trained classifiers is the most popular method for solving this issue [15]. You Only Look Once (YOLO) is one of the most well-known algorithms, and it refers to the ability to predict the type of object and its location in an image at a glance. An earlier study showed that YOLOv5 is the most effective version [16]. YOLOv5 architecture is partitioned into three parts:

3.1. Backbone

This Backbone extracts significant features from an input image. The framework used in YOLOv5 to extract practical attributes from an image is called CSP (Cross Stage Partial Networks). The SPP module significantly expands the network's receptive area and offers capabilities of different sizes [17]. The Bottleneck structure might lessen the redundancy of gradient information during the optimization of CNN compared to other large-scale CNNs.

3.2. Neck

The model's neck typically forms feature pyramids. Feature pyramids aid models in generalizing to a more extensive range of situations when object scaling is involved. Finding a similar object in various scales and sizes is made more accessible. Other models use different feature pyramid methodologies, such as the FPN and PANet. PANet is a neck for YOLOv5 to create a feature pyramid [17].

3.3. Head

Typically, the head is where the detection process ends. It produces final output vectors using anchor boxes that include bounding boxes and class probabilities [18].

A loss function connected to detection performance is used to train YOLO. The YOLO neural network rapidly extracts bounding boxes from images to recognize items using all of the image's properties. Rice disease detection applies the candidate box extraction method on the image to determine if an image includes disease and output its location [19]. The YOLO network divided the image into $N \times N$ grids; the candidate boxes are capable of detecting objects and predicting the possibility that one will be discovered in each candidate box [20]. Confidence represents the object's presence or absence in images and the precision with which it is positioned [21].

4. CNN INTRODUCTION

The neurons influenced the CNN algorithm structure in human and animal brains, widely employed in deep learning (DL). The fundamental advantage of CNN, it does so automatically and without human intervention, identifying the pertinent features [22]. The CNN architecture is made up of several levels or so-called multi-building blocks. CNN's architecture includes:

4.1. Convolutional Layer

It is CNN's central component. There are several convolutional filters in it. Correlating these filters with the input image, provided as N-dimensional metrics, results in the output metrics [23].

4.2. Pool Layer

This layer's primary function is to down sample the feature maps. Using this method, one may approximate large-scale feature maps at a smaller size. [24].

4.3. Activation Function

It generates the appropriate output to decide whether or not to fire a neuron in response to a specific input [25].

4.4. Fully Connected Layer

To modify the input vector linearly, the neuron uses a weights matrix. Next, a non-linear activation function is used to map the product non-linearly [26].

5. MATERIAL AND METHOD

The system's block diagram provides an overview in Figure 1.

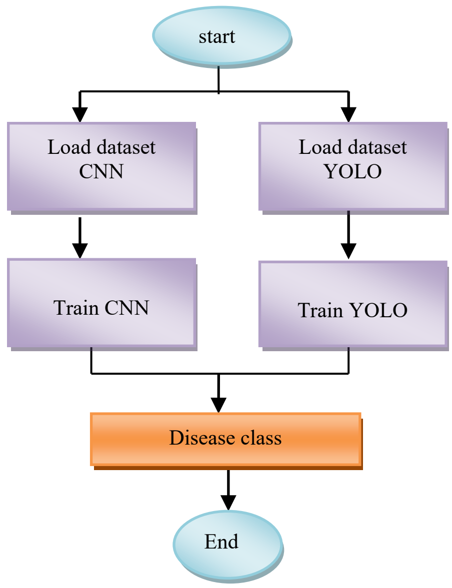

Figure 1. The system's block diagram

5.1. Rice Disease Detection Stage

The following steps to train YOLOv5 are illustrated in Figure 2.

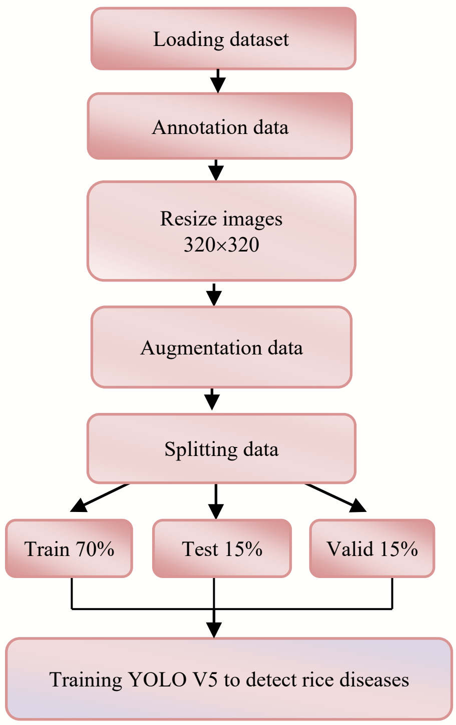

Figure 2. Steps of training YOLOv5

5.1.1. Loading Data

The dataset used in this article was obtained from the Kaggle website, which includes 13878 [27]. The dataset contains normal rice leaves images and nine types of distinct rice diseases (Bacterial leaf blight, Bacterial leaf streak, Blast, Hispa, Brown Spot, Dead heart, Downy mildew, Bacterial panicle, and Tungro).

5.1.2. Annotation Data

It is necessary to convert the dataset to the YOLOv5 format. Roboflow website is a developer framework for computer vision. This website excels in producing datasets for object detection. The dataset has received annotation, augmentation, and storing in YOLO format (meaning that a TXT file with the same image name must be available containing the type of class and four numbers representing the bounded box). Each object in the image is annotated with a Bounding Box (BB) in its text file. They are displayed as:(Class-ID): represents presence/absence of any object, (X center, Y center): represents coordinates center of the box. (Box width, Box height): represents the width and height of the box. All images labeled under two classes (disease and normal).

5.1.3. Resized Data, Augmentation, and Splitting

After the annotation dataset, the images were downsized to 320×320, and 35000 more images were produced using augmentation techniques such as rotating, flipping, and saturation. Afterwards, divide the annotation dataset into three parts: train 70%, valid 15%, and test 15%.

5.1.4. Training YOLOv5 Stage

The YOLOv5 was used to locate the disease's location. The data of all the bounding boxes in a single image must be placed in the single file text corresponding to that image since YOLOv5 reads the bounding box data from files ending in (.txt). After writing, the labels directory will include all label text files. Positive-negative (foreground-background) sample imbalance is one of the factors that most impact the algorithm's performance when training on an object detection job. In YOLOv5, the loss function for the bounding box is generalized IoU loss. To improve the model's capacity to identify rice-related diseases. To determine how different the model is from the actual forecast, the GIoU function is employed as the border loss' loss function.

5.2. Rice Disease Classification Stage

The following steps to train CNN are illustrated in Figure 3.

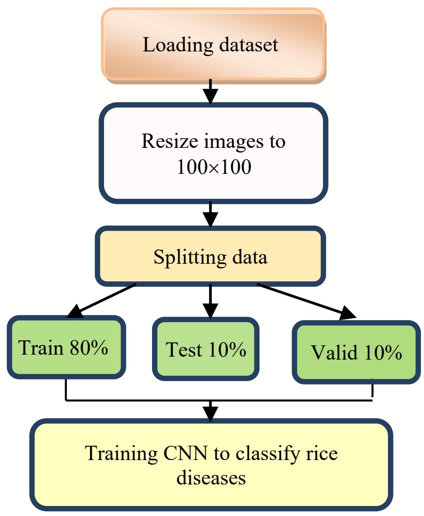

Figure 3. Steps of training CNN

5.2.1. Loading CNN Dataset

The database used in the CNN training phase is the same as the one used in the YOLO training (which was explained earlier), except for removing the normal class from the database because YOLO is the one that determines if the image is normal or not. Thus, the database used in CNN training will contain only the nine classes of diseases. The injury areas were cut off from the rest of the image (manually); thus, the number of images became 19920 (some images contain more than one infected area).

5.2.2. Data Resized and Splitting

All images must be the same size to be trained in CNN. Several different sizes were tried, and it was found that the size of 100×100 is the size that gives the best accuracy. The dataset was split into three parts: valid 10%, test 10%, and train 80%.

5.2.3. CNN Training Stage

Due to the close similarity of the rice diseases, it is necessary to construct a robust convolutional neural network to extract characteristics from the disease region and categorize it. To create the feature map, the proposed CNN consists of five max-pooling layers, each with a window (2×2), a stride of 2, a kernel (3×3), and eight convolutional layers. Employing ReLU as an activation function to transform linear data into non-linear data. The proposed models are made up of four convolutional layer blocks:

- 1st block: Consist of 64 filters spread over two convolutional layers.
- 2nd block: Consist of 128 filters spread over two convolutional layers.
- 3rd block: Consist of 256 filters spread over two convolutional layers.
- 4th block: Consist of 512 filters spread over two convolutional layers.

The suggested CNN of the classification's architecture is shown in Table 1.

Table 1. Architecture of the suggested CNN for classification

Layer	Channels	Input size
Block1: Conv 2D	64	(100×100×64)
Block1: Conv 2D	64	(100×100×64)
MaxPool 2D	---	(50×50×64)
Block2: Conv 2D	128	(50×50×128)
Block2: Conv 2D	128	(50×50×128)
MaxPool 2D	---	(25×25×128)
Block3: Conv 2D	256	(25×25×256)
Block3: Conv 2D	256	(25×25×256)
MaxPool 2D	---	(12×12×256)
Block 4: Conv2D	512	(12×12×512)
Block 4: Conv2D	512	(12×12×512)
MaxPool 2D	---	(6×6×512)
MaxPool 2D	---	(3×3×512)
Flatten	512	---
Dense1	256	---
Dense2	9	---

6. TESTING STAGE

In the testing phase, the image is passed to the YOLOv5 model to determine whether it is normal or diseased. If the image has a disease, YOLO creates a bounding box to the disease region, crops this region from the rest of the image, and passes it to the CNN model, which will classify it as one of the nine rice diseases. The steps involved in testing an image are shown in Figure 4.

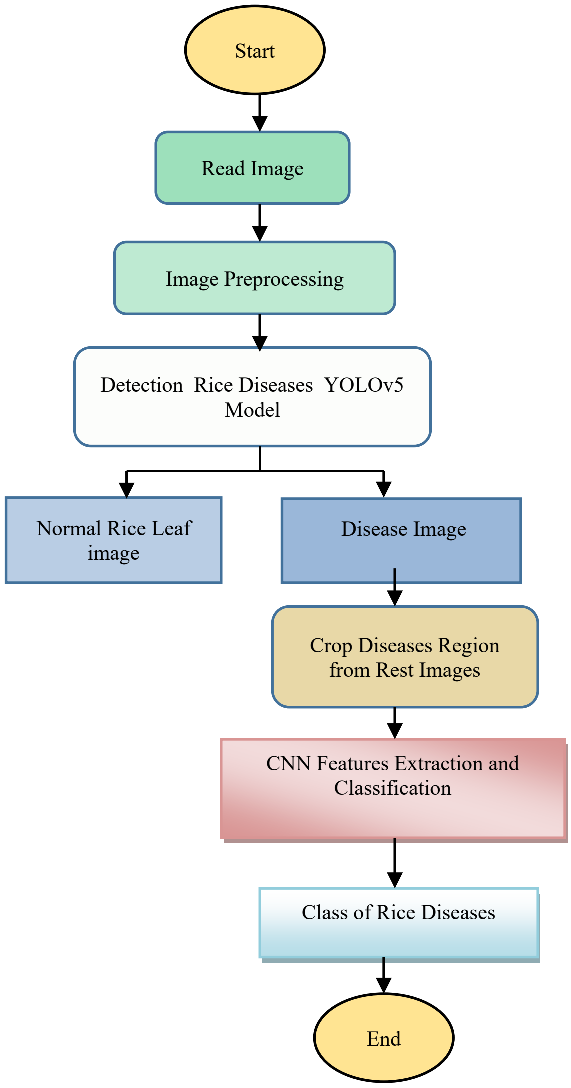

Figure 4. Steps of testing image

7. RESULTS

Normal leaves and nine of the most prevalent diseases that harm rice plants are included in this study's dataset of rice plant disease. YOLOv5 was used to detect rice diseases and determine whether leaves were normal or damaged, and CNN was used to identify the diseases. Most authors focus on identifying and categorizing a select few rice diseases. The proposed system treats a more significant number of rice diseases compared to previous studies. It solves some problems researchers faced, such as the diversity of lighting and the similarity of disease symptoms. In this experimental investigation, the efficacy of the suggested model is evaluated using a type of performance criteria. The Python Colab framework was used to conduct the experimental experiments. All applications were run on a laptop with an HP Core i5 8th generation, a 128 GB SSD, and

Windows 10 Home. YOLOv5's mAP was 94.60%, whereas CNN's accuracy was 97.28%. The parameters incorporated into the suggested model are shown in Table 2.

Table 2. Parameters used in the proposed system

Parameters	CNN	YOLO
Batch-Size	32	32
Optimizer	Adam	---
Image size	100	320
Loss	Sparse Categorical Cross entropy	---
Accuracy	97.28%	94.60%

At the prediction stage, the input image is the first pass through YOLOv5 to determine whether it is normal. If it is affected, a bounded box is then made around the disease region with the probability of being affected. Finally, the disease region is separated from the rest of the image to determine its classification through the CNN model. The CNN's training and validation accuracy graph demonstrates that neither an underfit nor an overfit model poses any problems, as shown in Figure 5.

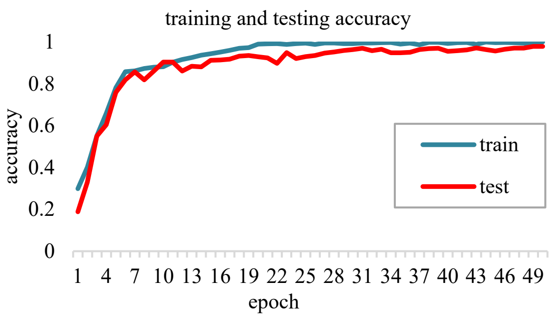

Figure 5. CNN's training and validation accuracy graph

While the Confusion Matrix of the YOLO model can also be used to express counts from predicted and actual values, the rate of rice disease detection as a "disease" class is 0.94%, and the model's diagnosis of the "normal" class is 0.99%, as shown in Table 3.

Table 3. Confusion matrix of training YOLOv5s

	Disease	Normal	Background
Disease	0.94	----	1.0
Normal	----	0.99	----
Background	0.06	0.01	----

Table 4. Evaluation measurements of the classification model

Class name	Precision	recall	F1-score	Samples
Bacterial leaf blight	0.99	0.98	0.98	211
Bacterial leaf streak	0.98	0.98	0.98	232
Bacterial panicle	0.95	0.98	0.96	235
Blast	1	1	1	210
Brown Spot	0.96	0.92	0.94	225
Dead_heart	0.98	0.99	0.98	211
Downy_mildew	0.98	0.99	0.99	259
Hispa	0.98	0.92	0.95	189
Tungro	0.94	1	0.97	220
	Total testing samples			1992
	Accuracy			0.97
	Macro average			0.97
	Weighted average			0.97

The evaluation of the classification model by Accuracy, Precision, Sensitivity (Recall), and the F-score for each class is shown in Table 4. When comparing the accuracy of different deep learning models such as AlexNet, Vgg19, Inception v3, Inception ResNet v2, Xception, Vgg16 and RESNET50 with the proposed CNN, we find that the proposed CNN is higher accuracy than the others, as shown in Table 5.

Table 5. The accuracy of the proposed CNN vs some other CNN techniques

Model	Accuracy
AlexNet	91.4%
Vgg19	73.3%
Inception v3	68%
Inception ResNet v2	87.4%
RESNET50	92.5
Proposed CNN	97.28%

The proposed system showed promising results compared to the work of previous researchers. Where detection and classification accuracy were achieved higher than in the previous work, a more significant number of rice diseases were covered in this study. A comparison of the results of the proposed system with some of the previous works is shown in Table 6.

Table 6. Comparison between the proposed system & some previous works

Ref.	Method	No. diseases	accuracy
[7]	Support Vector Machine SVM + CNN	Normal leaves and four types of diseases	96.8%
[8]	ResNets +DenseNets	five types of rice diseases	95%
[9]	YOLOv5	four different rice diseases	62%
[10]	YOLOv4	eight types of rice diseases	91.14%
[12]	Residual Neural Network	three types of diseases	95.83%
Proposed system	CNN+YOLOv5	Nine types of rice diseases	94.60% 97.28%

8. CONCLUSION

In this study, we provided a model for detecting rice diseases using the YOLOv5 technique and classifying disorders using CNN. We thoroughly examined the identification of rice diseases that included both groups of diseases and healthy plants. The highest classification accuracy by CNN is 97.28%, and YOLO's greatest average detection accuracy is 94.60%. As suggested, additional research can be conducted to identify and categorize all varieties of plant diseases. The fundamental difficulty in creating an object detection model using machine learning was gathering many training images with various background types, lighting conditions, aspect ratios, and size, shape, and size variations. By combining the strengths of YOLO and CNN, a hybrid model can provide a solution for object detection and classification that is highly accurate, computationally efficient, capable of handling multi-scale objects, robust to partial occlusion, and can leverage transfer learning. This system can be integrated with an IOT server to implement remote areas.

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