Image-Based Deep Learning Method for Detecting Diseases in Rice Plants

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ABSTRACT

India's rapidly growing population demands increased agricultural productivity, particularly in rice cultivation, which is vital to national food security. However, rice crops are highly susceptible to various leaf diseases such as Brown Spot, Blast, and Bacterial Blight, which significantly reduce yield and quality. Timely and accurate identification of these diseases is essential to prevent widespread outbreaks and reduce excessive pesticide use. This study proposes a deep learning-based approach for automated rice leaf disease detection. Three state-of-the-art models—YOLOv5, DenseNet-201, and ResNet-101—were evaluated using a publicly available rice disease dataset. All models were trained and tested on the Google Colab platform. This study aimed to identify the most effective and practical model for real-world deployment. The results show that YOLOv5 outperformed DenseNet-201 and ResNet-101 in detection accuracy, offering a robust and scalable solution for real-time disease identification. This work contributes to precision agriculture by enabling early diagnosis and informed decision-making, ultimately improving crop health and promoting sustainable farming practices.

Keywords-deep learning; DenseNet; ResNet; YOLOv5; rice leaf disease

I. INTRODUCTION

Rice is the main food for approximately 50% of the world's population, highlighting its vital role in global nutrition and food security. More than a hundred countries across the world cultivate rice. Approximately 700 million tons of rice are produced annually from the harvest of 158 million hectares of paddy. Compared to other continents, the majority of the world's rice is produced in Asia [1]. However, rapid climate change and global warming affect the agricultural industry [2]. A variety of plant diseases impact crop yield, both in quantity and quality, endangering the world's food supply. In recent years, several diseases have been observed, such as rice leaf blast, brown spot, blight, and rice curl [3]. Therefore, preventing diseases is essential to rice production [4]. Currently, manual diagnosis is the most commonly used technique for identifying diseases of rice crops. However, a more efficient and practical way to diagnose rice diseases is required, since not enough personnel are skilled enough to complete such duties promptly.

An automated method to detect outbreaks of rice disease could provide guidance on how to stop and cure the disease, reduce losses, and improve the yield and quality of agricultural goods. One of the most recent developments in agriculture is the application of AI and ML techniques to encourage farmers and researchers in many sectors with early identification of rice diseases [5]. Innovative and advanced technologies have improved the efficiency and productivity of rice-based systems to support food security [6]. With the rapid progress of computer technology, various machine learning algorithms have been explored to classify diseases that affect rice [7]. Deep learning has recently seen widespread use in various fields of computer vision and image analysis, consistently delivering promising results [8]. In addition, the development of deep learning and machine learning techniques has contributed significantly to advances in multiple areas, especially in agricultural applications such as disease detection from images.

Compared to machine learning, deep learning offers the benefit of extracting characteristics layer by layer and having its own feature generator, leading to faster and more precise detection [9]. Due to their strong feature extraction capabilities and autonomous learning, deep learning models have shown remarkable results in the identification of crop diseases [10]. However, the model's ability to extract numerous practical characteristics during training determines how well it works on plant disease detection.

II. RELATED RESEARCH

Many researchers have engaged in the field of identification and classification of rice diseases. Diseases are classified once a Region of Interest (RoI) of afflicted rice leaves has been extracted [11]. The study in [12] examined how rice plant diseases may be identified from images of sick plants. Agricultural research uses a wide range of classification techniques, such as Probabilistic Neural Networks (PNN), Genetic Algorithms (GA), K-Nearest Neighbor (KNN), and Support Vector Machines (SVM). In [13], an overview of the principles of machine learning and image preprocessing used in the identification and categorization of diseased rice leaves was provided. The stages included image preprocessing, feature extraction, normalization, segmentation, and classification. In [14], an algorithm was developed to identify the color and form characteristics of the diseased leaf portion, and then classify the diseases using MDC and KNN. Although the identification capacity of this method was very narrow, it had benefits in terms of accuracy and time complexity, producing positive outcomes for four diseases.

In [15], pre-trained CNN architectures, such as ResNet, were used to solve vanishing gradient issues. This study also incorporated self-attention methods to improve feature selection. The results showed that the ResNet34 model with self-attention outperformed cutting-edge methods in multiclass classification, achieving high precision in the detection and classification of rice leaf diseases. CNNs can detect and classify diseases, and the agriculture industry may be able to solve its challenges with the help of image processing [16]. In [17], a deep CNN was used to identify infection from ten prevalent rice crop diseases in leaves. In [18], a deep feature-oriented rice plant disease diagnosis method was proposed, using SVM. In [19], the segmentation and classification of leaf diseases in biofuel crops were explored using machine learning and computer vision methods. Techniques such as Naive Bayes (NB), Logistic Regression (LR), KNN, Random Forest (RF), and Regression Trees (RT) were used to classify diseases affecting crop leaves. In [20], CNNs were used to classify different pest and disease species. There are several object detection model families, including YOLO, MobileNet, Fast RCNN, Faster RCNN, and RCNN. YOLO models provide promising solutions in this field, which are known for their real-time object detection capabilities, as they enable timely management and intervention by precisely and swiftly identifying plant diseases. Using YOLO models in agricultural systems has several advantages, such as better crop health and production, lower labor costs, and greater disease detection efficiency.

III. RICE PLANT DISEASES

From seed to harvest, the rice plant can be affected by several diseases. The main harmful rice leaf diseases are listed below.

A. *Leaf Blast*

Rice blast disease is caused by a fungus and is considered one of the most devastating diseases affecting rice crops, responsible for up to 30% yield loss [21]. This disease initially appears as small necrotic lesions on the leaves. As the infection progresses, symptoms spread to the leaf sheath and blade. Eventually, it affects grain filling, resulting in poor-quality grains. The roots of the plant can also be affected, and the fungus is capable of infecting the plant at any growth stage. Rice blast is particularly severe, often destroying entire fields. The presence of spots on the plant may be an early indicator of the infection. Environmental factors can influence changes in crop size and shape. Registered fungicides are used to manage this disease.

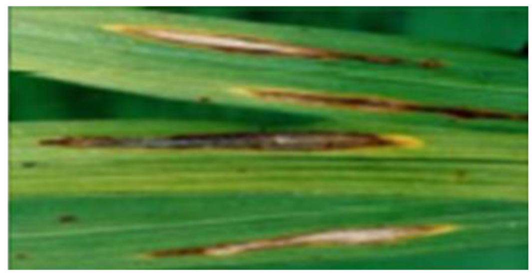

Fig. 1. Leaf blast.

B. *Bacterial Blight*

Bacterial blight (Figure 2) is a damaging disease that affects rice leaves and plants. It reduces the rice plant's vitality, causing 70% of the crop's grain to be lost, and can affect more than 100 acres [22]. This disease attacks in the early stages of plant growth. The bacterium that causes this disease can spread over the field due to strong winds or heavy rain. When bacterial blight affects rice plants, the leaves turn yellow and roll up, indicating that the disease is progressing, and the leaves turn straw in color.

Fig. 2. Bacterial blight.

C. *Brown Spot*

The symptoms of brown spot disease usually manifest as tiny oval to elongated lesions on the leaves of afflicted plants. As seen in Figure 3, these lesions may have a deeper brown border and a range in hue, from light brown to tan. Larger amounts of contaminated tissue may result from the lesions coalescing over time. It is encouraged by warm and humid conditions, which stimulate the growth and spread of fungal diseases [23]. Areas with thick plants, excessive humidity, and inadequate air circulation are often affected by the disease. Rain splash, wind, and machinery that comes into contact with contaminated plant material can all spread it.

Fig. 3. Brown spot.

D. *Leaf Scald*

The bacterium Xylella fastidiosa is the cause of leaf scald, or bacterial leaf scorch. Numerous plant species suffer from a variety of diseases caused by this bacterium. Trees are the main victims of leaf scald, which manifests as symptoms resembling water stress and leaf damage. Similar to symptoms observed in plants under drought stress, browning and blistering of the leaf edges are signs of leaf scald, as shown in Figure 4.

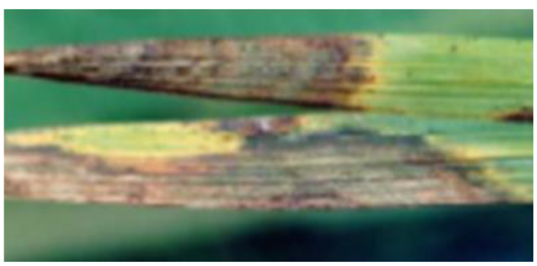

Fig. 4. Leaf scald.

E. *Sheath Blight*

Figure 5 shows sheath blight, also known as Rhizoctonia sheath blight, which is a devastating fungal disease that affects a variety of grasses, and one of its most economically important hosts is rice. The Rhizoctonia solani is the cause of this disease. Its symptoms usually manifest on the leaf sheaths, stems, and occasionally the leaves of infected plants.

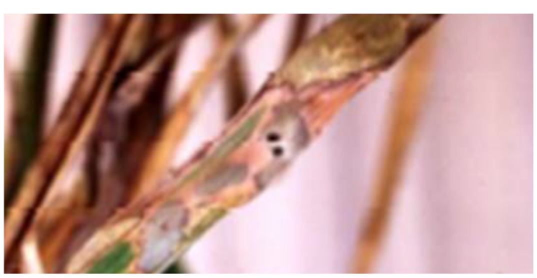

Fig. 5. Sheath blight.

IV. METHODOLOGY

A. *Proposed Method*

Figure 6 illustrates a pipeline for the detection of rice leaf diseases using deep learning models. The process starts with the collection of rice leaf images, which includes both healthy and diseased leaves (input dataset). In the next stage, image preprocessing is performed to improve the quality and uniformity of the model input. Preprocessing may involve resizing, normalization, noise removal, and segmentation. After preprocessing, the system identifies the type of disease from the leaf images. Diseases include bacterial leaf blight, brown spot, leaf blast, and leaf scald. Training data include preprocessed and labeled leaf samples. Data augmentation is applied, creating variations in the images to prevent overfitting. This data is used to train models that learn to recognize patterns and identify diseases. Accuracy, precision, recall, and F1 score are used to assess the trained model on test data.

B. *ResNet*

ResNet is used to analyze and extract key features from the images. By avoiding non-linear transformations through the use of skip-connections and identity approaches, the ResNet architecture enables direct gradient flow from back to front layers using the identity function [24]. This study used the ResNet-101 model. This CNN is made up of multiple convolutional layers that extract features and turn input images into hierarchical quality maps, which range from simple features such as borders and lines to more intricate features such as shapes and colors. Pooling layers are used to minimize the dimensionality of retrieved features, and fully connected layers integrate them and produce the class's final probability value. The more network layers, the more features the algorithm can learn. Recent studies show that network depth improves categorization accuracy. As a result, ResNet allows for greater accuracy from a much deeper network than from shallower networks while conducting image classification tasks.

C. *DenseNet*

DenseNet performs complex conversions that, to some extent, overcome the problem of a lack of consequent location information for features. DenseNet enhances feature propagation and reusability, making identification faster [25]. A nonlinear transformation $H(.)$ uses many approaches, including batch normalisation, ReLU unit activation, a 1×1 convolution layer to reduce total channels, and a 3×3 convolution layer for key-point rearrangement. DenseNet uses dense blocks to generate dense connections between layers. DenseNet's feedforward method connects each layer to the previous one. The gradient and loss function are accessible to all layer feature maps, resulting in improved gradient flow through the network. This study used the DenseNet-201 model.

D. *YOLOv5*

The YOLO family offers quick object identification methods, steadily becoming better and performing well for its size [26]. YOLOv5 is one of the most successful versions, according to previous research [27]. Figure 9 shows YOLOv5's architecture, which is separated into three parts.

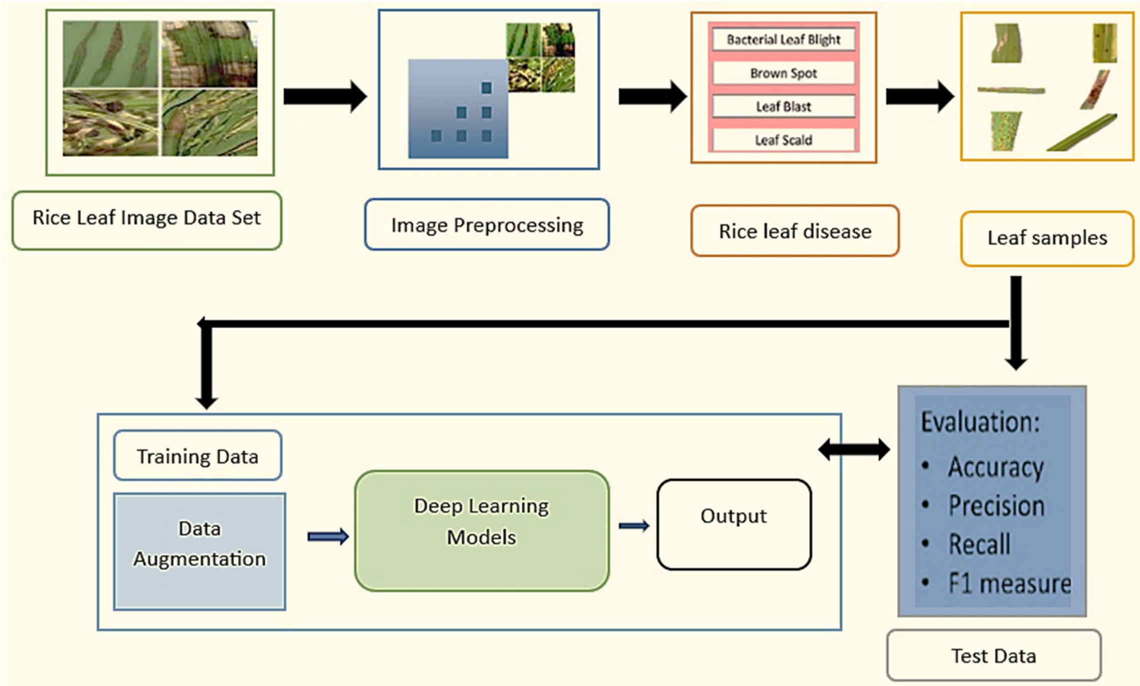

Fig. 6. Workflow of the proposed method for leaf disease detection..

1) Backbone

This part extracts important features from an input image, using a framework known as CSP (Cross Stage Partial networks). Compared to other large-scale CNNs, the bottleneck structure can reduce duplication of gradient information during training.

2) Neck

In deep learning models, the neck component is typically responsible for constructing feature pyramids, which play a critical role in managing object scaling. Feature pyramids enhance the model's ability to generalize across diverse scenarios and significantly improve the classification accuracy for five distinct rice diseases within the dataset, since they facilitate the detection of similar objects at varying sizes and scales. Various architectures employ different strategies for feature pyramid construction, such as feature pyramid networks and path aggregation networks. Specifically, YOLOv5 utilizes PANet as its neck module to build an effective feature pyramid structure.

3) Head

The detection procedure terminates at the head, which uses anchor boxes that comprise bounding boxes and class probabilities, to generate final output vectors. YOLO is trained using a loss function that directly relates to object detection accuracy. It efficiently identifies objects by analyzing the entire image and quickly generating bounding boxes based on its visual features. In the context of rice disease detection, YOLO applies a candidate box extraction technique to assess whether a disease is present in an image and to pinpoint its exact location. The image is divided into an $N \times N$ grid, where each grid cell predicts potential object boundaries and the likelihood of a disease being present within each predicted box.

E. Assessment Metrics

The following metrics were used to evaluate model performance:

- Accuracy is the proportion of correctly calculated sample points among all sample points, measured using:

$$Accuracy = \left(\frac{TP+TN}{TP+FP+TN+FN}\right) * 100 \quad (1)$$

- Precision measures how many of the positively predicted instances are actually positive, calculated using:

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

- Recall measures the actual negative instances to the total cases of disease, calculated using:

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

- F1-score: The harmonic mean of the model's recall and accuracy is known as the F1-score, calculated using:

$$F1 - score = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \quad (4)$$

In these formulas, TP and TN stand for the true positive and true negative predictions, while FP and FN stand for false positive and false negative predictions.

V. RESULTS

A. Dataset

The rice leaf disease dataset was collected through the Internet, totalling 2627 images in train and validation folders [28]. This dataset includes images with bacterial leaf blight, brown spot, healthy, leaf blast, leaf scald, and narrow brown spot.

B. Dataset Augmentation and Split

Data annotation was performed using the Roboflow platform to store it in the YOLO format. Every object in each image has a bounding box attached to its respective text file. After annotation, the images were resized to 320×320 pixels. Data augmentation involved flipping, rotation, and saturation, resulting in 35,000 images.

The annotated dataset was then split into two subsets for training (85%) and testing (15%). To ensure the robustness and generalizability of the deep learning models, k-fold cross-validation was used during the training phase. Specifically, 5-fold cross-validation was used, where the training dataset was split into five equal subsets. The model was trained on four subsets and validated on the remaining one, rotating the validation set in each iteration. The average performance across all folds was recorded to minimize variance due to data splitting and provide a more reliable estimate of model performance. Random search was used for hyperparameter tuning to optimize learning rate, dropout, etc.

C. Results

Generalized IoU (GioU) loss served as the bounding box's loss function. The GIoU function was used to calculate the degree of deviation between the model's prediction and the actual case.

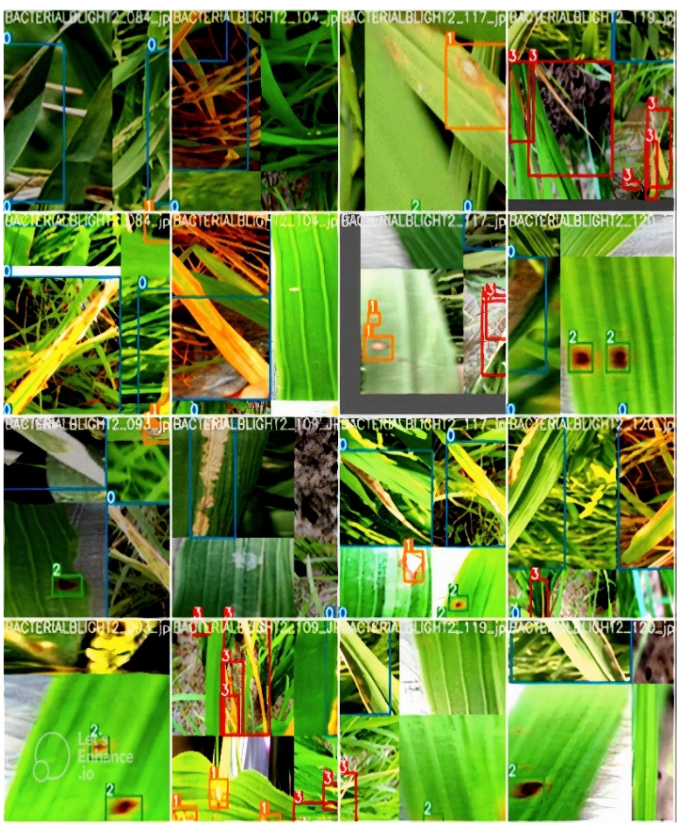

Fig. 7. Training process.

Fig. 8. Testing process.

In the training process, as shown in Figure 10, bounding boxes are color-coded based on the disease type: blue boxes (label 0) represent bacterial blight, orange boxes (label 1) indicate blast disease, and green boxes (label 2) correspond to brown spot diseases. The labels and predicted values are displayed accordingly in the test images. Initially, experiments were performed using deep learning models for normalized and augmented data. Table I shows the output results and Table II shows the training parameter settings.

TABLE I. COMPARISON OF EXPERIMENTAL RESULTS

Model	Accuracy	Precision	Recall	F1
ResNet-101	82.35%	0.8265	0.8523	0.8370
DenseNet-201	85.23%	0.8723	0.8714	0.8677
YOLOv5	89.95%	0.8996	0.8834	0.8979

TABLE II. PARAMETER SETTINGS

Parameter	Values
Learning rate	0.01
Epochs	100
Batch size	12
Dropout	0.005

Figure 9 shows class-wise confusion matrices. For the augmented dataset, YOLOv5 attained an average accuracy of 89.95%, and ResNet-101 achieved the lowest mean accuracy of 82.35%. Figure 10 depicts the five performance metrics of the three models. YOLOv5 consistently outperformed all others across all evaluation metrics, achieving the highest performance, especially in recall.

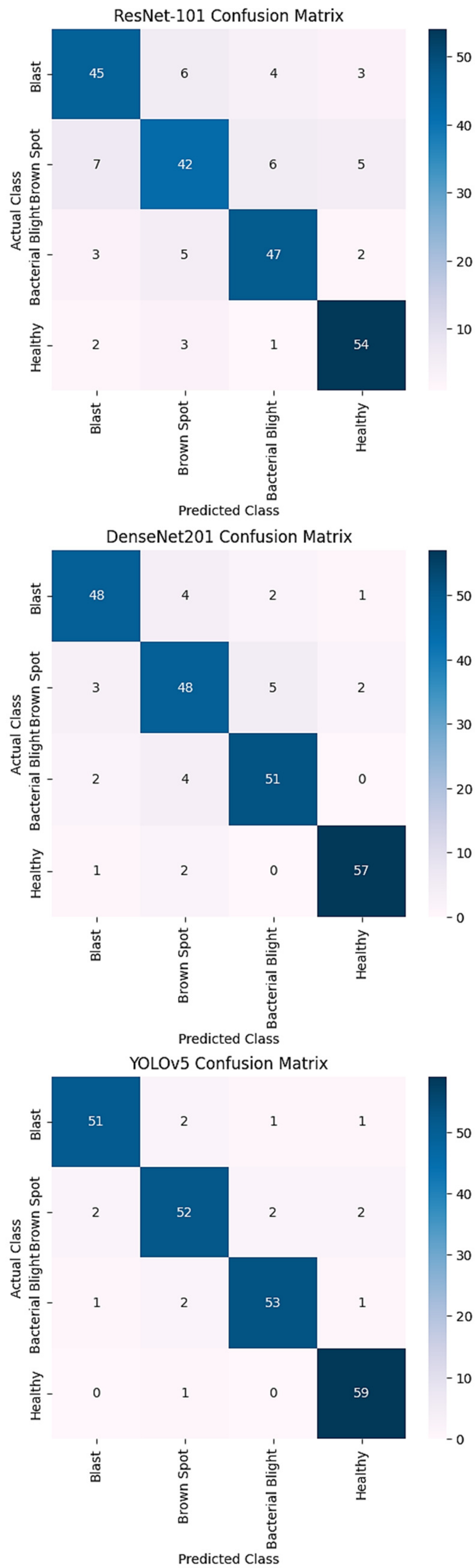

Fig. 9. Class-wise confusion matrices.

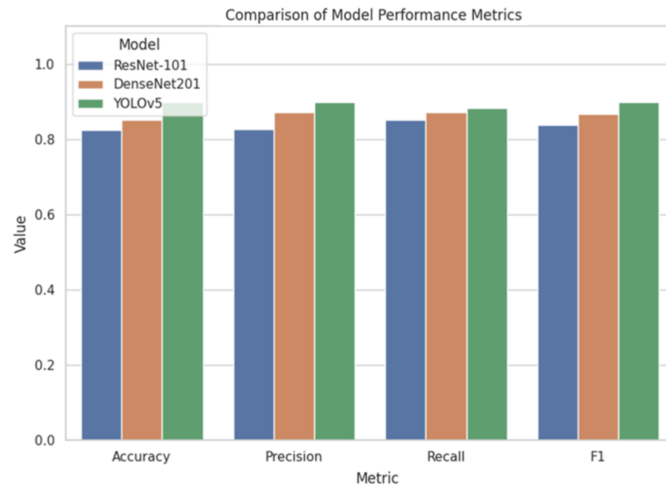

Fig. 10. Model performance comparison.

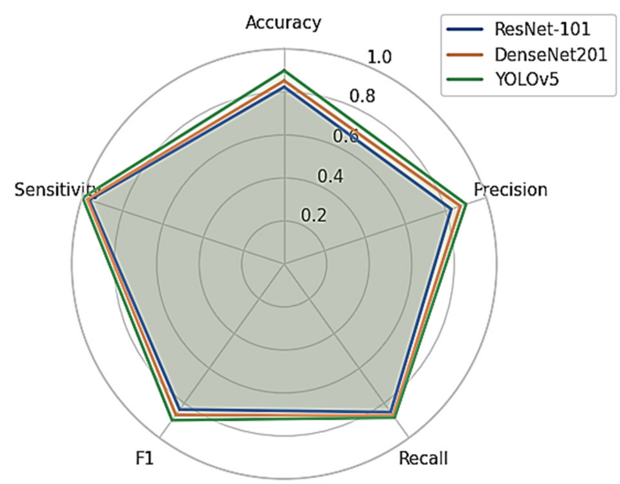

Fig. 11. Radar comparison.

The radar graphic in Figure 11 compares the YOLOv5, DenseNet-201, and ResNet-101 models. YOLOv5 achieved the highest overall performance in all criteria. In most criteria, DenseNet-201 outperformed ResNet-101 by a little margin. Particularly in recall, where the difference is negligible, all three models perform quite well. YOLOv5 has an advantage in accuracy and F1-score, with a more pronounced performance difference.

VI. CONCLUSION

The leaf is a primary site for the early manifestation of plant diseases, with different infections causing distinct visual symptoms that enable their differentiation. Given that rice serves as a basic food for more than half of the global population, ensuring the health of rice crops is of paramount importance. Diseases affecting rice plants significantly reduce both yield and grain quality. Conventional disease identification methods rely heavily on farmers' expertise and require extensive manual inspection of large agricultural areas, which is both time-consuming and labor-intensive. Recent advances have enabled the development of automated systems capable of leveraging the visual signatures of rice leaf diseases.

This study investigated the performance of three deep learning architectures—YOLOv5, DenseNet-201, and ResNet-101—for accurate classification and diagnosis of rice leaf diseases. Using a normalized and augmented dataset, the YOLOv5 model achieved the highest mean classification accuracy of 89.95%, along with a precision of 0.8996, a recall of 0.8834, and an F1-score of 0.8979, exhibiting its effectiveness for automated rice leaf disease diagnosis.

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